A FIRST JOURNEY THROUGH LINEAR ALGEBRA



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A First Journey Through Linear Algebra

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1.1: Systems of Equations, Geometry

Systems of Equations, Geometry

Outcomes

A. Relate the types of solution sets of a system of two (three) variables to the intersections of lines in a plane (the intersection of planes in three space)

As you may remember, linear equations like $2x + 3y = 6$ can be graphed as straight lines in the coordinate plane. We say that this equation is in two variables, in this case x and y. Suppose you have two such equations, each of which can be graphed as a straight line, and consider the resulting graph of two lines. What would it mean if there exists a point of intersection between the two lines? This point, which lies on *both* graphs, gives x and y values for which both equations are true. In other words, this point gives the ordered pair (x, y) that satisfy both equations. If the point (x, y) is a point of intersection, we say that (x, y) is a **solution** to the two equations. In linear algebra, we often are concerned with finding the solution(s) to a system of equations, if such solutions exist. First, we consider graphical representations of solutions and later we will consider the algebraic methods for finding solutions.

When looking for the intersection of two lines in a graph, several situations may arise. The following picture demonstrates the possible situations when considering two equations (two lines in the graph) involving two variables.

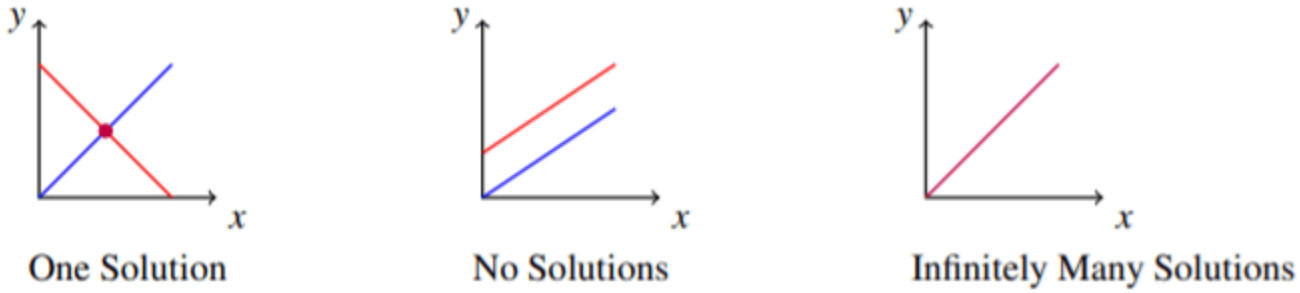


Figure 1.1.1

In the first diagram, there is a unique point of intersection, which means that there is only one (unique) solution to the two equations. In the second, there are no points of intersection and no solution. When no solution exists, this means that the two lines are parallel and they never intersect. The third situation which can occur, as demonstrated in diagram three, is that the two lines are really the same line. For example, $x + y = 1$ and $2x + 2y = 2$ are equations which when graphed yield the same line. In this case there are infinitely many points which are solutions of these two equations, as every ordered pair which is on the graph of the line satisfies both equations. When considering linear systems of equations, there are always three types of solutions possible; exactly one (unique) solution, infinitely many solutions, or no solution.

Example 1.1.1: A Graphical Solution

Use a graph to find the solution to the following system of equations

$$x + y = 3$$
$$y - x = 5$$

Solution

Through graphing the above equations and identifying the point of intersection, we can find the solution(s). Remember that we must have either one solution, infinitely many, or no solutions at all. The following graph shows the two equations, as well as the intersection. Remember, the point of intersection represents the solution of the two equations, or the (x, y) which satisfy both equations. In this case, there is one point of intersection at $(-1, 4)$ which means we have one unique solution, $x = -1, y = 4$.

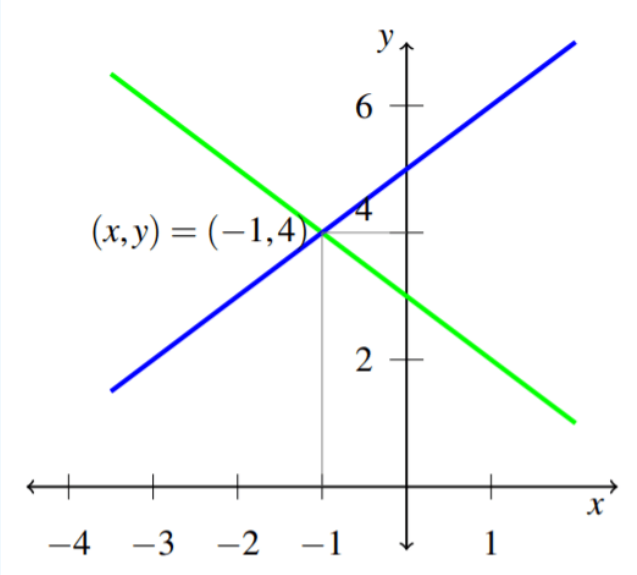


Figure 1.1.2

In the above example, we investigated the intersection point of two equations in two variables, x and y. Now we will consider the graphical solutions of three equations in two variables.

Consider a system of three equations in two variables. Again, these equations can be graphed as straight lines in the plane, so that the resulting graph contains three straight lines. Recall the three possible types of solutions; no solution, one solution, and infinitely many solutions. There are now more complex ways of achieving these situations, due to the presence of the third line. For example, you can imagine the case of three intersecting lines having no common point of intersection. Perhaps you can also imagine three intersecting lines which do intersect at a single point. These two situations are illustrated below.

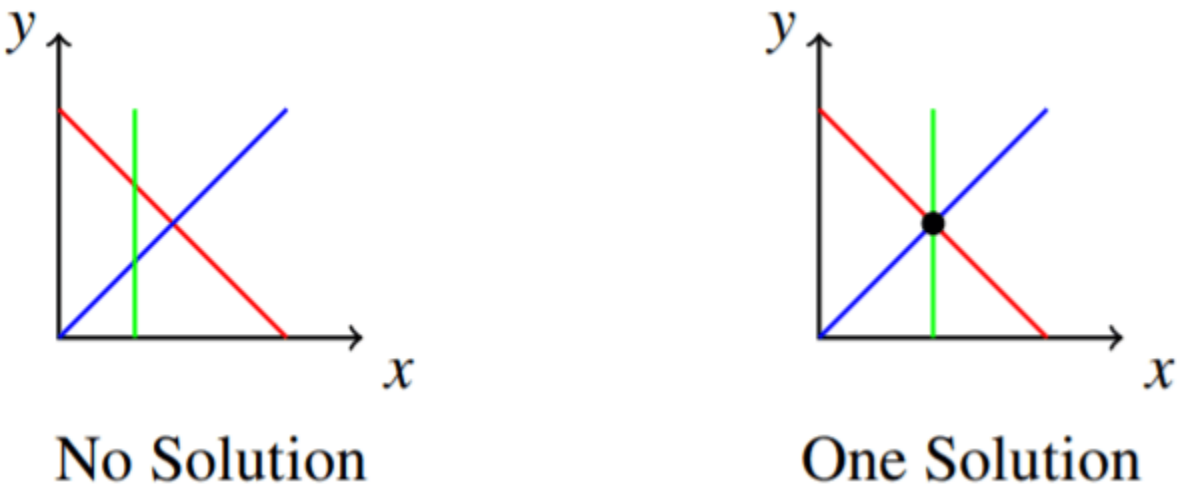


Figure 1.1.3

Consider the first picture above. While all three lines intersect with one another, there is no common point of intersection where all three lines meet at one point. Hence, there is no solution to the three equations. Remember, a solution is a point (x, y) which satisfies **all** three equations. In the case of the second picture, the lines intersect at a common point. This means that there

is one solution to the three equations whose graphs are the given lines. You should take a moment now to draw the graph of a system which results in three parallel lines. Next, try the graph of three identical lines. Which type of solution is represented in each of these graphs?

We have now considered the graphical solutions of systems of two equations in two variables, as well as three equations in two variables. However, there is no reason to limit our investigation to equations in two variables. We will now consider equations in three variables.

You may recall that equations in three variables, such as $2x + 4y - 5z = 8$, form a plane. Above, we were looking for intersections of lines in order to identify any possible solutions. When graphically solving systems of equations in three variables, we look for intersections of planes. These points of intersection give the (x, y, z) that satisfy all the equations in the system. What types of solutions are possible when working with three variables? Consider the following picture involving two planes, which are given by two equations in three variables.

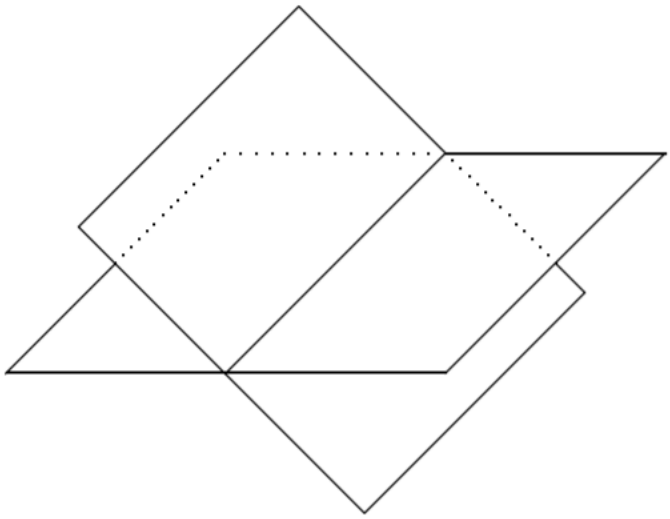


Figure 1.1.4

Notice how these two planes intersect in a line. This means that the points (x, y, z) on this line satisfy both equations in the system. Since the line contains infinitely many points, this system has infinitely many solutions.

It could also happen that the two planes fail to intersect. However, is it possible to have two planes intersect at a single point? Take a moment to attempt drawing this situation, and convince yourself that it is not possible! This means that when we have only two equations in three variables, there is no way to have a unique solution! Hence, the types of solutions possible for two equations in three variables are no solution or infinitely many solutions.

Now imagine adding a third plane. In other words, consider three equations in three variables. What types of solutions are now possible? Consider the following diagram.

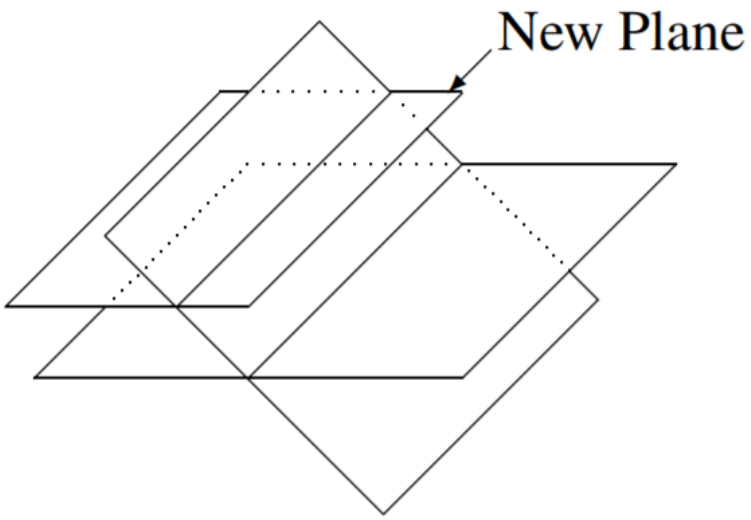


Figure 1.1.5

In this diagram, there is no point which lies in all three planes. There is no intersection between **all** planes so there is no solution. The picture illustrates the situation in which the line of intersection of the new plane with one of the original planes forms a line parallel to the line of intersection of the first two planes. However, in three dimensions, it is possible for two lines to fail to intersect even though they are not parallel. Such lines are called **skew lines**.

Recall that when working with two equations in three variables, it was not possible to have a unique solution. Is it possible when considering three equations in three variables? In fact, it is possible, and we demonstrate this situation in the following picture.

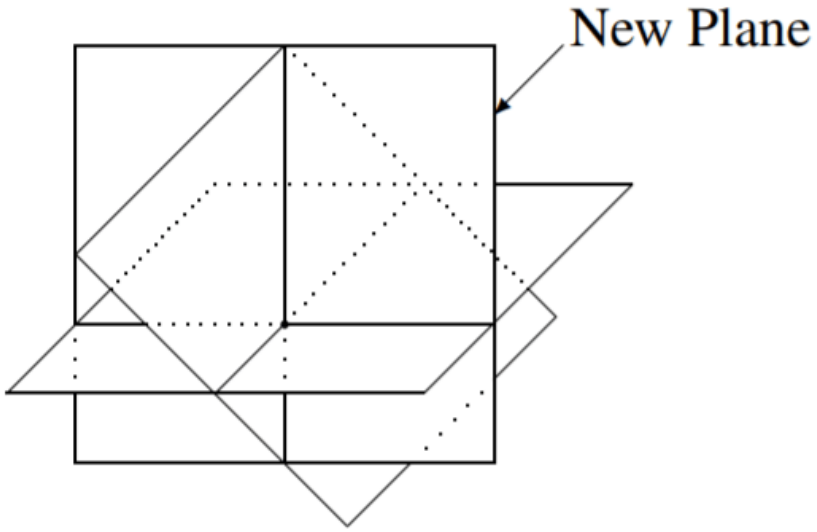


Figure 1.1.6

In this case, the three planes have a single point of intersection. Can you think of other types of solutions possible? Another is that the three planes could intersect in a line, resulting in infinitely many solutions, as in the following diagram.

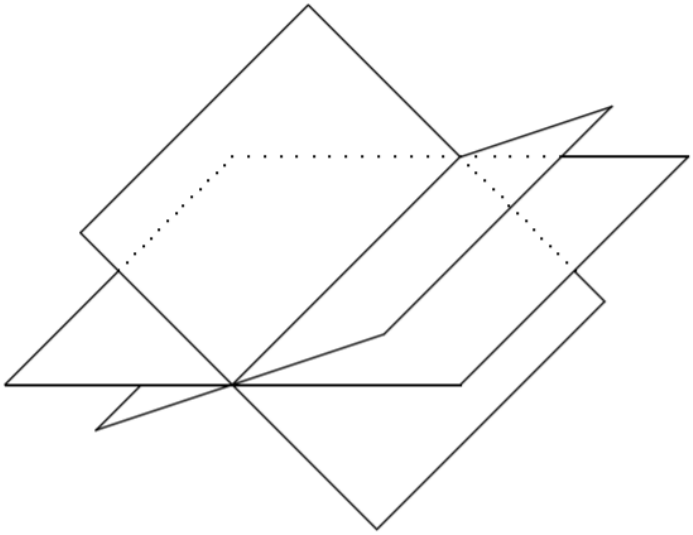


Figure 1.1.7

We have now seen how three equations in three variables can have no solution, a unique solution, or intersect in a line resulting in infinitely many solutions. It is also possible that the three equations graph the same plane, which also leads to infinitely many solutions.

You can see that when working with equations in three variables, there are many more ways to achieve the different types of solutions than when working with two variables. It may prove enlightening to spend time imagining (and drawing) many possible scenarios, and you should take some time to try a few.

You should also take some time to imagine (and draw) graphs of systems in more than three variables. Equations like $x + y - 2z + 4w = 8$ with more than three variables are often called **hyper-planes**. You may soon realize that it is tricky to draw the graphs of hyper-planes! Through the tools of linear algebra, we can algebraically examine these types of systems which are difficult to graph. In the following section, we will consider these algebraic tools.

Exercise 1.1.1

Graphically, find the point (x_1, y_1) which lies on both lines, $x + 3y = 1$ and $4x - y = 3$. That is, graph each line and see where they intersect.

Exercise 1.1.2

Graphically, find the point of intersection of the two lines, $3x + y = 3$ and $x + 2y = 1$. That is, graph each line and see where they intersect

Exercise 1.1.3

You have a system of k equations in two variables, $k \geq 2$. Explain the geometric significance of

a. No solution.
b. A unique solution.
c. An infinite number of solutions.

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1.2: Systems of Equations, Algebraic Procedures

Algebraic Procedures

Outcomes

A. Use elementary operations to find the solution to a linear system of equations.
B. Find the row-echelon form and reduced row-echelon form of a matrix.
C. Determine whether a system of linear equations has no solution, a unique solution or an infinite number of solutions from its .
D. Solve a system of equations using Gaussian Elimination and Gauss-Jordan Elimination.
E. Model a physical system with linear equations and then solve.

We have taken an in depth look at graphical representations of systems of equations, as well as how to find possible solutions graphically. Our attention now turns to working with systems algebraically.

Definition 1.2.1: System of Linear Equations

A **system of linear equations** is a list of equations,

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n &= b_1 \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n &= b_2 \\ &\vdots \\ a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n &= b_m \end{aligned}$$

where a_{ij} and b_j are real numbers. The above is a system of m equations in the n variables, $x_1, x_2 \cdots, x_n$. Written more simply in terms of summation notation, the above can be written in the form

$$\sum_{j=1}^{n} a_{ij}x_j = b_i, \;\; i = 1, 2, 3, \cdots, m$$

The relative size of m and n is not important here. Notice that we have allowed a_{ij} and b_j to be any real number. We can also call these numbers **scalars** . We will use this term throughout the text, so keep in mind that the term **scalar** just means that we are working with real numbers.

Now, suppose we have a system where $b_i = 0$ for all i. In other words every equation equals 0. This is a special type of system.

Definition 1.2.2: Homogeneous System of Equations

A system of equations is called **homogeneous** if each equation in the system is equal to 0. A homogeneous system has the form

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n &= 0 \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n &= 0 \\ &\vdots \\ a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n &= 0 \end{aligned}$$

where a_{ij} are scalars and x_i are variables.

Recall from the previous section that our goal when working with systems of linear equations was to find the point of intersection of the equations when graphed. In other words, we looked for the solutions to the system. We now wish to find these solutions algebraically. We want to find values for $x_1, \cdots, x_n$ which solve all of the equations. If such a set of values exists, we call $(x_1, \cdots, x_n)$

the **solution set**.

Recall the above discussions about the types of solutions possible. We will see that systems of linear equations will have one unique solution, infinitely many solutions, or no solution. Consider the following definition.

Definition 1.2.3: Consistent and Inconsistent Systems

A system of linear equations is called **consistent** if there exists at least one solution. It is called **inconsistent** if there is no solution.

If you think of each equation as a condition which must be satisfied by the variables, consistent would mean there is some choice of variables which can satisfy **all** the conditions. Inconsistent would mean there is no choice of the variables which can satisfy all of the conditions.

The following sections provide methods for determining if a system is consistent or inconsistent, and finding solutions if they exist.

Elementary Operations

We begin this section with an example. Recall from Example 1.1.1 that the solution to the given system was $(x, y) = (-1, 4)$.

Example 1.2.1: Verifying an Ordered Pair is a Solution

Algebraically verify that $(x, y) = (-1, 4)$ is a solution to the following system of equations.

$$\begin{aligned} x + y &= 3 \\ y - x &= 5 \end{aligned}$$

Solution

By graphing these two equations and identifying the point of intersection, we previously found that $(x, y) = (-1, 4)$ is the unique solution.

We can verify algebraically by substituting these values into the original equations, and ensuring that the equations hold. First, we substitute the values into the first equation and check that it equals 3.

$$x + y = (-1) + (4) = 3$$

This equals 3 as needed, so we see that $(-1, 4)$ is a solution to the first equation. Substituting the values into the second equation yields

$$y - x = (4) - (-1) = 4 + 1 = 5$$

which is true. For $(x, y) = (-1, 4)$ each equation is true and therefore, this is a solution to the system.

Now, the interesting question is this: If you were not given these numbers to verify, how could you algebraically determine the solution? Linear algebra gives us the tools needed to answer this question. The following basic operations are important tools that we will utilize.

Definition 1.2.4: Elementary Operations

Elementary operations are those operations consisting of the following.

1. Interchange the order in which the equations are listed.
2. Multiply any equation by a nonzero number.
3. Replace any equation with itself added to a multiple of another equation.

It is important to note that none of these operations will change the set of solutions of the system of equations. In fact, elementary operations are the *key tool* we use in linear algebra to find solutions to systems of equations.

Consider the following example.

Example 1.2.2: Effects of an Elementary Operation

Show that the system

$$\begin{aligned} x+y &= 7 \\ 2x-y &= 8 \end{aligned}$$

has the same solution as the system

$$\begin{aligned} x+y &= 7 \\ -3y &= -6 \end{aligned}$$

Solution

Notice that the second system has been obtained by taking the second equation of the first system and adding -2 times the first equation, as follows:

$$2x-y+(-2)(x+y) = 8+(-2)(7)$$

By simplifying, we obtain

$$-3y = -6$$

which is the second equation in the second system. Now, from here we can solve for y and see that $y=2$. Next, we substitute this value into the first equation as follows

$$x+y = x+2 = 7$$

Hence $x=5$ and so $(x,y)=(5,2)$ is a solution to the second system. We want to check if $(5,2)$ is also a solution to the first system. We check this by substituting $(x,y)=(5,2)$ into the system and ensuring the equations are true.

$$\begin{aligned} x+y &= (5)+(2) = 7 \\ 2x-y &= 2(5)-(2) = 8 \end{aligned}$$

Hence, $(5,2)$ is also a solution to the first system.

This example illustrates how an elementary operation applied to a system of two equations in two variables does not affect the solution set. However, a linear system may involve many equations and many variables and there is no reason to limit our study to small systems. For any size of system in any number of variables, the solution set is still the collection of solutions to the equations. In every case, the above operations of Definition 1.2.4 do not change the set of solutions to the system of linear equations.

In the following theorem, we use the notation E_i to represent an equation, while b_i denotes a constant.

Theorem 1.2.1: Elementary Operations and Solutions

Suppose you have a system of two linear equations

$$\begin{aligned} E_1 &= b_1 \\ E_2 &= b_2 \end{aligned} \tag{1.2.1}$$

Then the following systems have the same solution set as (1.2.1):

1. $$\begin{aligned} E_2 &= b_2 \\ E_1 &= b_1 \end{aligned} \tag{1.2.2}$$

2. $$\begin{aligned} E_1 &= b_1 \\ kE_2 &= kb_2 \end{aligned} \tag{1.2.3}$$

for any scalar k, provided $k \neq 0$.

3. $$\begin{aligned} E_1 &= b_1 \\ E_2 + kE_1 &= b_2 + kb_1 \end{aligned} \tag{1.2.4}$$

for any scalar k (including $k = 0$).

Before we proceed with the proof of Theorem 1.2.1, let us consider this theorem in context of Example 1.2.2. Then,

$$\begin{aligned} E_1 &= x + y, \quad b_1 = 7 \\ E_2 &= 2x - y, \quad b_2 = 8 \end{aligned}$$

Recall the elementary operations that we used to modify the system in the solution to the example. First, we added (-2) times the first equation to the second equation. In terms of Theorem 1.2.1, this action is given by

$$E_2 + (-2)\, E_1 = b_2 + (-2)\, b_1$$

or

$$2x - y + (-2)\,(x + y) = 8 + (-2)\, 7$$

This gave us the second system in Example 1.2.2, given by

$$\begin{aligned} E_1 &= b_1 \\ E_2 + (-2)\, E_1 &= b_2 + (-2)\, b_1 \end{aligned}$$

From this point, we were able to find the solution to the system. Theorem 1.2.1 tells us that the solution we found is in fact a solution to the original system.

We will now prove Theorem 1.2.1.

Proof available at the end of this section.

Stated simply, the above theorem shows that the elementary operations do not change the solution set of a system of equations.

We will now look at an example of a system of three equations and three variables. Similarly to the previous examples, the goal is to find values for x, y, z such that each of the given equations are satisfied when these values are substituted in.

Example 1.2.3: Solving a System of Equations with Elementary Operations

Find the solutions to the system,

$$\begin{aligned} x + 3y + 6z &= 25 \\ 2x + 7y + 14z &= 58 \\ 2y + 5z &= 19 \end{aligned} \tag{1.2.5}$$

Solution

We can relate this system to Theorem 1.2.1 above. In this case, we have

$$\begin{aligned} E_1 &= x + 3y + 6z, \quad b_1 = 25 \\ E_2 &= 2x + 7y + 14z, \quad b_2 = 58 \\ E_3 &= 2y + 5z, \quad b_3 = 19 \end{aligned}$$

Theorem 1.2.1 claims that if we do elementary operations on this system, we will not change the solution set. Therefore, we can solve this system using the elementary operations given in Definition 1.2.4. First, replace the second equation by (-2) times the first equation added to the second. This yields the system

$$\begin{aligned} x + 3y + 6z &= 25 \\ y + 2z &= 8 \\ 2y + 5z &= 19 \end{aligned} \tag{1.2.6}$$

Now, replace the third equation with (-2) times the second added to the third. This yields the system

$$\begin{aligned} x+3y+6z &= 25 \\ y+2z &= 8 \\ z &= 3 \end{aligned} \tag{1.2.7}$$

At this point, we can easily find the solution. Simply take $z=3$ and substitute this back into the previous equation to solve for y, and similarly to solve for x.

$$\begin{aligned} x+3y+6\left(3\right) = x+3y+18 &= 25 \\ y+2\left(3\right) = y+6 &= 8 \\ z &= 3 \end{aligned}$$

The second equation is now

$$y+6=8$$

You can see from this equation that $y=2$. Therefore, we can substitute this value into the first equation as follows:

$$x+3\left(2\right)+18=25$$

By simplifying this equation, we find that $x=1$. Hence, the solution to this system is $(x,y,z)=(1,2,3)$. This process is called **back substitution**.

Alternatively, in (1.2.7) you could have continued as follows. Add (-2) times the third equation to the second and then add (-6) times the second to the first. This yields

$$\begin{aligned} x+3y &= 7 \\ y &= 2 \\ z &= 3 \end{aligned}$$

Now add (-3) times the second to the first. This yields

$$\begin{aligned} x &= 1 \\ y &= 2 \\ z &= 3 \end{aligned}$$

a system which has the same solution set as the original system. This avoided back substitution and led to the same solution set. It is your decision which you prefer to use, as both methods lead to the correct solution, $(x,y,z)=(1,2,3)$.

Answers

Theorem 1.2.1**: Elementary Operations and Solutions**

1. The proof that the systems (1.2.1) and (1.2.2) have the same solution set is as follows. Suppose that $(x_1,\cdots,x_n)$ is a solution to $E_1=b_1, E_2=b_2$. We want to show that this is a solution to the system in (1.2.2) above. This is clear, because the system in (1.2.2) is the original system, but listed in a different order. Changing the order does not effect the solution set, so $(x_1,\cdots,x_n)$ is a solution to (1.2.2).
2. Next we want to prove that the systems (1.2.1) and (1.2.3) have the same solution set. That is $E_1=b_1, E_2=b_2$ has the same solution set as the system $E_1=b_1, kE_2=kb_2$ provided $k\neq 0$. Let $(x_1,\cdots,x_n)$ be a solution of $E_1=b_1, E_2=b_2$,. We want to show that it is a solution to $E_1=b_1, kE_2=kb_2$. Notice that the only difference between these two systems is that the second involves multiplying the equation, $E_2=b_2$ by the scalar k. Recall that when you multiply both sides of an equation by the same number, the sides are still equal to each other. Hence if $(x_1,\cdots,x_n)$ is a solution to $E_2=b_2$, then it will also be a solution to $kE_2=kb_2$. Hence, $(x_1,\cdots,x_n)$ is also a solution to (1.2.3).
   Similarly, let $(x_1,\cdots,x_n)$ be a solution of $E_1=b_1, kE_2=kb_2$. Then we can multiply the equation $kE_2=kb_2$ by the scalar $1/k$, which is possible only because we have required that $k\neq 0$. Just as above, this action preserves equality and we obtain the equation $E_2=b_2$. Hence $(x_1,\cdots,x_n)$ is also a solution to $E_1=b_1, E_2=b_2$.
3. Finally, we will prove that the systems (1.2.1) and (1.2.4) have the same solution set. We will show that any solution of $E_1=b_1, E_2=b_2$ is also a solution of (1.2.4). Then, we will show that any solution of (1.2.4) is also a solution of $E_1=b_1, E_2=b_2$. Let $(x_1,\cdots,x_n)$ be a solution to $E_1=b_1, E_2=b_2$. Then in particular it solves $E_1=b_1$. Hence, it solves the first equation in (1.2.4). Similarly, it also solves $E_2=b_2$. By our proof of (1.2.3), it also solves $kE_1=kb_1$. Notice that if we add E_2 and kE_1, this is equal to b_2+kb_1. Therefore, if $(x_1,\cdots,x_n)$ solves $E_1=b_1, E_2=b_2$ it must also solve $E_2+kE_1=b_2+kb_1$.
   Now suppose $(x_1,\cdots,x_n)$ solves the system $E_1=b_1, E_2+kE_1=b_2+kb_1$. Then in particular it is a solution of $E_1=b_1$. Again by our proof of (1.2.3), it is also a solution to $kE_1=kb_1$. Now if we subtract these equal quantities from both sides of $E_2+kE_1=b_2+kb_1$ we obtain $E_2=b_2$, which shows that the solution also satisfies $E_1=b_1, E_2=b_2$.

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1.3: Gaussian Elimination

The work we did in the previous section will always find the solution to the system. In this section, we will explore a less cumbersome way to find the solutions. First, we will represent a linear system with an **augmented matrix.** A **matrix** is simply a rectangular array of numbers. The size or dimension of a matrix is defined as $m \times n$ where m is the number of rows and n is the number of columns. In order to construct an augmented matrix from a linear system, we create a **coefficient matrix** from the coefficients of the variables in the system, as well as a **constant matrix** from the constants. The coefficients from one equation of the system create one row of the augmented matrix.

For example, consider the linear system in Example 1.2.3

$$\begin{aligned} x + 3y + 6z &= 25 \\ 2x + 7y + 14z &= 58 \\ 2y + 5z &= 19 \end{aligned}$$

This system can be written as an augmented matrix, as follows

$$\begin{bmatrix} 1 & 3 & 6 & 25 \\ 2 & 7 & 14 & 58 \\ 0 & 2 & 5 & 19 \end{bmatrix}$$

Notice that it has exactly the same information as the original system. Here it is understood that the first column contains the coefficients from x in each equation, in order, $\begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix}$. Similarly, we create a column from the coefficients on y in each equation, $\begin{bmatrix} 3 \\ 7 \\ 2 \end{bmatrix}$ and a column from the coefficients on z in each equation, $\begin{bmatrix} 6 \\ 14 \\ 5 \end{bmatrix}$. For a system of more than three variables, we would continue in this way constructing a column for each variable. Similarly, for a system of less than three variables, we simply construct a column for each variable.

Finally, we construct a column from the constants of the equations, $\begin{bmatrix} 25 \\ 58 \\ 19 \end{bmatrix}$.

The rows of the augmented matrix correspond to the equations in the system. For example, the top row in the augmented matrix, $\left[\begin{array}{ccc|c} 1 & 3 & 6 & 25 \end{array}\right]$ corresponds to the equation

$$x + 3y + 6z = 25.$$

Consider the following definition.

Definition 1.3.1: Augmented Matrix of a Linear System

For a linear system of the form

$$\begin{aligned} a_{11}x_1 + \cdots + a_{1n}x_n &= b_1 \\ &\vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n &= b_m \end{aligned}$$

where the x_i are variables and the a_{ij} and b_i are constants, the augmented matrix of this system is given by

$$\begin{bmatrix} a_{11} & \cdots & a_{1n} & b_1 \\ \vdots & & \vdots & \vdots \\ a_{m1} & \cdots & a_{mn} & b_m \end{bmatrix}$$

Now, consider elementary operations in the context of the augmented matrix. The elementary operations in Definition 1.2.4 can be

used on the rows just as we used them on equations previously. Changes to a system of equations in as a result of an elementary operation are equivalent to changes in the augmented matrix resulting from the corresponding row operation. Note that Theorem 1.2.1 implies that any elementary row operations used on an augmented matrix will not change the solution to the corresponding system of equations. We now formally define elementary row operations. These are the *key tool* we will use to find solutions to systems of equations.

Definition 1.3.2: Elementary Row Operations

The **elementary row operations** (also known as **row operations**) consist of the following

1. Switch two rows.
2. Multiply a row by a nonzero number.
3. Replace a row by any multiple of another row added to it.

Recall how we solved Example 1.2.3. We can do the exact same steps as above, except now in the context of an augmented matrix and using row operations. The augmented matrix of this system is

$$\left[\begin{array}{rrrr} 1 & 3 & 6 & 25 \\ 2 & 7 & 14 & 58 \\ 0 & 2 & 5 & 19 \end{array}\right]$$

Thus the first step in solving the system given by (1.2.5) would be to take (-2) times the first row of the augmented matrix and add it to the second row,

$$\left[\begin{array}{rrrr} 1 & 3 & 6 & 25 \\ 0 & 1 & 2 & 8 \\ 0 & 2 & 5 & 19 \end{array}\right]$$

Note how this corresponds to (1.2.6). Next take (-2) times the second row and add to the third,

$$\left[\begin{array}{rrrr} 1 & 3 & 6 & 25 \\ 0 & 1 & 2 & 8 \\ 0 & 0 & 1 & 3 \end{array}\right]$$

This augmented matrix corresponds to the system

$$\begin{aligned} x + 3y + 6z &= 25 \\ y + 2z &= 8 \\ z &= 3 \end{aligned}$$

which is the same as (1.2.7). By back substitution you obtain the solution $x = 1, y = 2,$ and $z = 3$.

Through a systematic procedure of row operations, we can simplify an augmented matrix and carry it to **row-echelon form** or **reduced row-echelon form**, which we define next. These forms are used to find the solutions of the system of equations corresponding to the augmented matrix.

In the following definitions, the term **leading entry** refers to the first nonzero entry of a row when scanning the row from left to right.

Definition 1.3.3: Row-Echelon Form

An augmented matrix is in **row-echelon form** if

1. All nonzero rows are above any rows of zeros.
2. Each leading entry of a row is in a column to the right of the leading entries of any row above it.
3. Each leading entry of a row is equal to 1.

We also consider another reduced form of the augmented matrix which has one further condition.

Definition 1.3.4: Reduced Row-Echelon Form

An augmented matrix is in **reduced row-echelon form** if

1. All nonzero rows are above any rows of zeros.
2. Each leading entry of a row is in a column to the right of the leading entries of any rows above it.
3. Each leading entry of a row is equal to 1.
4. All entries in a column above and below a leading entry are zero.

Notice that the first three conditions on a reduced row-echelon form matrix are the same as those for row-echelon form.

Hence, every reduced row-echelon form matrix is also in row-echelon form. The converse is not necessarily true; we cannot assume that every matrix in row-echelon form is also in reduced row-echelon form. However, it often happens that the row-echelon form is sufficient to provide information about the solution of a system.

The following examples describe matrices in these various forms. As an exercise, take the time to carefully verify that they are in the specified form.

Example 1.3.1: Not in Row-Echelon Form

The following augmented matrices are not in row-echelon form (and therefore also not in reduced row-echelon form).

$$\begin{bmatrix} 0 & 0 & 0 & 0 \\ 1 & 2 & 3 & 3 \\ 0 & 1 & 0 & 2 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 2 & 3 \\ 2 & 4 & -6 \\ 4 & 0 & 7 \end{bmatrix}, \begin{bmatrix} 0 & 2 & 3 & 3 \\ 1 & 5 & 0 & 2 \\ 7 & 5 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

Example 1.3.2: Matrices in Row-Echelon Form

The following augmented matrices are in row-echelon form, but not in reduced row-echelon form.

$$\begin{bmatrix} 1 & 0 & 6 & 5 & 8 & 2 \\ 0 & 0 & 1 & 2 & 7 & 3 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 3 & 5 & 4 \\ 0 & 1 & 0 & 7 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 6 & 0 \\ 0 & 1 & 4 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Notice that we could apply further row operations to these matrices to carry them to reduced row-echelon form. Take the time to try that on your own. Consider the following matrices, which are in reduced row-echelon form.

Example 1.3.3: Matrices in Reduced Row-Echelon Form

The following augmented matrices are in reduced row-echelon form.

$$\begin{bmatrix} 1 & 0 & 0 & 5 & 0 & 0 \\ 0 & 0 & 1 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 0 & 4 \\ 0 & 1 & 0 & 3 \\ 0 & 0 & 1 & 2 \end{bmatrix}$$

One way in which the row-echelon form of a matrix is useful is in identifying the pivot positions and pivot columns of the matrix.

Definition 1.3.5: Pivot Position and Pivot Column

A **pivot position** in a matrix is the location of a leading entry in the row-echelon form of a matrix.

A **pivot column** is a column that contains a pivot position.

For example consider the following.

Example 1.3.4: Pivot Position

Let

$$A = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 3 & 2 & 1 & 6 \\ 4 & 4 & 4 & 10 \end{bmatrix}$$

Where are the pivot positions and pivot columns of the augmented matrix A?

Solution

The row-echelon form of this matrix is

$$\begin{bmatrix} 1 & 2 & 3 & 4 \\ 0 & 1 & 2 & \frac{3}{2} \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

This is all we need in this example, but note that this matrix is not in reduced row-echelon form.

In order to identify the pivot positions in the original matrix, we look for the leading entries in the row-echelon form of the matrix. Here, the entry in the first row and first column, as well as the entry in the second row and second column are the leading entries. Hence, these locations are the pivot positions. We identify the pivot positions in the original matrix, as in the following:

$$\begin{bmatrix} \boxed{1} & 2 & 3 & 4 \\ 3 & \boxed{2} & 1 & 6 \\ 4 & 4 & 4 & 10 \end{bmatrix}$$

Thus the pivot columns in the matrix are the first two columns.

The following is an algorithm for carrying a matrix to row-echelon form and reduced row-echelon form. You may wish to use this algorithm to carry the above matrix to row-echelon form or reduced row-echelon form yourself for practice.

Algorithm 1.3.1: Reduced Row-Echelon Form Algorithm

This algorithm provides a method for using row operations to take a matrix to its reduced row-echelon form. We begin with the matrix in its original form.

1. Starting from the left, find the first nonzero column. This is the first pivot column, and the position at the top of this column is the first pivot position. Switch rows if necessary to place a nonzero number in the first pivot position.
2. Use row operations to make the entries below the first pivot position (in the first pivot column) equal to zero.
3. Ignoring the row containing the first pivot position, repeat steps 1 and 2 with the remaining rows. Repeat the process until there are no more rows to modify.
4. Divide each nonzero row by the value of the leading entry, so that the leading entry becomes 1. The matrix will then be in row-echelon form.

   The following step will carry the matrix from row-echelon form to reduced row-echelon form.

5. Moving from right to left, use row operations to create zeros in the entries of the pivot columns which are above the pivot positions. The result will be a matrix in reduced row-echelon form.

Most often we will apply this algorithm to an augmented matrix in order to find the solution to a system of linear equations. However, we can use this algorithm to compute the reduced row-echelon form of any matrix which could be useful in other applications.

Consider the following example of Algorithm 1.3.1.

Example 1.3.5: Finding Row-Echelon Form and Reduced Row-Echelon Form of a Matrix

Let

$$A = \begin{bmatrix} 0 & -5 & -4 \\ 1 & 4 & 3 \\ 5 & 10 & 7 \end{bmatrix}$$

Find the row-echelon form of A. Then complete the process until A is in reduced row-echelon form.

Solution

In working through this example, we will use the steps outlined in Algorithm 1.3.1.

1. The first pivot column is the first column of the matrix, as this is the first nonzero column from the left. Hence the first pivot position is the one in the first row and first column. Switch the first two rows to obtain a nonzero entry in the first pivot position, outlined in a box below.

$$\begin{bmatrix} \boxed{1} & 4 & 3 \\ 0 & -5 & -4 \\ 5 & 10 & 7 \end{bmatrix}$$

2. Step two involves creating zeros in the entries below the first pivot position. The first entry of the second row is already a zero. All we need to do is subtract 5 times the first row from the third row. The resulting matrix is

$$\begin{bmatrix} 1 & 4 & 3 \\ 0 & -5 & -4 \\ 0 & 10 & 8 \end{bmatrix}$$

3. Now ignore the top row. Apply steps 1 and 2 to the smaller matrix

$$\begin{bmatrix} -5 & -4 \\ 10 & 8 \end{bmatrix}$$

In this matrix, the first column is a pivot column, and -5 is in the first pivot position. Therefore, we need to create a zero below it. To do this, add 2 times the first row (of this matrix) to the second. The resulting matrix is

$$\begin{bmatrix} -5 & -4 \\ 0 & 0 \end{bmatrix}$$

Our original matrix now looks like

$$\begin{bmatrix} 1 & 4 & 3 \\ 0 & -5 & -4 \\ 0 & 0 & 0 \end{bmatrix}$$

We can see that there are no more rows to modify.

4. Now, we need to create leading 1s in each row. The first row already has a leading 1 so no work is needed here. Divide the second row by -5 to create a leading 1. The resulting matrix is

$$\begin{bmatrix} 1 & 4 & 3 \\ 0 & 1 & \frac{4}{5} \\ 0 & 0 & 0 \end{bmatrix}$$

This matrix is now in row-echelon form.

5. Now create zeros in the entries above pivot positions in each column, in order to carry this matrix all the way to reduced row-echelon form. Notice that there is no pivot position in the third column so we do not need to create any zeros in this column! The column in which we need to create zeros is the second. To do so, subtract 4 times the second row from the first row. The resulting matrix is

$$\begin{bmatrix} 1 & 0 & -\frac{1}{5} \\ 0 & 1 & \frac{4}{5} \\ 0 & 0 & 0 \end{bmatrix}$$

This matrix is now in reduced row-echelon form.

The above algorithm gives you a simple way to obtain the row-echelon form and reduced row-echelon form of a matrix. The main idea is to do row operations in such a way as to end up with a matrix in row-echelon form or reduced row-echelon form. This process is important because the resulting matrix will allow you to describe the solutions to the corresponding linear system of equations in a meaningful way.

In the next example, we look at how to solve a system of equations using the corresponding augmented matrix.

Example 1.3.6: Finding the Solution to a System

Give the complete solution to the following system of equations

$$\begin{aligned} 2x + 4y - 3z &= -1 \\ 5x + 10y - 7z &= -2 \\ 3x + 6y + 5z &= 9 \end{aligned}$$

Solution

The augmented matrix for this system is

$$\begin{bmatrix} 2 & 4 & -3 & -1 \\ 5 & 10 & -7 & -2 \\ 3 & 6 & 5 & 9 \end{bmatrix}$$

In order to find the solution to this system, we wish to carry the augmented matrix to reduced row-echelon form. We will do so using Algorithm 1.3.1. Notice that the first column is nonzero, so this is our first pivot column. The first entry in the first row, 2, is the first leading entry and it is in the first pivot position. We will use row operations to create zeros in the entries below the 2. First, replace the second row with -5 times the first row plus 2 times the second row. This yields

$$\begin{bmatrix} 2 & 4 & -3 & -1 \\ 0 & 0 & 1 & 1 \\ 3 & 6 & 5 & 9 \end{bmatrix}$$

Now, replace the third row with -3 times the first row plus to 2 times the third row. This yields

$$\begin{bmatrix} 2 & 4 & -3 & -1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 21 \end{bmatrix}$$

Now the entries in the first column below the pivot position are zeros. We now look for the second pivot column, which in this case is column three. Here, the 1 in the second row and third column is in the pivot position. We need to do just one row operation to create a zero below the 1.

Taking -1 times the second row and adding it to the third row yields

$$\begin{bmatrix} 2 & 4 & -3 & -1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 20 \end{bmatrix}$$

We could proceed with the algorithm to carry this matrix to row-echelon form or reduced row-echelon form. However, remember that we are looking for the solutions to the system of equations. Take another look at the third row of the matrix. Notice that it corresponds to the equation

$$0x + 0y + 0z = 20$$

There is no solution to this equation because for all x, y, z, the left side will equal 0 and $0 \neq 20$. This shows there is no solution to the given system of equations. In other words, this system is inconsistent.

The following is another example of how to find the solution to a system of equations by carrying the corresponding augmented matrix to reduced row-echelon form.

Example 1.3.7: An Infinite Set of Solutions

Give the complete solution to the system of equations

$$\begin{aligned} 3x - y - 5z &= 9 \\ y - 10z &= 0 \\ -2x + y &= -6 \end{aligned} \tag{1.3.1}$$

Solution

The augmented matrix of this system is

$$\begin{bmatrix} 3 & -1 & -5 & 9 \\ 0 & 1 & -10 & 0 \\ -2 & 1 & 0 & -6 \end{bmatrix}$$

In order to find the solution to this system, we will carry the augmented matrix to reduced row-echelon form, using Algorithm 1.3.1. The first column is the first pivot column. We want to use row operations to create zeros beneath the first entry in this column, which is in the first pivot position. Replace the third row with 2 times the first row added to 3 times the third row. This gives

$$\begin{bmatrix} 3 & -1 & -5 & 9 \\ 0 & 1 & -10 & 0 \\ 0 & 1 & -10 & 0 \end{bmatrix}$$

Now, we have created zeros beneath the 3 in the first column, so we move on to the second pivot column (which is the second column) and repeat the procedure. Take -1 times the second row and add to the third row.

$$\begin{bmatrix} 3 & -1 & -5 & 9 \\ 0 & 1 & -10 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

The entry below the pivot position in the second column is now a zero. Notice that we have no more pivot columns because we have only two leading entries.

At this stage, we also want the leading entries to be equal to one. To do so, divide the first row by 3.

$$\begin{bmatrix} 1 & -\frac{1}{3} & -\frac{5}{3} & 3 \\ 0 & 1 & -10 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

This matrix is now in row-echelon form.

Let's continue with row operations until the matrix is in reduced row-echelon form. This involves creating zeros above the pivot positions in each pivot column. This requires only one step, which is to add $\frac{1}{3}$ times the second row to the first row.

$$\left[\begin{array}{cccc} 1 & 0 & -5 & 3 \\ 0 & 1 & -10 & 0 \\ 0 & 0 & 0 & 0 \end{array}\right]$$

This is in reduced row-echelon form, which you should verify using Definition 1.3.4. The equations corresponding to this reduced row-echelon form are

$$\begin{aligned} x - 5z &= 3 \\ y - 10z &= 0 \end{aligned}$$

or

$$\begin{aligned} x &= 3 + 5z \\ y &= 10z \end{aligned}$$

Observe that z is not restrained by any equation. In fact, z can equal any number. For example, we can let $z = t$, where we can choose t to be any number. In this context t is called a **parameter** . Therefore, the solution set of this system is

$$\begin{aligned} x &= 3 + 5t \\ y &= 10t \\ z &= t \end{aligned}$$

where t is arbitrary. The system has an infinite set of solutions which are given by these equations. For any value of t we select, $x, y,$ and z will be given by the above equations. For example, if we choose $t = 4$ then the corresponding solution would be

$$\begin{aligned} x &= 3 + 5(4) = 23 \\ y &= 10(4) = 40 \\ z &= 4 \end{aligned}$$

In Example 1.3.7 the solution involved one parameter. It may happen that the solution to a system involves more than one parameter, as shown in the following example.

Example 1.3.8: A Two Parameter Set of Solutions

Find the solution to the system

$$\begin{aligned} x + 2y - z + w &= 3 \\ x + y - z + w &= 1 \\ x + 3y - z + w &= 5 \end{aligned}$$

Solution

The augmented matrix is

$$\left[\begin{array}{ccccc} 1 & 2 & -1 & 1 & 3 \\ 1 & 1 & -1 & 1 & 1 \\ 1 & 3 & -1 & 1 & 5 \end{array}\right]$$

We wish to carry this matrix to row-echelon form. Here, we will outline the row operations used. However, make sure that you understand the steps in terms of Algorithm 1.3.1.

Take -1 times the first row and add to the second. Then take -1 times the first row and add to the third. This yields

$$\left[\begin{array}{ccccc} 1 & 2 & -1 & 1 & 3 \\ 0 & -1 & 0 & 0 & -2 \\ 0 & 1 & 0 & 0 & 2 \end{array}\right]$$

Now add the second row to the third row and divide the second row by -1.

$$\begin{bmatrix} 1 & 2 & -1 & 1 & 3 \\ 0 & 1 & 0 & 0 & 2 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{1.3.2}$$

This matrix is in row-echelon form and we can see that x and y correspond to pivot columns, while z and w do not. Therefore, we will assign parameters to the variables z and w. Assign the parameter s to z and the parameter t to w. Then the first row yields the equation $x + 2y - s + t = 3$, while the second row yields the equation $y = 2$. Since $y = 2$, the first equation becomes $x + 4 - s + t = 3$ showing that the solution is given by

$$\begin{aligned} x &= -1 + s - t \\ y &= 2 \\ z &= s \\ w &= t \end{aligned}$$

It is customary to write this solution in the form

$$\begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} -1 + s - t \\ 2 \\ s \\ t \end{bmatrix} \tag{1.3.3}$$

This example shows a system of equations with an infinite solution set which depends on two parameters. It can be less confusing in the case of an infinite solution set to first place the augmented matrix in reduced row-echelon form rather than just row-echelon form before seeking to write down the description of the solution.

In the above steps, this means we don't stop with the row-echelon form in equation (1.3.2). Instead we first place it in reduced row-echelon form as follows.

$$\begin{bmatrix} 1 & 0 & -1 & 1 & -1 \\ 0 & 1 & 0 & 0 & 2 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Then the solution is $y = 2$ from the second row and $x = -1 + z - w$ from the first. Thus letting $z = s$ and $w = t$, the solution is given by (1.3.3).

You can see here that there are two paths to the correct answer, which both yield the same answer. Hence, either approach may be used. The process which we first used in the above solution is called **Gaussian Elimination** This process involves carrying the matrix to row-echelon form, converting back to equations, and using back substitution to find the solution. When you do row operations until you obtain reduced row-echelon form, the process is called **Gauss-Jordan Elimination**.

We have now found solutions for systems of equations with no solution and infinitely many solutions, with one parameter as well as two parameters. Recall the three types of solution sets which we discussed in the previous section; no solution, one solution, and infinitely many solutions. Each of these types of solutions could be identified from the graph of the system. It turns out that we can also identify the type of solution from the reduced row-echelon form of the augmented matrix.

- *No Solution:* In the case where the system of equations has no solution, the row-echelon form of the augmented matrix will have a row of the form

  $$\left[\begin{array}{ccc|c} 0 & 0 & 0 & 1 \end{array}\right]$$

  This row indicates that the system is inconsistent and has no solution.
- *One Solution:* In the case where the system of equations has one solution, every column of the coefficient matrix is a pivot column. The following is an example of an augmented matrix in reduced row-echelon form for a system of equations with one solution.

  $$\begin{bmatrix} 1 & 0 & 0 & 5 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 2 \end{bmatrix}$$

- *Infinitely Many Solutions:* In the case where the system of equations has infinitely many solutions, the solution contains parameters. There will be columns of the coefficient matrix which are not pivot columns. The following are examples of augmented matrices in reduced row-echelon form for systems of equations with infinitely many solutions.

$$\left[\begin{array}{cccc} 1 & 0 & 0 & 5 \\ 0 & 1 & 2 & -3 \\ 0 & 0 & 0 & 0 \end{array}\right]$$

or

$$\left[\begin{array}{cccc} 1 & 0 & 0 & 5 \\ 0 & 1 & 0 & -3 \end{array}\right]$$

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1.4: Uniqueness of the Reduced Row-Echelon Form

As we have seen in earlier sections, we know that every matrix can be brought into reduced row-echelon form by a sequence of elementary row operations. Here we will prove that the resulting matrix is unique; in other words, the resulting matrix in reduced row-echelon does not depend upon the particular sequence of elementary row operations or the order in which they were performed.

Let A be the augmented matrix of a homogeneous system of linear equations in the variables $x_1, x_2, \cdots, x_n$ which is also in reduced row-echelon form. The matrix A divides the set of variables in two different types. We say that x_i is a *basic variable* whenever A has a leading 1 in column number i, in other words, when column i is a pivot column. Otherwise we say that x_i is a *free variable*.

Recall Example 1.3.8.

Example 1.4.1: Basic and Free Variables

Find the basic and free variables in the system

$$\begin{aligned} x + 2y - z + w &= 3 \\ x + y - z + w &= 1 \\ x + 3y - z + w &= 5 \end{aligned}$$

Solution

Recall from the solution of Example 1.3.8 that the row-echelon form of the augmented matrix of this system is given by

$$\left[\begin{array}{rrrrr} 1 & 2 & -1 & 1 & 3 \\ 0 & 1 & 0 & 0 & 2 \\ 0 & 0 & 0 & 0 & 0 \end{array}\right]$$

You can see that columns 1 and 2 are pivot columns. These columns correspond to variables x and y, making these the basic variables. Columns 3 and 4 are not pivot columns, which means that z and w are free variables.

We can write the solution to this system as

$$\begin{aligned} x &= -1 + s - t \\ y &= 2 \\ z &= s \\ w &= t \end{aligned}$$

Here the free variables are written as parameters, and the basic variables are given by linear functions of these parameters.

In general, all solutions can be written in terms of the free variables. In such a description, the free variables can take any values (they become parameters), while the basic variables become simple linear functions of these parameters. Indeed, a basic variable x_i is a linear function of *only* those free variables x_j with $j > i$. This leads to the following observation.

Proposition 1.4.1: Basic and Free Variables

If x_i is a basic variable of a homogeneous system of linear equations, then any solution of the system with $x_j = 0$ for all those free variables x_j with $j > i$ must also have $x_i = 0$.

Using this proposition, we prove a lemma which will be used in the proof of the main result of this section below.

Lemma 1.4.1: Solutions and the Reduced Row-Echelon Form of a Matrix

Let A and B be two distinct augmented matrices for two homogeneous systems of m equations in n variables, such that A and B are each in reduced row-echelon. Then, the two systems do not have exactly the same solutions.

Proof available at the end of this section.

Now, we say that the matrix B is **equivalent** to the matrix A provided that B can be obtained from A by performing a sequence of elementary row operations beginning with A. The importance of this concept lies in the following result.

Theorem 1.4.1: Equivalent Matrices

The two linear systems of equations corresponding to two equivalent augmented matrices have exactly the same solutions.

Proof available at the end of this section.

Now, we can use Lemma 1.4.1 and Theorem 1.4.1 to prove the main result of this section.

Theorem 1.4.2: Uniqueness of the Reduced Row-Echelon Form

Every matrix A is equivalent to a unique matrix in reduced row-echelon form.

Proof available at the end of this section.

According to this theorem we can say that each matrix A has a unique reduced row-echelon form.

Answers

Lemma 1.4.1: Solutions and the Reduced Row-Echelon Form of a Matrix

With respect to the linear systems associated with the matrices A and B, there are two cases to consider:

- Case 1: the two systems have the same basic variables
- Case 2: the two systems do not have the same basic variables

In case 1, the two matrices will have exactly the same pivot positions. However, since A and B are not identical, there is some row of A which is different from the corresponding row of B and yet the rows each have a pivot in the same column position. Let i be the index of this column position. Since the matrices are in reduced row-echelon form, the two rows must differ at some entry in a column $j > i$. Let these entries be a in A and b in B, where $a \neq b$. Since A is in reduced row-echelon form, if x_j were a basic variable for its linear system, we would have $a = 0$. Similarly, if x_j were a basic variable for the linear system of the matrix B, we would have $b = 0$. Since a and b are unequal, they cannot both be equal to 0, and hence x_j cannot be a basic variable for both linear systems. However, since the systems have the same basic variables, x_j must then be a free variable for each system. We now look at the solutions of the systems in which x_j is set equal to 1 and all other free variables are set equal to 0. For this choice of parameters, the solution of the system for matrix A has $x_j = -a$, while the solution of the system for matrix B has $x_j = -b$, so that the two systems have different solutions.

In case 2, there is a variable x_i which is a basic variable for one matrix, let's say A, and a free variable for the other matrix B. The system for matrix B has a solution in which $x_i = 1$ and $x_j = 0$ for all other free variables x_j. However, by Proposition 1.4.1this cannot be a solution of the system for the matrix A. This completes the proof of case 2.

Theorem 1.4.1: Equivalent Matrices

The proof of this theorem is left as an exercise.

Theorem 1.4.2: Uniqueness of the Reduced Row-Echelon Form

Let A be an $m \times n$ matrix and let B and C be matrices in reduced row-echelon form, each equivalent to A. It suffices to show that $B = C$.

Let A^+ be the matrix A augmented with a new rightmost column consisting entirely of zeros. Similarly, augment matrices B and C each with a rightmost column of zeros to obtain B^+ and C^+. Note that B^+ and C^+ are matrices in reduced row-echelon form which are obtained from A^+ by respectively applying the same sequence of elementary row operations which were used to obtain B and C from A.

Now, A^+, B^+, and C^+ can all be considered as augmented matrices of homogeneous linear systems in the variables $x_1, x_2, \cdots, x_n$. Because B^+ and C^+ are each equivalent to A^+, Theorem 1.4.1 ensures that all three homogeneous linear systems have exactly the same solutions. By Lemma 1.4.1 we conclude that $B^+ = C^+$. By construction, we must also have $B = C$.

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1.5: RANK AND HOMOGENEOUS SYSTEMS

Rank and Homogeneous Systems

There is a special type of system which requires additional study. This type of system is called a homogeneous system of equations, which we defined above in Definition 1.2.3. Our focus in this section is to consider what types of solutions are possible for a homogeneous system of equations.

Consider the following definition.

Definition 1.5.1: Trivial Solution

Consider the homogeneous system of equations given by

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n &= 0 \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n &= 0 \\ &\vdots \\ a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n &= 0 \end{aligned}$$

Then, $x_1 = 0, x_2 = 0, \cdots, x_n = 0$ is always a solution to this system. We call this the **trivial solution** .

If the system has a solution in which not all of the $x_1, \cdots, x_n$ are equal to zero, then we call this solution **nontrivial** . The trivial solution does not tell us much about the system, as it says that $0 = 0$! Therefore, when working with homogeneous systems of equations, we want to know when the system has a nontrivial solution.

Suppose we have a homogeneous system of m equations, using n variables, and suppose that $n > m$. In other words, there are more variables than equations. Then, it turns out that this system always has a nontrivial solution. Not only will the system have a nontrivial solution, but it also will have infinitely many solutions. It is also possible, but not required, to have a nontrivial solution if $n = m$ and $n < m$.

Consider the following example.

Example 1.5.1: Solutions to a Homogeneous System of Equations

Find the nontrivial solutions to the following homogeneous system of equations

$$\begin{aligned} 2x + y - z &= 0 \\ x + 2y - 2z &= 0 \end{aligned}$$

Solution

Notice that this system has $m = 2$ equations and $n = 3$ variables, so $n > m$. Therefore by our previous discussion, we expect this system to have infinitely many solutions.

The process we use to find the solutions for a homogeneous system of equations is the same process we used in the previous section. First, we construct the augmented matrix, given by

$$\begin{bmatrix} 2 & 1 & -1 & 0 \\ 1 & 2 & -2 & 0 \end{bmatrix}$$

Then, we carry this matrix to its reduced row-echelon form, given below.

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 \end{bmatrix}$$

The corresponding system of equations is

$$x = 0$$
$$y - z = 0$$

Since z is not restrained by any equation, we know that this variable will become our parameter. Let $z = t$ where t is any number. Therefore, our solution has the form

$$x = 0$$
$$y = z = t$$
$$z = t$$

Hence this system has infinitely many solutions, with one parameter t.

Suppose we were to write the solution to the previous example in another form. Specifically,

$$x = 0$$
$$y = 0 + t$$
$$z = 0 + t$$

can be written as

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} + t \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

Notice that we have constructed a column from the constants in the solution (all equal to 0), as well as a column corresponding to the coefficients on t in each equation. While we will discuss this form of solution more in further chapters, for now consider the column of coefficients of the parameter t. In this case, this is the column $\begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$.

There is a special name for this column, which is **basic solution**. The basic solutions of a system are columns constructed from the coefficients on parameters in the solution. We often denote basic solutions by X_1, X_2 etc., depending on how many solutions occur. Therefore, Example 1.5.1 has the basic solution $X_1 = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$.

We explore this further in the following example.

Example 1.5.2: Basic Solutions of a Homogeneous System

Consider the following homogeneous system of equations.

$$x + 4y + 3z = 0$$
$$3x + 12y + 9z = 0$$

Find the basic solutions to this system.

Solution

The augmented matrix of this system and the resulting reduced row-echelon form are

$$\begin{bmatrix} 1 & 4 & 3 & 0 \\ 3 & 12 & 9 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 4 & 3 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

When written in equations, this system is given by

$$x + 4y + 3z = 0$$

Notice that only x corresponds to a pivot column. In this case, we will have two parameters, one for y and one for z. Let $y = s$ and $z = t$ for any numbers s and t. Then, our solution becomes

$$x = -4s - 3t$$
$$y = s$$
$$z = t$$

which can be written as

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} + s \begin{bmatrix} -4 \\ 1 \\ 0 \end{bmatrix} + t \begin{bmatrix} -3 \\ 0 \\ 1 \end{bmatrix}$$

You can see here that we have two columns of coefficients corresponding to parameters, specifically one for s and one for t. Therefore, this system has two basic solutions! These are

$$X_1 = \begin{bmatrix} -4 \\ 1 \\ 0 \end{bmatrix}, X_2 = \begin{bmatrix} -3 \\ 0 \\ 1 \end{bmatrix}$$

We now present a new definition.

Definition 1.5.2: Linear Combination

Let $X_1, \cdots, X_n, V$ be column matrices. Then V is said to be a **linear combination** of the columns $X_1, \cdots, X_n$ if there exist scalars, $a_1, \cdots, a_n$ such that

$$V = a_1 X_1 + \cdots + a_n X_n$$

A remarkable result of this section is that a linear combination of the basic solutions is again a solution to the system. Even more remarkable is that every solution can be written as a linear combination of these solutions. Therefore, if we take a linear combination of the two solutions to Example 1.5.2, this would also be a solution. For example, we could take the following linear combination

$$3 \begin{bmatrix} -4 \\ 1 \\ 0 \end{bmatrix} + 2 \begin{bmatrix} -3 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} -18 \\ 3 \\ 2 \end{bmatrix}$$

You should take a moment to verify that

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} -18 \\ 3 \\ 2 \end{bmatrix}$$

is in fact a solution to the system in Example 1.5.2.

Another way in which we can find out more information about the solutions of a homogeneous system is to consider the **rank** of the associated coefficient matrix. We now define what is meant by the rank of a matrix.

Definition 1.5.3: Rank of a Matrix

Let A be a matrix and consider any row-echelon form of A. Then, the number r of leading entries of A does not depend on the row-echelon form you choose, and is called the **rank** of A. We denote it by Rank(A).

Similarly, we could count the number of pivot positions (or pivot columns) to determine the rank of A.

Example 1.5.3: Finding the Rank of a Matrix

Consider the matrix

$$\begin{bmatrix} 1 & 2 & 3 \\ 1 & 5 & 9 \\ 2 & 4 & 6 \end{bmatrix}$$

What is its rank?

Solution

First, we need to find the reduced row-echelon form of A. Through the usual algorithm, we find that this is

$$\begin{bmatrix} \boxed{1} & 0 & -1 \\ 0 & \boxed{1} & 2 \\ 0 & 0 & 0 \end{bmatrix}$$

Here we have two leading entries, or two pivot positions, shown above in boxes.The rank of A is $r = 2$.

Notice that we would have achieved the same answer if we had found the row-echelon form of A instead of the reduced row-echelon form.

Suppose we have a homogeneous system of m equations in n variables, and suppose that $n > m$. From our above discussion, we know that this system will have infinitely many solutions. If we consider the rank of the coefficient matrix of this system, we can find out even more about the solution. Note that we are looking at just the coefficient matrix, not the entire augmented matrix.

Theorem 1.5.1: Rank and Solutions to a Homogeneous System

Let A be the $m \times n$ coefficient matrix corresponding to a homogeneous system of equations, and suppose A has rank r. Then, the solution to the corresponding system has $n - r$ parameters.

Consider our above Example 1.5.2 in the context of this theorem. The system in this example has $m = 2$ equations in $n = 3$ variables. First, because $n > m$, we know that the system has a nontrivial solution, and therefore infinitely many solutions. This tells us that the solution will contain at least one parameter. The rank of the coefficient matrix can tell us even more about the solution! The rank of the coefficient matrix of the system is 1, as it has one leading entry in row-echelon form. Theorem 1.5.1 tells us that the solution will have $n - r = 3 - 1 = 2$ parameters. You can check that this is true in the solution to Example 1.5.2.

Notice that if $n = m$ or $n < m$, it is possible to have either a unique solution (which will be the trivial solution) or infinitely many solutions.

We are not limited to homogeneous systems of equations here. The rank of a matrix can be used to learn about the solutions of any system of linear equations. In the previous section, we discussed that a system of equations can have no solution, a unique solution, or infinitely many solutions. Suppose the system is consistent, whether it is homogeneous or not. The following theorem tells us how we can use the rank to learn about the type of solution we have.

Theorem 1.5.2: Rank and Solutions to a Consistent System of Equations

Let A be the $m \times (n + 1)$ augmented matrix corresponding to a consistent system of equations in n variables, and suppose A has rank r. Then

1. the system has a unique solution if $r = n$
2. the system has infinitely many solutions if $r < n$

We will not present a formal proof of this, but consider the following discussions.

1. *No Solution* The above theorem assumes that the system is consistent, that is, that it has a solution. It turns out that it is possible for the augmented matrix of a system with no solution to have any rank r as long as $r > 1$. Therefore, we must know that the system is consistent in order to use this theorem!

2. *Unique Solution* Suppose $r = n$. Then, there is a pivot position in every column of the coefficient matrix of A. Hence, there is a unique solution.
3. *Infinitely Many Solutions* Suppose $r < n$. Then there are infinitely many solutions. There are less pivot positions (and hence less leading entries) than columns, meaning that not every column is a pivot column. The columns which are not pivot columns correspond to parameters. In fact, in this case we have $n - r$ parameters.

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1.6: Balancing Chemical Reactions

The tools of linear algebra can also be used in the subject area of Chemistry, specifically for balancing chemical reactions.

Consider the chemical reaction

$$SnO_2 + H_2 \rightarrow Sn + H_2O$$

Here the elements involved are tin (Sn), oxygen (O), and hydrogen (H). A chemical reaction occurs and the result is a combination of tin (Sn) and water (H_2O). When considering chemical reactions, we want to investigate how much of each element we began with and how much of each element is involved in the result.

An important theory we will use here is the mass balance theory. It tells us that we cannot create or delete elements within a chemical reaction. For example, in the above expression, we must have the same number of oxygen, tin, and hydrogen on both sides of the reaction. Notice that this is not currently the case. For example, there are two oxygen atoms on the left and only one on the right. In order to fix this, we want to find numbers x, y, z, w such that

$$xSnO_2 + yH_2 \rightarrow zSn + wH_2O$$

where both sides of the reaction have the same number of atoms of the various elements.

This is a familiar problem. We can solve it by setting up a system of equations in the variables x, y, z, w. Thus you need

$$\begin{aligned} Sn: &\quad x = z \\ O: &\quad 2x = w \\ H: &\quad 2y = 2w \end{aligned}$$

We can rewrite these equations as

$$\begin{aligned} Sn: &\quad x - z = 0 \\ O: &\quad 2x - w = 0 \\ H: &\quad 2y - 2w = 0 \end{aligned}$$

The augmented matrix for this system of equations is given by

$$\begin{bmatrix} 1 & 0 & -1 & 0 & 0 \\ 2 & 0 & 0 & -1 & 0 \\ 0 & 2 & 0 & -2 & 0 \end{bmatrix}$$

The reduced row-echelon form of this matrix is

$$\begin{bmatrix} 1 & 0 & 0 & -\frac{1}{2} & 0 \\ 0 & 1 & 0 & -1 & 0 \\ 0 & 0 & 1 & -\frac{1}{2} & 0 \end{bmatrix}$$

The solution is given by

$$\begin{aligned} x - \tfrac{1}{2}w &= 0 \\ y - w &= 0 \\ z - \tfrac{1}{2}w &= 0 \end{aligned}$$

which we can write as

$$\begin{aligned} x &= \tfrac{1}{2}t \\ y &= t \\ z &= \tfrac{1}{2}t \\ w &= t \end{aligned}$$

For example, let $w = 2$ and this would yield $x = 1, y = 2,$ and $z = 1$. We can put these values back into the expression for the reaction which yields

$$SnO_2 + 2H_2 \to Sn + 2H_2O$$

Observe that each side of the expression contains the same number of atoms of each element. This means that it preserves the total number of atoms, as required, and so the chemical reaction is balanced.

Consider another example.

Example 1.6.1: Balancing a Chemical Reaction

Potassium is denoted by K, oxygen by O, phosphorus by P and hydrogen by H. Consider the reaction given by

$$KOH + H_3PO_4 \to K_3PO_4 + H_2O$$

Balance this chemical reaction.

Solution

We will use the same procedure as above to solve this problem. We need to find values for x, y, z, w such that

$$xKOH + yH_3PO_4 \to zK_3PO_4 + wH_2O$$

preserves the total number of atoms of each element.

Finding these values can be done by finding the solution to the following system of equations.

$$\begin{aligned} K: &\quad x = 3z \\ O: &\quad x + 4y = 4z + w \\ H: &\quad x + 3y = 2w \\ P: &\quad y = z \end{aligned}$$

The augmented matrix for this system is

$$\begin{bmatrix} 1 & 0 & -3 & 0 & 0 \\ 1 & 4 & -4 & -1 & 0 \\ 1 & 3 & 0 & -2 & 0 \\ 0 & 1 & -1 & 0 & 0 \end{bmatrix}$$

and the reduced row-echelon form is

$$\begin{bmatrix} 1 & 0 & 0 & -1 & 0 \\ 0 & 1 & 0 & -\frac{1}{3} & 0 \\ 0 & 0 & 1 & -\frac{1}{3} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The solution is given by

$$\begin{aligned} x - w &= 0 \\ y - \tfrac{1}{3}w &= 0 \\ z - \tfrac{1}{3}w &= 0 \end{aligned}$$

which can be written as

$$\begin{aligned} x &= t \\ y &= \tfrac{1}{3}t \\ z &= \tfrac{1}{3}t \\ w &= t \end{aligned}$$

Choose a value for t, say 3. Then $w = 3$ and this yields $x = 3, y = 1, z = 1$. It follows that the balanced reaction is given by

$$3KOH + 1H_3PO_4 \to 1K_3PO_4 + 3H_2O$$

Note that this results in the same number of atoms on both sides.

Of course these numbers you are finding would typically be the number of moles of the molecules on each side. Thus three moles of KOH added to one mole of H_3PO_4 yields one mole of K_3PO_4 and three moles of H_2O.

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1.7: Dimensionless Variables

This section shows how solving systems of equations can be used to determine appropriate dimensionless variables. It is only an introduction to this topic and considers a specific example of a simple airplane wing shown below. We assume for simplicity that it is a flat plane at an angle to the wind which is blowing against it with speed V as shown.

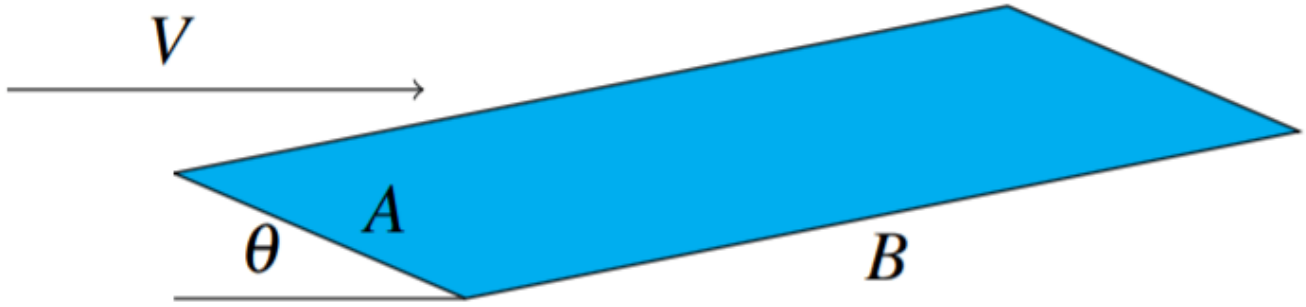


Figure 1.7.1

The angle θ is called the angle of incidence, B is the span of the wing and A is called the chord. Denote by l the lift. Then this should depend on various quantities like θ, V, B, A and so forth. Here is a table which indicates various quantities on which it is reasonable to expect l to depend.

Table 1.7.1

Variable	Symbol	Units
chord	A	m
span	B	m
angle incidence	θ	$m^0 kg^0 sec^0$
speed of wind	V	$msec^{-1}$
speed of sound	V_0	$msec^{-1}$
density of air	ρ	kgm^{-3}
viscosity	μ	$kgsec^{-1}m^{-1}$
lift	l	$kgsec^{-2}m$

Here m denotes meters, $\sec$ refers to seconds and kg refers to kilograms. All of these are likely familiar except for μ, which we will discuss in further detail now.

Viscosity is a measure of how much internal friction is experienced when the fluid moves. It is roughly a measure of how “sticky" the fluid is. Consider a piece of area parallel to the direction of motion of the fluid. To say that the viscosity is large is to say that the tangential force applied to this area must be large in order to achieve a given change in speed of the fluid in a direction normal to the tangential force. Thus

$$\mu\,(\text{area})\,(\text{velocity gradient}) = \text{ tangential force}$$

Hence

$$(\text{units on } \mu)\, m^2 \left(\frac{m}{\sec m}\right) = kg \sec^{-2} m$$

Thus the units on μ are

$$kg\sec^{-1}m^{-1}$$

as claimed above.

Returning to our original discussion, you may think that we would want

$$l = f(A, B, \theta, V, V_0, \rho, \mu)$$

This is very cumbersome because it depends on seven variables. Also, it is likely that without much care, a change in the units such as going from meters to feet would result in an incorrect value for l. The way to get around this problem is to look for l as a function of dimensionless variables multiplied by something which has units of force. It is helpful because first of all, you will likely have fewer independent variables and secondly, you could expect the formula to hold independent of the way of specifying length, mass and so forth. One looks for

$$l = f(g_1, \cdots, g_k)\,\rho V^2 AB$$

where the units on $\rho V^2 AB$ are

$$\frac{kg}{m^3}\left(\frac{m}{\sec}\right)^2 m^2 = \frac{kg \times m}{\sec^2}$$

which are the units of force. Each of these g_i is of the form

$$A^{x_1}B^{x_2}\theta^{x_3}V^{x_4}V_0^{x_5}\rho^{x_6}\mu^{x_7} \tag{1.7.1}$$

and each g_i is independent of the dimensions. That is, this expression must not depend on meters, kilograms, seconds, etc. Thus, placing in the units for each of these quantities, one needs

$$m^{x_1}m^{x_2}\left(m^{x_4}\sec^{-x_4}\right)\left(m^{x_5}\sec^{-x_5}\right)\left(kgm^{-3}\right)^{x_6}\left(kg\sec^{-1}m^{-1}\right)^{x_7} = m^0 kg^0 \sec^0$$

Notice that there are no units on θ because it is just the radian measure of an angle. Hence its dimensions consist of length divided by length, thus it is dimensionless. Then this leads to the following equations for the x_i.

$$\begin{aligned} m: &\quad x_1 + x_2 + x_4 + x_5 - 3x_6 - x_7 = 0 \\ \sec: &\quad -x_4 - x_5 - x_7 = 0 \\ kg: &\quad x_6 + x_7 = 0 \end{aligned}$$

The augmented matrix for this system is

$$\begin{bmatrix} 1 & 1 & 0 & 1 & 1 & -3 & -1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

The reduced row-echelon form is given by

$$\begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

and so the solutions are of the form

$$\begin{aligned} x_1 &= -x_2 - x_7 \\ x_3 &= x_3 \\ x_4 &= -x_5 - x_7 \\ x_6 &= -x_7 \end{aligned} \tag{1.7.2}$$

Thus, in terms of vectors, the solution is

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix} = \begin{bmatrix} -x_2 - x_7 \\ x_2 \\ x_3 \\ -x_5 - x_7 \\ x_5 \\ -x_7 \\ x_7 \end{bmatrix}$$

Thus the free variables are x_2, x_3, x_5, x_7. By assigning values to these, we can obtain dimensionless variables by placing the values obtained for the x_i in the formula (1.7.1). For example, let $x_2 = 1$ and all the rest of the free variables are 0. This yields

$$x_1 = -1, x_2 = 1, x_3 = 0, x_4 = 0, x_5 = 0, x_6 = 0, x_7 = 0$$

The dimensionless variable is then $A^{-1}B^1$. This is the ratio between the span and the chord. It is called the aspect ratio, denoted as AR. Next let $x_3 = 1$ and all others equal zero. This gives for a dimensionless quantity the angle θ. Next let $x_5 = 1$ and all others equal zero. This gives

$$x_1 = 0, x_2 = 0, x_3 = 0, x_4 = -1, x_5 = 1, x_6 = 0, x_7 = 0$$

Then the dimensionless variable is $V^{-1}V_0^1$. However, it is written as V/V_0. This is called the Mach number $\mathcal{M}$. Finally, let $x_7 = 1$ and all the other free variables equal 0. Then

$$x_1 = -1, x_2 = 0, x_3 = 0, x_4 = -1, x_5 = 0, x_6 = -1, x_7 = 1$$

then the dimensionless variable which results from this is $A^{-1}V^{-1}\rho^{-1}\mu$. It is customary to write it as $Re = (AV\rho)/\mu$. This one is called the Reynold's number. It is the one which involves viscosity. Thus we would look for

$$l = f(Re, AR, \theta, \mathcal{M})\, kg \times m/\sec^2$$

This is quite interesting because it is easy to vary Re by simply adjusting the velocity or A but it is hard to vary things like μ or ρ. Note that all the quantities are easy to adjust. Now this could be used, along with wind tunnel experiments to get a formula for the lift which would be reasonable. You could also consider more variables and more complicated situations in the same way.

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1.8: An Application to Resistor Networks

The tools of linear algebra can be used to study the application of resistor networks. An example of an electrical circuit is below.

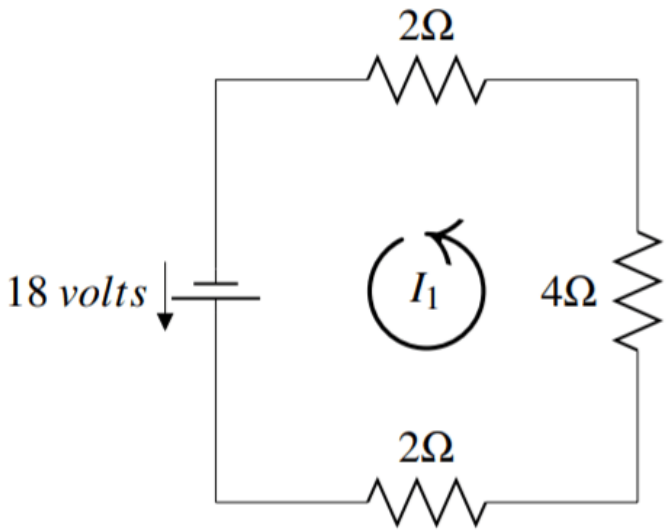


Figure 1.8.1

The jagged lines ( ) denote resistors and the numbers next to them give their resistance in ohms, written as Ω. The voltage source ( ) causes the current to flow in the direction from the shorter of the two lines toward the longer (as indicated by the arrow). The current for a circuit is labeled I_k.

In the above figure, the current I_1 has been labeled with an arrow in the counter clockwise direction. This is an entirely arbitrary decision and we could have chosen to label the current in the clockwise direction. With our choice of direction here, we define a positive current to flow in the counter clockwise direction and a negative current to flow in the clockwise direction.

The goal of this section is to use the values of resistors and voltage sources in a circuit to determine the current. An essential theorem for this application is Kirchhoff's law.

Theorem 1.8.1: Kirchhoff's Law

The sum of the resistance (R) times the amps (I) in the counter clockwise direction around a loop equals the sum of the voltage sources (V) in the same direction around the loop.

Kirchhoff's law allows us to set up a system of linear equations and solve for any unknown variables. When setting up this system, it is important to trace the circuit in the counter clockwise direction. If a resistor or voltage source is crossed against this direction, the related term must be given a negative sign.

We will explore this in the next example where we determine the value of the current in the initial diagram.

Example 1.8.1: Solving for Current

Applying Kirchhoff's Law to the diagram below, determine the value for I_1.

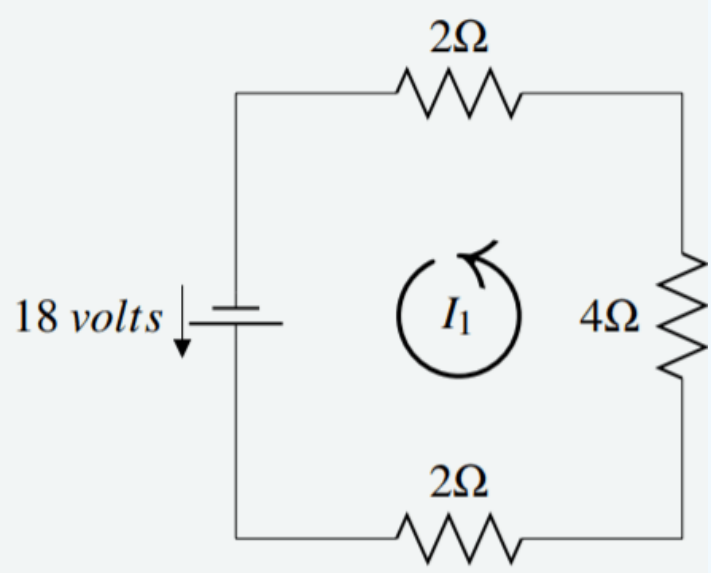


Figure 1.8.2

Solution

Begin in the bottom left corner, and trace the circuit in the counter clockwise direction. At the first resistor, multiplying resistance and current gives $2I_1$. Continuing in this way through all three resistors gives $2I_1 + 4I_1 + 2I_1$. This must equal the voltage source in the same direction. Notice that the direction of the voltage source matches the counter clockwise direction specified, so the voltage is positive.

Therefore the equation and solution are given by

$$\begin{aligned} 2I_1 + 4I_1 + 2I_1 &= 18 \\ 8I_1 &= 18 \\ I_1 &= \frac{9}{4}A \end{aligned} \tag{1.8.1}$$

Since the answer is positive, this confirms that the current flows counter clockwise.

Example 1.8.2 Solving for Current

Applying Kirchhoff's Law to the diagram below, determine the value for I_1.

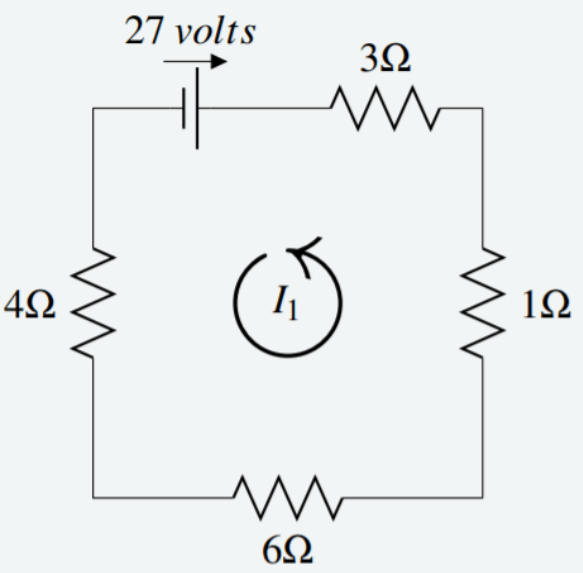


Figure 1.8.3

Solution

Begin in the top left corner this time, and trace the circuit in the counter clockwise direction. At the first resistor, multiplying resistance and current gives $4I_1$. Continuing in this way through the four resistors gives $4I_1 + 6I_1 + 1I_1 + 3I_1$. This must equal the voltage source in the same direction. Notice that the direction of the voltage source is opposite to the counter clockwise direction, so the voltage is negative.

Therefore the equation and solution are given by

$$\begin{aligned} 4I_1 + 6I_1 + 1I_1 + 3I_1 &= -27 \\ 14I_1 &= -27 \\ I_1 &= -\frac{27}{14} A \end{aligned} \tag{1.8.2}$$

Since the answer is negative, this tells us that the current flows clockwise.

A more complicated example follows. Two of the circuits below may be familiar; they were examined in the examples above. However as they are now part of a larger system of circuits, the answers will differ.

Example 1.8.3: Unknown Currents

The diagram below consists of four circuits. The current (I_k) in the four circuits is denoted by I_1, I_2, I_3, I_4. Using Kirchhoff's Law, write an equation for each circuit and solve for each current.

Solution

The circuits are given in the following diagram.

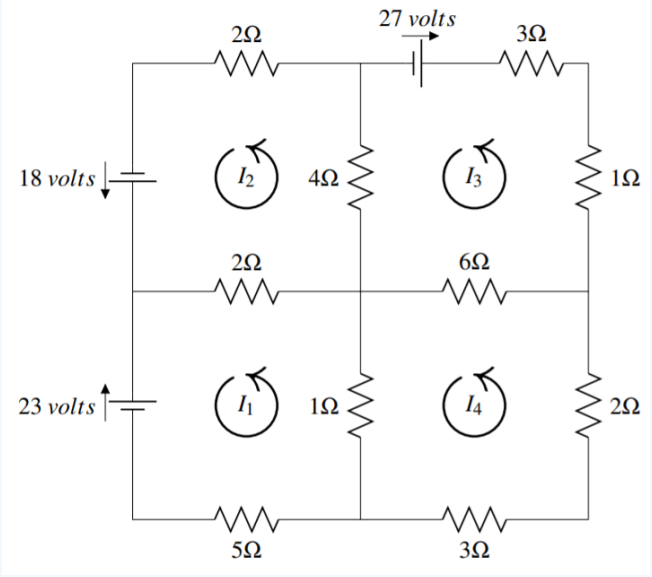


Figure 1.8.4

Starting with the top left circuit, multiply the resistance by the amps and sum the resulting products. Specifically, consider the resistor labeled 2Ω that is part of the circuits of I_1 and I_2. Notice that current I_2 runs through this in a positive (counter clockwise) direction, and I_1 runs through in the opposite (negative) direction. The product of resistance and amps is then $2(I_2 - I_1) = 2I_2 - 2I_1$. Continue in this way for each resistor, and set the sum of the products equal to the voltage source to write the equation:

$$2I_2 - 2I_1 + 4I_2 - 4I_3 + 2I_2 = 18$$

The above process is used on each of the other three circuits, and the resulting equations are:

Upper right circuit:

$$4I_3 - 4I_2 + 6I_3 - 6I_4 + I_3 + 3I_3 = -27$$

Lower right circuit:

$$3I_4 + 2I_4 + 6I_4 - 6I_3 + I_4 - I_1 = 0$$

Lower left circuit:

$$5I_1 + I_1 - I_4 + 2I_1 - 2I_2 = -23$$

Notice that the voltage for the upper right and lower left circuits are negative due to the clockwise direction they indicate.

The resulting system of four equations in four unknowns is

$$\begin{aligned} 2I_2 - 2I_1 + 4I_2 - 4I_3 + 2I_2 &= 18 \\ 4I_3 - 4I_2 + 6I_3 - 6I_4 + I_3 + I_3 &= -27 \\ 2I_4 + 3I_4 + 6I_4 - 6I_3 + I_4 - I_1 &= 0 \\ 5I_1 + I_1 - I_4 + 2I_1 - 2I_2 &= -23 \end{aligned} \tag{1.8.3}$$

Simplifying and rearranging with variables in order, we have:

$$\begin{aligned} -2I_1 + 8I_2 - 4I_3 &= 18 \\ -4I_2 + 14I_3 - 6I_4 &= -27 \\ -I_1 - 6I_3 + 12I_4 &= 0 \\ 8I_1 - 2I_2 - I_4 &= -23 \end{aligned} \tag{1.8.4}$$

The augmented matrix is

$$\begin{bmatrix} -2 & 8 & -4 & 0 & 18 \\ 0 & -4 & 14 & -6 & -27 \\ -1 & 0 & -6 & 12 & 0 \\ 8 & -2 & 0 & -1 & -23 \end{bmatrix}$$

The solution to this matrix is

$$\begin{aligned} I_1 &= -3A \\ I_2 &= \frac{1}{4}A \\ I_3 &= -\frac{5}{2}A \\ I_4 &= -\frac{3}{2}A \end{aligned} \tag{1.8.5}$$

This tells us that currents $I_1, I_3,$ and I_4 travel clockwise while I_2 travels counter clockwise.

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1.9: Exercises

Exercises

Exercise 1.9.1

Graphically, find the point (x_1, y_1) which lies on both lines, $x + 3y = 1$ and $4x - y = 3$. That is, graph each line and see where they intersect.

Answer available at the end of this section.

Exercise 1.9.2

Graphically, find the point of intersection of the two lines $3x + y = 3$ and $x + 2y = 1$. That is, graph each line and see where they intersect.

Answer available at the end of this section.

Exercise 1.9.3

Do the three lines, $x + 2y = 1$, $2x - y = 1$, and $4x + 3y = 3$ have a common point of intersection? If so, find the point and if not, tell why they don't have such a common point of intersection.

Answer available at the end of this section.

Exercise 1.9.4

Do the three planes, $x + y - 3z = 2$, $2x + y + z = 1$, and $3x + 2y - 2z = 0$ have a common point of intersection? If so, find one and if not, tell why there is no such point.

Answer available at the end of this section.

Exercise 1.9.5

Four times the weight of Gaston is 150 pounds more than the weight of Ichabod. Four times the weight of Ichabod is 660 pounds less than seventeen times the weight of Gaston. Four times the weight of Gaston plus the weight of Siegfried equals 290 pounds. Brunhilde would balance all three of the others. Find the weights of the four people.

Answer available at the end of this section.

Exercise 1.9.6

Consider the following augmented matrix in which $*$ denotes an arbitrary number and $\blacksquare$ denotes a nonzero number. Determine whether the given augmented matrix is consistent. If consistent, is the solution unique?

$$\begin{bmatrix} \blacksquare & * & * & * & * & * \\ 0 & \blacksquare & * & * & 0 & * \\ 0 & 0 & \blacksquare & * & * & * \\ 0 & 0 & 0 & 0 & \blacksquare & * \end{bmatrix}$$

Answer available at the end of this section.

Exercise 1.9.7

Consider the following augmented matrix in which $*$ denotes an arbitrary number and $\blacksquare$ denotes a nonzero number. Determine whether the given augmented matrix is consistent. If consistent, is the solution unique?

$$\begin{bmatrix} \blacksquare & * & * & * \\ 0 & \blacksquare & * & * \\ 0 & 0 & \blacksquare & * \end{bmatrix}$$

Answer available at the end of this section.

Exercise 1.9.8

Consider the following augmented matrix in which $*$ denotes an arbitrary number and $\blacksquare$ denotes a nonzero number. Determine whether the given augmented matrix is consistent. If consistent, is the solution unique?

$$\begin{bmatrix} \blacksquare & * & * & * & * & * \\ 0 & \blacksquare & 0 & * & 0 & * \\ 0 & 0 & 0 & \blacksquare & * & * \\ 0 & 0 & 0 & 0 & \blacksquare & * \end{bmatrix}$$

Exercise 1.9.9

Consider the following augmented matrix in which $*$ denotes an arbitrary number and $\blacksquare$ denotes a nonzero number. Determine whether the given augmented matrix is consistent. If consistent, is the solution unique?

$$\begin{bmatrix} \blacksquare & * & * & * & * & * \\ 0 & \blacksquare & * & * & 0 & * \\ 0 & 0 & 0 & 0 & \blacksquare & 0 \\ 0 & 0 & 0 & 0 & * & \blacksquare \end{bmatrix}$$

Answer available at the end of this section.

Exercise 1.9.10

Suppose a system of equations has fewer equations than variables. Will such a system necessarily be consistent? If so, explain why and if not, give an example which is not consistent.

Answer available at the end of this section.

Exercise 1.9.11

If a system of equations has more equations than variables, can it have a solution? If so, give an example and if not, tell why not.

Answer available at the end of this section.

Exercise 1.9.12

Find h such that

$$\begin{bmatrix} 2 & h & 4 \\ 3 & 6 & 7 \end{bmatrix}$$

is the augmented matrix of an *inconsistent* system.

Answer available at the end of this section.

Exercise 1.9.13

Find h such that

$$\begin{bmatrix} 1 & h & 3 \\ 2 & 4 & 6 \end{bmatrix}$$

is the augmented matrix of a *consistent* system.

Answer available at the end of this section.

Exercise 1.9.14

Find h such that

$$\begin{bmatrix} 1 & 1 & 4 \\ 3 & h & 12 \end{bmatrix}$$

is the augmented matrix of a *consistent* system.

Answer available at the end of this section.

Exercise 1.9.15

Choose h and k such that the augmented matrix shown has each of the following:

a. one solution
b. no solution
c. infinitely many solutions

$$\begin{bmatrix} 1 & h & 2 \\ 2 & 4 & k \end{bmatrix}$$

Answer available at the end of this section.

Exercise 1.9.16

Choose h and k such that the augmented matrix shown has each of the following:

a. one solution
b. no solution

c. infinitely many solutions

$$\begin{bmatrix} 1 & 2 & 2 \\ 2 & h & k \end{bmatrix}$$

Answer available at the end of this section.

Exercise 1.9.17

Determine if the system is consistent. If so, is the solution unique?

$$\begin{aligned} x + 2y + z - w &= 2 \\ x - y + z + w &= 1 \\ 2x + y - z &= 1 \\ 4x + 2y + z &= 5 \end{aligned}$$

Answer available at the end of this section.

Exercise 1.9.18

Determine if the system is consistent. If so, is the solution unique?

$$\begin{aligned} x + 2y + z - w &= 2 \\ x - y + z + w &= 0 \\ 2x + y - z &= 1 \\ 4x + 2y + z &= 3 \end{aligned}$$

Answer available at the end of this section.

Exercise 1.9.19

Determine which matrices are in reduced row-echelon form.

a. $\begin{bmatrix} 1 & 2 & 0 \\ 0 & 1 & 7 \end{bmatrix}$

b. $\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 2 \\ 0 & 0 & 0 & 0 \end{bmatrix}$

c. $\begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 5 \\ 0 & 0 & 1 & 2 & 0 & 4 \\ 0 & 0 & 0 & 0 & 1 & 3 \end{bmatrix}$

Answer available at the end of this section.

Exercise 1.9.20

Row reduce the following matrix to obtain the row-echelon form. Then continue to obtain the reduced row-echelon form.

$$\begin{bmatrix} 2 & -1 & 3 & -1 \\ 1 & 0 & 2 & 1 \\ 1 & -1 & 1 & -2 \end{bmatrix}$$

Exercise 1.9.21

Row reduce the following matrix to obtain the row-echelon form. Then continue to obtain the reduced row-echelon form.

$$\begin{bmatrix} 0 & 0 & -1 & -1 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & -1 \end{bmatrix}$$

Exercise 1.9.22

Row reduce the following matrix to obtain the row-echelon form. Then continue to obtain the reduced row-echelon form.

$$\begin{bmatrix} 3 & -6 & -7 & -8 \\ 1 & -2 & -2 & -2 \\ 1 & -2 & -3 & -4 \end{bmatrix}$$

Exercise 1.9.23

Row reduce the following matrix to obtain the row-echelon form. Then continue to obtain the reduced row-echelon form.

$$\begin{bmatrix} 2 & 4 & 5 & 15 \\ 1 & 2 & 3 & 9 \\ 1 & 2 & 2 & 6 \end{bmatrix}$$

Exercise 1.9.24

Row reduce the following matrix to obtain the row-echelon form. Then continue to obtain the reduced row-echelon form.

$$\begin{bmatrix} 4 & -1 & 7 & 10 \\ 1 & 0 & 3 & 3 \\ 1 & -1 & -2 & 1 \end{bmatrix}$$

Exercise 1.9.25

Row reduce the following matrix to obtain the row-echelon form. Then continue to obtain the reduced row-echelon form.

$$\begin{bmatrix} 3 & 5 & -4 & 2 \\ 1 & 2 & -1 & 1 \\ 1 & 1 & -2 & 0 \end{bmatrix}$$

Exercise 1.9.26

Row reduce the following matrix to obtain the row-echelon form. Then continue to obtain the reduced row-echelon form.

$$\begin{bmatrix} -2 & 3 & -8 & 7 \\ 1 & -2 & 5 & -5 \\ 1 & -3 & 7 & -8 \end{bmatrix}$$

Exercise 1.9.27

Find the solution of the system whose augmented matrix is

$$\left[\begin{array}{cccc} 1 & 2 & 0 & 2 \\ 1 & 3 & 4 & 2 \\ 1 & 0 & 2 & 1 \end{array}\right]$$

Exercise 1.9.28

Find the solution of the system whose augmented matrix is

$$\left[\begin{array}{cccc} 1 & 2 & 0 & 2 \\ 2 & 0 & 1 & 1 \\ 3 & 2 & 1 & 3 \end{array}\right]$$

Answer available at the end of this section.

Exercise 1.9.29

Find the solution of the system whose augmented matrix is

$$\left[\begin{array}{cccc} 1 & 1 & 0 & 1 \\ 1 & 0 & 4 & 2 \end{array}\right]$$

Answer available at the end of this section.

Exercise 1.9.30

Find the solution of the system whose augmented matrix is

$$\left[\begin{array}{cccccc} 1 & 0 & 2 & 1 & 1 & 2 \\ 0 & 1 & 0 & 1 & 2 & 1 \\ 1 & 2 & 0 & 0 & 1 & 3 \\ 1 & 0 & 1 & 0 & 2 & 2 \end{array}\right]$$

Answer available at the end of this section.

Exercise 1.9.31

Find the solution of the system whose augmented matrix is

$$\left[\begin{array}{cccccc} 1 & 0 & 2 & 1 & 1 & 2 \\ 0 & 1 & 0 & 1 & 2 & 1 \\ 0 & 2 & 0 & 0 & 1 & 3 \\ 1 & -1 & 2 & 2 & 2 & 0 \end{array}\right]$$

Answer available at the end of this section.

Exercise 1.9.32

Find the solution to the system of equations, $7x + 14y + 15z = 22$, $2x + 4y + 3z = 5$, and $3x + 6y + 10z = 13$.

Answer available at the end of this section.

Exercise 1.9.33

Find the solution to the system of equations, $3x - y + 4z = 6$, $y + 8z = 0$, and $-2x + y = -4$.

Answer available at the end of this section.

Exercise 1.9.34

Find the solution to the system of equations, $9x - 2y + 4z = -17$, $13x - 3y + 6z = -25$, and $-2x - z = 3$.

Answer available at the end of this section.

Exercise 1.9.35

Find the solution to the system of equations, $65x + 84y + 16z = 546$, $81x + 105y + 20z = 682$, and $84x + 110y + 21z = 713$.

Answer available at the end of this section.

Exercise 1.9.36

Find the solution to the system of equations, $8x + 2y + 3z = -3, 8x + 3y + 3z = -1$, and $4x + y + 3z = -9$.

Answer available at the end of this section.

Exercise 1.9.37

Find the solution to the system of equations, $-8x + 2y + 5z = 18, -8x + 3y + 5z = 13$, and $-4x + y + 5z = 19$.

Answer available at the end of this section.

Exercise 1.9.38

Find the solution to the system of equations, $3x - y - 2z = 3$, $y - 4z = 0$, and $-2x + y = -2$.

Answer available at the end of this section.

Exercise 1.9.39

Find the solution to the system of equations, $-9x + 15y = 66, -11x + 18y = 79$, $-x + y = 4$, and $z = 3$.

Answer available at the end of this section.

Exercise 1.9.40

Find the solution to the system of equations, $-19x + 8y = -108$, $-71x + 30y = -404$, $-2x + y = -12$, $4x + z = 14$.

Answer available at the end of this section.

Exercise 1.9.41

Suppose a system of equations has fewer equations than variables and you have found a solution to this system of equations. Is it possible that your solution is the only one? Explain.

Answer available at the end of this section.

Exercise 1.9.42

Suppose a system of linear equations has a 2×4 augmented matrix and the last column is a pivot column. Could the system of linear equations be consistent? Explain.

Answer available at the end of this section.

Exercise 1.9.43

Suppose the coefficient matrix of a system of n equations with n variables has the property that every column is a pivot column. Does it follow that the system of equations must have a solution? If so, must the solution be unique? Explain.

Answer available at the end of this section.

Exercise 1.9.44

Suppose there is a unique solution to a system of linear equations. What must be true of the pivot columns in the augmented matrix?

Answer available at the end of this section.

Exercise 1.9.45

The steady state temperature, u, of a plate solves Laplace's equation, $\Delta u = 0$. One way to approximate the solution is to divide the plate into a square mesh and require the temperature at each node to equal the average of the temperature at the four adjacent nodes. In the following picture, the numbers represent the observed temperature at the indicated nodes. Find the temperature at the interior nodes, indicated by x, y, z, and w. One of the equations is $z = 0.05in\frac{1}{4}(10 + 0 + w + x)$.

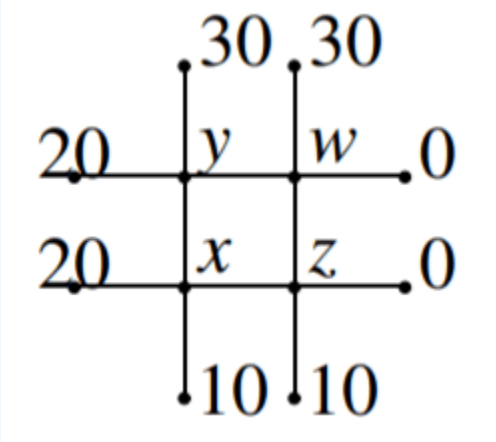


Figure 1.9.1

Answer available at the end of this section.

Exercise 1.9.46

Find the rank of the following matrix.

$$\begin{bmatrix} 4 & -16 & -1 & -5 \\ 1 & -4 & 0 & -1 \\ 1 & -4 & -1 & -2 \end{bmatrix}$$

Exercise 1.9.47

Find the rank of the following matrix.

$$\begin{bmatrix} 3 & 6 & 5 & 12 \\ 1 & 2 & 2 & 5 \\ 1 & 2 & 1 & 2 \end{bmatrix}$$

Exercise 1.9.48

Find the rank of the following matrix.

$$\begin{bmatrix} 0 & 0 & -1 & 0 & 3 \\ 1 & 4 & 1 & 0 & -8 \\ 1 & 4 & 0 & 1 & 2 \\ -1 & -4 & 0 & -1 & -2 \end{bmatrix}$$

Exercise 1.9.49

Find the rank of the following matrix.

$$\begin{bmatrix} 4 & -4 & 3 & -9 \\ 1 & -1 & 1 & -2 \\ 1 & -1 & 0 & -3 \end{bmatrix}$$

Exercise 1.9.50

Find the rank of the following matrix.

$$\begin{bmatrix} 2 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 7 \\ 1 & 0 & 0 & 1 & 7 \end{bmatrix}$$

Exercise 1.9.51

Find the rank of the following matrix.

$$\begin{bmatrix} 4 & 15 & 29 \\ 1 & 4 & 8 \\ 1 & 3 & 5 \\ 3 & 9 & 15 \end{bmatrix}$$

Exercise 1.9.52

Find the rank of the following matrix.

$$\begin{bmatrix} 0 & 0 & -1 & 0 & 1 \\ 1 & 2 & 3 & -2 & -18 \\ 1 & 2 & 2 & -1 & -11 \\ -1 & -2 & -2 & 1 & 11 \end{bmatrix}$$

Exercise 1.9.53

Find the rank of the following matrix.

$$\begin{bmatrix} 1 & -2 & 0 & 3 & 11 \\ 1 & -2 & 0 & 4 & 15 \\ 1 & -2 & 0 & 3 & 11 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Exercise 1.9.54

Find the rank of the following matrix.

$$\begin{bmatrix} -2 & -3 & -2 \\ 1 & 1 & 1 \\ 1 & 0 & 1 \\ -3 & 0 & -3 \end{bmatrix}$$

Exercise 1.9.55

Find the rank of the following matrix.

$$\begin{bmatrix} 4 & 4 & 20 & -1 & 17 \\ 1 & 1 & 5 & 0 & 5 \\ 1 & 1 & 5 & -1 & 2 \\ 3 & 3 & 15 & -3 & 6 \end{bmatrix}$$

Exercise 1.9.56

Find the rank of the following matrix.

$$\begin{bmatrix} -1 & 3 & 4 & -3 & 8 \\ 1 & -3 & -4 & 2 & -5 \\ 1 & -3 & -4 & 1 & -2 \\ -2 & 6 & 8 & -2 & 4 \end{bmatrix}$$

Exercise 1.9.57

Suppose A is an $m \times n$ matrix. Explain why the rank of A is always no larger than $\min(m, n)$.

Answer available at the end of this section.

Exercise 1.9.58

State whether each of the following sets of data are possible for the matrix equation $AX = B$. If possible, describe the solution set. That is, tell whether there exists a unique solution, no solution or infinitely many solutions. Here, $[A|B]$ denotes the augmented matrix.

a. A is a 5×6 matrix, $rank(A) = 4$ and $rank[A|B] = 4$.
b. A is a 3×4 matrix, $rank(A) = 3$ and $rank[A|B] = 2$.
c. A is a 4×2 matrix, $rank(A) = 4$ and $rank[A|B] = 4$.
d. A is a 5×5 matrix, $rank(A) = 4$ and $rank[A|B] = 5$.
e. A is a 4×2 matrix, $rank(A) = 2$ and $rank[A|B] = 2$.

Answer available at the end of this section.

Exercise 1.9.59

Consider the system $-5x + 2y - z = 0$ and $-5x - 2y - z = 0$. Both equations equal zero and so $-5x + 2y - z = -5x - 2y - z$ which is equivalent to $y = 0$. Does it follow that x and z can equal anything? Notice that when $x = 1$, $z = -4$, and $y = 0$ are plugged in to the equations, the equations do not equal 0. Why?

Answer available at the end of this section.

Exercise 1.9.60

Balance the following chemical reactions.

a. $KNO_3 + H_2CO_3 \rightarrow K_2CO_3 + HNO_3$
b. $AgI + Na_2S \rightarrow Ag_2S + NaI$
c. $Ba_3N_2 + H_2O \rightarrow Ba(OH)_2 + NH_3$
d. $CaCl_2 + Na_3PO_4 \rightarrow Ca_3(PO_4)_2 + NaCl$

Answer available at the end of this section.

Exercise 1.9.61

In the section on dimensionless variables it was observed that $\rho V^2 AB$ has the units of force. Describe a systematic way to obtain such combinations of the variables which will yield something which has the units of force.

Exercise 1.9.62

Consider the following diagram of four circuits.

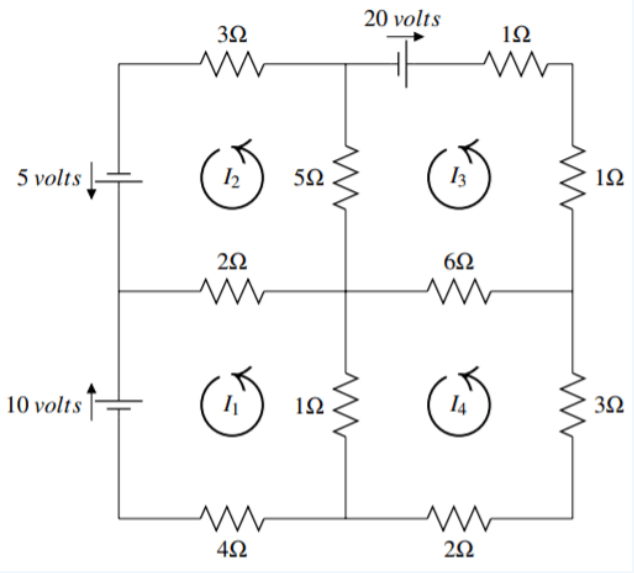


Figure 1.9.2

The current in amps in the four circuits is denoted by I_1, I_2, I_3, I_4 and it is understood that the motion is in the counter clockwise direction. If I_k ends up being negative, then it just means the current flows in the clockwise direction.

In the above diagram, the top left circuit should give the equation

$$2I_2 - 2I_1 + 5I_2 - 5I_3 + 3I_2 = 5$$

For the circuit on the lower left, you should have

$$4I_1 + I_1 - I_4 + 2I_1 - 2I_2 = -10$$

Write equations for each of the other two circuits and then give a solution to the resulting system of equations.

Answer available at the end of this section.

Exercise 1.9.63

Consider the following diagram of three circuits.

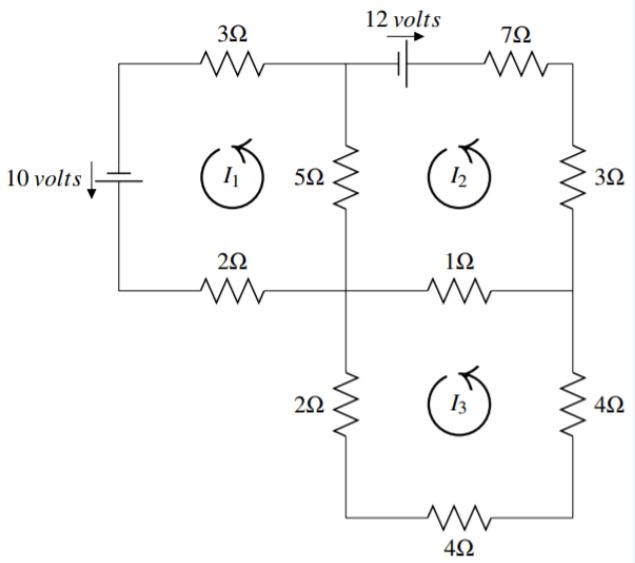


Figure 1.9.3

The current in amps in the four circuits is denoted by I_1, I_2, I_3 and it is understood that the motion is in the counter clockwise direction. If I_k ends up being negative, then it just means the current flows in the clockwise direction.

Find I_1, I_2, I_3.

Answer available at the end of this section.

Answers

Exercise 1.9.1

$\begin{matrix} x+3y=1 \\ 4x-y=3 \end{matrix}$, Solution is: $[x=\frac{10}{13}, y=\frac{1}{13}]$.

Exercise 1.9.2

$\begin{matrix} 3x+y=3 \\ x+2y=1 \end{matrix}$, Solution is: $[x=1, y=0]$

Exercise 1.9.3

$\begin{matrix} x+2y=1 \\ 2x-y=1 \\ 4x+3y=3 \end{matrix}$, Solution is: $\left[x=\frac{3}{5}, y=\frac{1}{5}\right]$

Exercise 1.9.4

No solution exists. You can see this by writing the augmented matrix and doing row operations. $\begin{bmatrix} 1 & 1 & -3 & 2 \\ 2 & 1 & 1 & 1 \\ 3 & 2 & -2 & 0 \end{bmatrix}$, row echelon form: $\begin{bmatrix} 1 & 0 & 4 & 0 \\ 0 & 1 & -7 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$. Thus one of the equation says $0=1$ in an equivalent system of equations.

Exercise 1.9.5

$\begin{matrix} 4g-I=150 \\ 4I-17g=-660 \\ 4g+s=290 \\ g+I+s-b=0 \end{matrix}$, Solution is: $\{g=60, I=90, b=200, s=50\}$

Exercise 1.9.6

The solution exists but is not unique.

Exercise 1.9.7

A solution exists and is unique.

Exercise 1.9.9

There might be a solution. If so, there are infinitely many.

Exercise 1.9.10

No. Consider $x+y+z=2$ and $x+y+z=1$.

Exercise 1.9.11

These can have a solution. For example, $x+y=1, 2x+2y=2, 3x+3y=3$ even has an infinite set of solutions.

Exercise 1.9.12

$h=4$

Exercise 1.9.13

Any h will work.

Exercise 1.9.14

Any h will work.

Exercise 1.9.15

If $h \neq 2$ there will be a unique solution for any k. If $h=2$ and $k \neq 4$, there are no solutions. If $h=2$ and $k=4$, then there are infinitely many solutions.

Exercise 1.9.16

If $h \neq 4$, then there is exactly one solution. If $h=4$ and $k \neq 4$, then there are no solutions. If $h=4$ and $k=4$, then there are infinitely many solutions.

Exercise 1.9.17

There is no solution. The system is inconsistent. You can see this from the augmented matrix. $\left[\begin{array}{rrrrr} 1 & 2 & 1 & -1 & 2 \\ 1 & -1 & 1 & 1 & 1 \\ 2 & 1 & -1 & 0 & 1 \\ 4 & 2 & 1 & 0 & 5 \end{array}\right]$, reduced row-echelon form: $\left[\begin{array}{rrrrr} 1 & 0 & 0 & \frac{1}{3} & 0 \\ 0 & 1 & 0 & -\frac{2}{3} & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{array}\right]$.

Exercise 1.9.18

Solution is: $\left[w=\frac{3}{2}y-1, x=\frac{2}{3}-\frac{1}{2}y, z=\frac{1}{3}\right]$

Exercise 1.9.19

a. This one is not.
b. This one is.
c. This one is.

Exercise 1.9.28

The reduced row-echelon form is $\left[\begin{array}{rrrr} 1 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 1 & -\frac{1}{4} & \frac{3}{4} \\ 0 & 0 & 0 & 0 \end{array}\right]$. Therefore, the solution is of the form $z=t, y=\frac{3}{4}+t\left(\frac{1}{4}\right), x=\frac{1}{2}-\frac{1}{2}t$ where $t \in \mathbb{R}$.

Exercise 1.9.29

The reduced row-echelon form is $\left[\begin{array}{rrrr} 1 & 0 & 4 & 2 \\ 0 & 1 & -4 & -1 \end{array}\right]$ and so the solution is $z=t, y=4t, x=2-4t$.

Exercise 1.9.30

The reduced row-echelon form is $\left[\begin{array}{rrrrrr} 1 & 0 & 0 & 0 & 9 & 3 \\ 0 & 1 & 0 & 0 & -4 & 0 \\ 0 & 0 & 1 & 0 & -7 & -1 \\ 0 & 0 & 0 & 1 & 6 & 1 \end{array}\right]$ and so $x_5=t, x_4=1-6t, x_3=-1+7t, x_2=4t, x_1=3-9t$.

Exercise 1.9.31

The reduced row-echelon form is $\left[\begin{array}{rrrrrr} 1 & 0 & 2 & 0 & -\frac{1}{2} & \frac{5}{2} \\ 0 & 1 & 0 & 0 & \frac{1}{2} & \frac{3}{2} \\ 0 & 0 & 0 & 1 & \frac{3}{2} & -\frac{1}{2} \\ 0 & 0 & 0 & 0 & 0 & 0 \end{array}\right]$. Therefore, let $x_5=t, x_3=s$. Then the other variables are given by $x_4=-\frac{1}{2}-\frac{3}{2}t, x_2=\frac{3}{2}-t\frac{1}{2},, x_1 = \frac{5}{2}+\frac{1}{2}t-2s$.

Exercise 1.9.32

Solution is: $[x=1-2t, z=1, y=t]$

Exercise 1.9.33

Solution is: $[x=2-4t, y=-8t, z=t]$

Exercise 1.9.34

Solution is: $[x=-1, y=2, z=-1]$

Exercise 1.9.35

Solution is: $[x=2, y=4, z=5]$

Exercise 1.9.36

Solution is: $[x=1, y=2, z=-5]$

Exercise 1.9.37

Solution is: $[x=-1, y=-5, z=4]$

Exercise 1.9.38

Solution is: $[x=2t+1, y=4t, z=t]$

Exercise 1.9.39

Solution is: $[x=1, y=5, z=3]$

Exercise 1.9.40

Solution is: $[x=4, y=-4, z=-2]$

Exercise 1.9.41

No. Consider $x+y+z=2$ and $x+y+z=1$.

Exercise 1.9.42

No. This would lead to $0=1$.

Exercise 1.9.43

Yes. It has a unique solution.

Exercise 1.9.44

The last column must not be a pivot column. The remaining columns must each be pivot columns.

Exercise 1.9.45

You need $\begin{array}{l} \frac{1}{4}(20+30+w+x)-y=0 \\ \frac{1}{4}(y+30+0+z)-w=0 \\ \frac{1}{4}(20+y+z+10)-x=0 \\ \frac{1}{4}(x+w+0+10)-z=0 \end{array}$, Solution is: $[w=15, x=15, y=20, z=10]$.

Exercise 1.9.57

It is because you cannot have more than $\min(m,n)$ nonzero rows in the reduced row-echelon form. Recall that the number of pivot columns is the same as the number of nonzero rows from the description of this reduced row-echelon form.

Exercise 1.9.58

a. This says B is in the span of four of the columns. Thus the columns are not independent. Infinite solution set.
b. This surely can't happen. If you add in another column, the rank does not get smaller.
c. This says B is in the span of the columns and the columns must be independent. You can't have the rank equal 4 if you only have two columns.
d. This says B is not in the span of the columns. In this case, there is no solution to the system of equations represented by the augmented matrix.
e. In this case, there is a unique solution since the columns of A are independent.

Exercise 1.9.59

These are not legitimate row operations. They do not preserve the solution set of the system.

Exercise 1.9.60

Exercise 1.9.62

The other two equations are

$$\begin{array}{c} 6I_3-6I_4+I_3+I_3+5I_3-5I_2=-20 \\ 2I_4+3I_4+6I_4-6I_3+I_4-I_1=0 \end{array} \tag{1.9.1}$$

Then the system is

$$\begin{array}{c} 2I_2-2I_1+5I_2-5I_3+3I_2=5 \\ 4I_1+I_1-I_4+2I_1-2I_2=-10 \\ 6I_3-6I_4+I_3+I_3+5I_3-5I_2=-20 \\ 2I_4+3I_4+6I_4-6I_3+I_4-I_1=0 \end{array}$$

The solution is:

$$\begin{array}{l} I_1=-\frac{750}{373} \\ I_2=-\frac{1421}{1119} \\ I_3=-\frac{3061}{1119} \\ I_4=-\frac{1718}{1119} \end{array} \tag{1.9.2}$$

Exercise 1.9.63

You have

$$\begin{array}{c} 2I_1+5I_1+3I_1-5I_2=10 \\ I_2-I_3+3I_2+7I_2+5I_2-5I_1=-12 \\ 2I_3+4I_3+4I_3+I_3-I_2=0 \end{array} \tag{1.9.3}$$

Simplifying this yields

$$\begin{array}{c} 10I_1-5I_2=10 \\ -5I_1+16I_2-I_3=-12 \\ -I_2+11I_3=0 \end{array} \tag{1.9.4}$$

The solution is given by

$$I_1=\frac{218}{295}, I_2=-\frac{154}{295}, I_3=-\frac{14}{295}$$

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1.10: SUPPLEMENTARY NOTES - HOMOGENEOUS SYSTEMS OF EQUATIONS

Homogeneous systems of linear equations in which each equation is set equal to zero. There are two possibilities either there is just one solution or there are infinitely many solutions. If there is just one solution, do you know what that solution would be?

1.10.1: Homogeneous Equations

1.10.1E: Homogeneous Equations

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1.10.1: HOMOGENEOUS EQUATIONS

A system of equations in the variables $x_1, x_2, \ldots, x_n$ is called **homogeneous** if all the constant terms are zero—that is, if each equation of the system has the form

$$a_1x_1 + a_2x_2 + \cdots + a_nx_n = 0$$

Clearly $x_1 = 0, x_2 = 0, \ldots, x_n = 0$ is a solution to such a system; it is called the **trivial solution**. Any solution in which at least one variable has a nonzero value is called a **nontrivial solution**. Our chief goal in this section is to give a useful condition for a homogeneous system to have nontrivial solutions. The following example is instructive.

Example 1.10.1.1

Show that the following homogeneous system has nontrivial solutions.

$$\begin{array}{rcrcrcrcl} x_1 & - & x_2 & + & 2x_3 & - & x_4 & = & 0 \\ 2x_1 & + & 2x_2 & & & + & x_4 & = & 0 \\ 3x_1 & + & x_2 & + & 2x_3 & - & x_4 & = & 0 \end{array}$$

Solution

The reduction of the augmented matrix to reduced row-echelon form is outlined below.

$$\begin{bmatrix} 1 & -1 & 2 & -1 & 0 \\ 2 & 2 & 0 & 1 & 0 \\ 3 & 1 & 2 & -1 & 0 \end{bmatrix} \to \begin{bmatrix} 1 & -1 & 2 & -1 & 0 \\ 0 & 4 & -4 & 3 & 0 \\ 0 & 4 & -4 & 2 & 0 \end{bmatrix} \to \begin{bmatrix} 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

The leading variables are x_1, x_2, and x_4, so x_3 is assigned as a parameter—say $x_3 = t$. Then the general solution is $x_1 = -t$, $x_2 = t$, $x_3 = t$, $x_4 = 0$. Hence, taking $t = 1$ (say), we get a nontrivial solution: $x_1 = -1$, $x_2 = 1$, $x_3 = 1$, $x_4 = 0$.

The existence of a nontrivial solution in Example 1.10.1.1 is ensured by the presence of a parameter in the solution. This is due to the fact that there is a *nonleading* variable (x_3 in this case). But there *must* be a nonleading variable here because there are four variables and only three equations (and hence at *most* three leading variables). This discussion generalizes to a proof of the following fundamental theorem.

Theorem 1.10.1.1

If a homogeneous system of linear equations has more variables than equations, then it has a nontrivial solution (in fact, infinitely many).

Proof

Suppose there are m equations in n variables where $n > m$, and let R denote the reduced row-echelon form of the augmented matrix. If there are r leading variables, there are $n - r$ nonleading variables, and so $n - r$ parameters. Hence, it suffices to show that $r < n$. But $r \leq m$ because R has r leading 1s and m rows, and $m < n$ by hypothesis. So $r \leq m < n$, which gives $r < n$.

□

Note that the converse of Theorem 1.10.1.1 is not true: if a homogeneous system has nontrivial solutions, it need not have more variables than equations (the system $x_1 + x_2 = 0$, $2x_1 + 2x_2 = 0$ has nontrivial solutions but $m = 2 = n$.) Theorem 1.10.1.1 is very useful in applications. The next example provides an illustration from geometry.

Example 1.10.1.2

We call the graph of an equation $ax^2 + bxy + cy^2 + dx + ey + f = 0$ a **conic** if the numbers a, b, and c are not all zero. Show that there is at least one conic through any five points in the plane that are not all on a line.

Solution

Let the coordinates of the five points be (p_1, q_1), (p_2, q_2), (p_3, q_3), (p_4, q_4), and (p_5, q_5). The graph of $ax^2 + bxy + cy^2 + dx + ey + f = 0$ passes through (p_i, q_i) if

$$ap_i^2 + bp_iq_i + cq_i^2 + dp_i + eq_i + f = 0$$

This gives five equations, one for each i, linear in the six variables a, b, c, d, e, and f. Hence, there is a nontrivial solution by Theorem 1.10.1.1. If $a = b = c = 0$, the five points all lie on the line with equation $dx + ey + f = 0$, contrary to assumption. Hence, one of a, b, c is nonzero.

Linear Combinations and Basic Solutions

As for rows, two columns are regarded as **equal** if they have the same number of entries and corresponding entries are the same. Let $\mathbf{x}$ and $\mathbf{y}$ be columns with the same number of entries. As for elementary row operations, their **sum** $\mathbf{x} + \mathbf{y}$ is obtained by adding corresponding entries and, if k is a number, the **scalar product** $k\mathbf{x}$ is defined by multiplying each entry of $\mathbf{x}$ by k. More precisely:

$$\text{If } \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \text{ and } \mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \text{ then } \mathbf{x} + \mathbf{y} = \begin{bmatrix} x_1 + y_1 \\ x_2 + y_2 \\ \vdots \\ x_n + y_n \end{bmatrix} \text{ and } k\mathbf{x} = \begin{bmatrix} kx_1 \\ kx_2 \\ \vdots \\ kx_n \end{bmatrix}.$$

A sum of scalar multiples of several columns is called a **linear combination** of these columns. For example, $s\mathbf{x} + t\mathbf{y}$ is a linear combination of $\mathbf{x}$ and $\mathbf{y}$ for any choice of numbers s and t.

Example 1.10.1.3

$$\text{If } \mathbf{x} = \begin{bmatrix} 3 \\ -2 \end{bmatrix} \text{ and } \mathbf{y} = \begin{bmatrix} -1 \\ 1 \end{bmatrix} \text{ then } 2\mathbf{x} + 5\mathbf{y} = \begin{bmatrix} 6 \\ -4 \end{bmatrix} + \begin{bmatrix} -5 \\ 5 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}..$$

Example 1.10.1.4

Let $\mathbf{x} = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \mathbf{y} = \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix}$ and $\mathbf{z} = \begin{bmatrix} 3 \\ 1 \\ 1 \end{bmatrix}$. If $\mathbf{v} = \begin{bmatrix} 0 \\ -1 \\ 2 \end{bmatrix}$ and $\mathbf{w} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$, determine whether $\mathbf{v}$ and $\mathbf{w}$ are linear combinations of $\mathbf{x}$, $\mathbf{y}$ and $\mathbf{z}$.

Solution

For $\mathbf{v}$, we must determine whether numbers r, s, and t exist such that $\mathbf{v} = r\mathbf{x} + s\mathbf{y} + t\mathbf{z}$, that is, whether

$$\begin{bmatrix} 0 \\ -1 \\ 2 \end{bmatrix} = r\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} + s\begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} + t\begin{bmatrix} 3 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} r + 2s + 3t \\ s + t \\ r + t \end{bmatrix}$$

Equating corresponding entries gives a system of linear equations $r + 2s + 3t = 0$, $s + t = -1$, and $r + t = 2$ for r, s, and t. By gaussian elimination, the solution is $r = 2 - k$, $s = -1 - k$, and $t = k$ where k is a parameter. Taking $k = 0$, we see that $\mathbf{v} = 2\mathbf{x} - \mathbf{y}$ is a linear combination of $\mathbf{x}$, $\mathbf{y}$, and $\mathbf{z}$.

Turning to $\mathbf{w}$, we again look for r, s, and t such that $\mathbf{w} = r\mathbf{x} + s\mathbf{y} + t\mathbf{z}$; that is,

$$\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = r\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} + s\begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} + t\begin{bmatrix} 3 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} r+2s+3t \\ s+t \\ r+t \end{bmatrix}$$

leading to equations $r + 2s + 3t = 1$, $s + t = 1$, and $r + t = 1$ for real numbers r, s, and t. But this time there is *no* solution as the reader can verify, so $\mathbf{w}$ is *not* a linear combination of $\mathbf{x}$, $\mathbf{y}$, and $\mathbf{z}$.

Our interest in linear combinations comes from the fact that they provide one of the best ways to describe the general solution of a homogeneous system of linear equations. When solving such a system with n variables $x_1, x_2, \ldots, x_n$, write the variables as a column[1] matrix: $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$. The trivial solution is denoted $\mathbf{0} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$. As an illustration, the general solution in Example 1.10.1.1 is $x_1 = -t$, $x_2 = t$, $x_3 = t$, and $x_4 = 0$, where t is a parameter, and we would now express this by saying that the general solution is $\mathbf{x} = \begin{bmatrix} -t \\ t \\ t \\ 0 \end{bmatrix}$, where t is arbitrary.

Note

The reason for using columns will be apparent later.

Now let $\mathbf{x}$ and $\mathbf{y}$ be two solutions to a homogeneous system with n variables. Then any linear combination $s\mathbf{x} + t\mathbf{y}$ of these solutions turns out to be again a solution to the system. More generally:

Any linear combination of solutions to a homogeneous system is again a solution. (1.10.1.1)

In fact, suppose that a typical equation in the system is $a_1x_1 + a_2x_2 + \cdots + a_nx_n = 0$, and suppose that $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$, $\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$ are solutions. Then $a_1x_1 + a_2x_2 + \cdots + a_nx_n = 0$ and $a_1y_1 + a_2y_2 + \cdots + a_ny_n = 0$. Hence $s\mathbf{x} + t\mathbf{y} = \begin{bmatrix} sx_1 + ty_1 \\ sx_2 + ty_2 \\ \vdots \\ sx_n + ty_n \end{bmatrix}$ is also a solution because

$$\begin{aligned} a_1(sx_1 + ty_1) + a_2(sx_2 + ty_2) + \cdots + a_n(sx_n + ty_n) \\ &= [a_1(sx_1) + a_2(sx_2) + \cdots + a_n(sx_n)] + [a_1(ty_1) + a_2(ty_2) + \cdots + a_n(ty_n)] \\ &= s(a_1x_1 + a_2x_2 + \cdots + a_nx_n) + t(a_1y_1 + a_2y_2 + \cdots + a_ny_n) \\ &= s(0) + t(0) \\ &= 0 \end{aligned}$$

A similar argument shows that Statement 1.10.1.1 is true for linear combinations of more than two solutions.

The remarkable thing is that *every* solution to a homogeneous system is a linear combination of certain particular solutions and, in fact, these solutions are easily computed using the gaussian algorithm. Here is an example.

Example 1.10.1.5

Solve the homogeneous system with coefficient matrix

$$A = \begin{bmatrix} 1 & -2 & 3 & -2 \\ -3 & 6 & 1 & 0 \\ -2 & 4 & 4 & -2 \end{bmatrix}$$

Solution

The reduction of the augmented matrix to reduced form is

$$\begin{bmatrix} 1 & -2 & 3 & -2 & 0 \\ -3 & 6 & 1 & 0 & 0 \\ -2 & 4 & 4 & -2 & 0 \end{bmatrix} \to \begin{bmatrix} 1 & -2 & 0 & -\frac{1}{5} & 0 \\ 0 & 0 & 1 & -\frac{3}{5} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

so the solutions are $x_1 = 2s + \frac{1}{5}t$, $x_2 = s$, $x_3 = \frac{3}{5}t$, and $x_4 = t$ by gaussian elimination. Hence we can write the general solution $\mathbf{x}$ in the matrix form

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 2s + \frac{1}{5}t \\ s \\ \frac{3}{5}t \\ t \end{bmatrix} = s \begin{bmatrix} 2 \\ 1 \\ 0 \\ 0 \end{bmatrix} + t \begin{bmatrix} \frac{1}{5} \\ 0 \\ \frac{3}{5} \\ 1 \end{bmatrix} = s\mathbf{x}_1 + t\mathbf{x}_2.$$

Here $\mathbf{x}_1 = \begin{bmatrix} 2 \\ 1 \\ 0 \\ 0 \end{bmatrix}$ and $\mathbf{x}_2 = \begin{bmatrix} \frac{1}{5} \\ 0 \\ \frac{3}{5} \\ 1 \end{bmatrix}$ are particular solutions determined by the gaussian algorithm.

The solutions $\mathbf{x}_1$ and $\mathbf{x}_2$ in Example $1.10.1.5$ are denoted as follows:

Definition $1.10.1.5$: Basic Solutions

The gaussian algorithm systematically produces solutions to any homogeneous linear system, called **basic solutions**, one for every parameter.

Moreover, the algorithm gives a routine way to express *every* solution as a linear combination of basic solutions as in Example $1.10.1.5$, where the general solution $\mathbf{x}$ becomes

$$\mathbf{x} = s \begin{bmatrix} 2 \\ 1 \\ 0 \\ 0 \end{bmatrix} + t \begin{bmatrix} \frac{1}{5} \\ 0 \\ \frac{3}{5} \\ 1 \end{bmatrix} = s \begin{bmatrix} 2 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \frac{1}{5}t \begin{bmatrix} 1 \\ 0 \\ 3 \\ 5 \end{bmatrix}$$

Hence by introducing a new parameter $r = t/5$ we can multiply the original basic solution $\mathbf{x}_2$ by 5 and so eliminate fractions. For this reason:

Convention:
Any nonzero scalar multiple of a basic solution will still be called a basic solution.

In the same way, the gaussian algorithm produces basic solutions to *every* homogeneous system, one for each parameter (there are *no* basic solutions if the system has only the trivial solution). Moreover every solution is given by the algorithm as a linear combination of these basic solutions (as in Example $1.10.1.5$). If A has rank r, Theorem $1.10.1.2$ shows that there are exactly $n - r$ parameters, and so $n - r$ basic solutions. This proves Theorem $1.10.1.2$:

Theorem 1.10.1.2

Let A be an $m \times n$ matrix of rank r, and consider the homogeneous system in n variables with A as coefficient matrix. Then:

1. The system has exactly $n - r$ basic solutions, one for each parameter.
2. Every solution is a linear combination of these basic solutions.

Example 1.10.1.6

Find basic solutions of the homogeneous system with coefficient matrix A, and express every solution as a linear combination of the basic solutions, where

$$A = \begin{bmatrix} 1 & -3 & 0 & 2 & 2 \\ -2 & 6 & 1 & 2 & -5 \\ 3 & -9 & -1 & 0 & 7 \\ -3 & 9 & 2 & 6 & -8 \end{bmatrix}$$

Solution

The reduction of the augmented matrix to reduced row-echelon form is

$$\begin{bmatrix} 1 & -3 & 0 & 2 & 2 & 0 \\ -2 & 6 & 1 & 2 & -5 & 0 \\ 3 & -9 & -1 & 0 & 7 & 0 \\ -3 & 9 & 2 & 6 & -8 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -3 & 0 & 2 & 2 & 0 \\ 0 & 0 & 1 & 6 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

so the general solution is $x_1 = 3r - 2s - 2t$, $x_2 = r$, $x_3 = -6s + t$, $x_4 = s$, and $x_5 = t$ where r, s, and t are parameters. In matrix form this is

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} 3r - 2s - 2t \\ r \\ -6s + t \\ s \\ t \end{bmatrix} = r \begin{bmatrix} 3 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + s \begin{bmatrix} -2 \\ 0 \\ -6 \\ 1 \\ 0 \end{bmatrix} + t \begin{bmatrix} -2 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}$$

Hence basic solutions are

$$\mathbf{x}_1 = \begin{bmatrix} 3 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \ \mathbf{x}_2 = \begin{bmatrix} -2 \\ 0 \\ -6 \\ 1 \\ 0 \end{bmatrix}, \ \mathbf{x}_3 = \begin{bmatrix} -2 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}$$

1.10.1E: Homogeneous Equations

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1.10.1E: Homogeneous Equations

Exercise $1.10.1E.1$

Consider the following statements about a system of linear equations with augmented matrix A. In each case either prove the statement or give an example for which it is false.

a. If the system is homogeneous, every solution is trivial.
b. If the system has a nontrivial solution, it cannot be homogeneous.
c. If there exists a trivial solution, the system is homogeneous.
d. If the system is consistent, it must be homogeneous.

Now assume that the system is homogeneous.

e. If there exists a nontrivial solution, there is no trivial solution.
f. If there exists a solution, there are infinitely many solutions.
g. If there exist nontrivial solutions, the row-echelon form of A has a row of zeros.
h. If the row-echelon form of A has a row of zeros, there exist nontrivial solutions.
i. If a row operation is applied to the system, the new system is also homogeneous.

Answer available at the end of this section.

Exercise $1.10.1E.2$

In each of the following, find all values of a for which the system has nontrivial solutions, and determine all solutions in each case.

a. $$\begin{aligned} x - 2y + z &= 0 \\ x + ay - 3z &= 0 \\ -x + 6y - 5z &= 0 \end{aligned}$$
b. $$\begin{aligned} x + 2y + z &= 0 \\ x + 3y + 6z &= 0 \\ 2x + 3y + az &= 0 \end{aligned}$$
c. $$\begin{aligned} x + y - z &= 0 \\ ay - z &= 0 \\ x + y + az &= 0 \end{aligned}$$
d. $$\begin{aligned} ax + y + z &= 0 \\ x + y - z &= 0 \\ x + y + az &= 0 \end{aligned}$$

Answer available at the end of this section.

Exercise $1.10.1E.3$

Let $\mathbf{x} = \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix}$, $\mathbf{y} = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$, and $\mathbf{z} = \begin{bmatrix} 1 \\ 1 \\ -2 \end{bmatrix}$. In each case, either write $\mathbf{v}$ as a linear combination of $\mathbf{x}$, $\mathbf{y}$, and $\mathbf{z}$, or show that it is not such a linear combination.

a. $\mathbf{v} = \begin{bmatrix} 0 \\ 1 \\ -3 \end{bmatrix}$

b. $\mathbf{v} = \begin{bmatrix} 4 \\ 3 \\ -4 \end{bmatrix}$

c. $\mathbf{v} = \begin{bmatrix} 3 \\ 1 \\ 0 \end{bmatrix}$

d. $\mathbf{v} = \begin{bmatrix} 3 \\ 0 \\ 3 \end{bmatrix}$

Answer available at the end of this section.

Exercise $1.10.1E.4$

In each case, either express $\mathbf{y}$ as a linear combination of $\mathbf{a}_1$, $\mathbf{a}_2$, and $\mathbf{a}_3$, or show that it is not such a linear combination. Here:

$$\mathbf{a}_1 = \begin{bmatrix} -1 \\ 3 \\ 0 \\ 1 \end{bmatrix}, \ \mathbf{a}_2 = \begin{bmatrix} 3 \\ 1 \\ 2 \\ 0 \end{bmatrix}, \text{ and } \mathbf{a}_3 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

a. $\mathbf{y} = \begin{bmatrix} 1 \\ 2 \\ 4 \\ 0 \end{bmatrix}$

b. $\mathbf{y} = \begin{bmatrix} -1 \\ 9 \\ 2 \\ 6 \end{bmatrix}$

Answer available at the end of this section.

Exercise $1.10.1E.5$

For each of the following homogeneous systems, find a set of basic solutions and express the general solution as a linear combination of these basic solutions.

a.
$$\begin{array}{rcrcrcrcrcl} x_1 & + & 2x_2 & - & x_3 & + & 2x_4 & + & x_5 & = & 0 \\ x_1 & + & 2x_2 & + & 2x_3 & & & + & x_5 & = & 0 \\ 2x_1 & + & 4x_2 & - & 2x_3 & + & 3x_4 & + & x_5 & = & 0 \end{array}$$

b.
$$\begin{array}{rcrcrcrcrcl} x_1 & + & 2x_2 & - & x_3 & + & x_4 & + & x_5 & = & 0 \\ -x_1 & - & 2x_2 & + & 2x_3 & & & + & x_5 & = & 0 \\ -x_1 & - & 2x_2 & + & 3x_3 & + & x_4 & + & 3x_5 & = & 0 \end{array}$$

c.
$$\begin{array}{rcrcrcrcrcl} x_1 & + & x_2 & - & x_3 & + & 2x_4 & + & x_5 & = & 0 \\ x_1 & + & 2x_2 & - & x_3 & + & x_4 & + & x_5 & = & 0 \\ 2x_1 & + & 3x_2 & - & x_3 & + & 2x_4 & + & x_5 & = & 0 \\ 4x_1 & + & 5x_2 & - & 2x_3 & + & 5x_4 & + & 2x_5 & = & 0 \end{array}$$

d. $$\begin{array}{rcrcrcrcrcl} x_1 & + & x_2 & - & 2x_3 & - & 2x_4 & + & 2x_5 & = & 0 \\ 2x_1 & + & 2x_2 & - & 4x_3 & - & 4x_4 & + & x_5 & = & 0 \\ x_1 & - & x_2 & + & 2x_3 & + & 4x_4 & + & x_5 & = & 0 \\ -2x_1 & - & 4x_2 & + & 8x_3 & + & 10x_4 & + & x_5 & = & 0 \end{array}$$

Answer available at the end of this section.

Exercise $1.10.1E.6$

a. Does Theorem 1.3.1 imply that the system $\begin{cases} -z + 3y = 0 \\ 2x - 6y = 0 \end{cases}$ has nontrivial solutions? Explain.

b. Show that the converse to Theorem 1.3.1 is not true. That is, show that the existence of nontrivial solutions does *not* imply that there are more variables than equations.

Answer available at the end of this section.

Exercise $1.10.1E.7$

In each case determine how many solutions (and how many parameters) are possible for a homogeneous system of four linear equations in six variables with augmented matrix A. Assume that A has nonzero entries. Give all possibilities.

Rank $A = 2$. Rank $A = 1$. A has a row of zeros. The row-echelon form of A has a row of zeros.

Answer available at the end of this section.

Exercise $1.10.1E.8$

The graph of an equation $ax + by + cz = 0$ is a plane through the origin (provided that not all of a, b, and c are zero). Use Theorem 1.3.1 to show that two planes through the origin have a point in common other than the origin $(0, 0, 0)$.

Exercise $1.10.1E.1$

a. Show that there is a line through any pair of points in the plane. [*Hint*: Every line has equation $ax + by + c = 0$, where a, b, and c are not all zero.]

b. Generalize and show that there is a plane $ax + by + cz + d = 0$ through any three points in space.

Answer available at the end of this section.

Exercise $1.10.1E.10$

The graph of

$$a(x^2 + y^2) + bx + cy + d = 0$$

is a circle if $a \neq 0$. Show that there is a circle through any three points in the plane that are not all on a line.

Exercise $1.10.1E.11$

Consider a homogeneous system of linear equations in n variables, and suppose that the augmented matrix has rank r. Show that the system has nontrivial solutions if and only if $n > r$.

Answer available at the end of this section.

Exercise $1.10.1E.12$

If a consistent (possibly nonhomogeneous) system of linear equations has more variables than equations, prove that it has more than one solution.

Answers

Exercise $1.10.1E.1$

b. False. $A = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 \end{bmatrix}$

d. False. $A = \begin{bmatrix} 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix}$

f. False. $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$

Exercise $1.10.1E.2$

b. $a = -3$, $x = 9t$, $y = -5t$, $z = t$

d. $a = 1$, $x = -t$, $y = t$, $z = 0$; or $a = -1$, $x = t$, $y = 0$, $z = t$

Exercise $1.10.1E.3$

b. Not a linear combination.

d. $\mathbf{v} = \mathbf{x} + 2\mathbf{y} - \mathbf{z}$

Exercise $1.10.1E.4$

b. $\mathbf{y} = 2\mathbf{a}_1 - \mathbf{a}_2 + 4\mathbf{a}_3$.

Exercise $1.10.1E.5$

b. $r \begin{bmatrix} -2 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + s \begin{bmatrix} -2 \\ 0 \\ -1 \\ 1 \\ 0 \end{bmatrix} + t \begin{bmatrix} -3 \\ 0 \\ -2 \\ 0 \\ 1 \end{bmatrix}$

d. $s \begin{bmatrix} 0 \\ 2 \\ 1 \\ 0 \\ 0 \end{bmatrix} + t \begin{bmatrix} -1 \\ 3 \\ 0 \\ 1 \\ 0 \end{bmatrix}$

Exercise $1.10.1E.6$

b. The system in (a) has nontrivial solutions.

Exercise $1.10.1E.7$

a. By Theorem 1.3.2, there are $n - r = 6 - 1 = 5$ parameters and thus infinitely many solutions.

d. If R is the row-echelon form of A, then R has a row of zeros and 4 rows in all. Hence R has $r = rank\ A = 1$, 2, or 3. Thus there are $n - r = 6 - r = 5$, 4, or 3 parameters and thus infinitely many solutions.

Exercise $1.10.1E.1$

b. That the graph of $ax + by + cz = d$ contains three points leads to 3 linear equations homogeneous in variables a, b, c, and d. Apply Theorem 1.3.1.

Exercise $1.10.1E.11$

b. There are $n - r$ parameters (Theorem $1.10.1E.2$), so there are nontrivial solutions if and only if $n - r > 0$.

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2: MATRICES

2.1: Matrix Arithmetic

2.2: Multiplication of Matrices

Matrix Operations GeoGebra Demo by Kevin Hopkins

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2.1: Matrix Arithmetic

Outcomes

A. Perform the matrix operations of matrix addition, scalar multiplication, transposition and matrix multiplication. Identify when these operations are not defined. Represent these operations in terms of the entries of a matrix.
B. Prove algebraic properties for matrix addition, scalar multiplication, transposition, and matrix multiplication. Apply these properties to manipulate an algebraic expression involving matrices.
C. Compute the inverse of a matrix using row operations, and prove identities involving matrix inverses.
D. Solve a linear system using matrix algebra.
E. Use multiplication by an elementary matrix to apply row operations.
F. Write a matrix as a product of elementary matrices.

You have now solved systems of equations by writing them in terms of an augmented matrix and then doing row operations on this augmented matrix. It turns out that matrices are important not only for systems of equations but also in many applications.

Recall that a **matrix** is a rectangular array of numbers. Several of them are referred to as **matrices**. For example, here is a matrix.

$$\begin{bmatrix} 1 & 2 & 3 & 4 \\ 5 & 2 & 8 & 7 \\ 6 & -9 & 1 & 2 \end{bmatrix} \tag{2.1.1}$$

Recall that the size or dimension of a matrix is defined as $m \times n$ where m is the number of rows and n is the number of columns. The above matrix is a 3×4 matrix because there are three rows and four columns. You can remember the columns are like columns in a Greek temple. They stand upright while the rows lay flat like rows made by a tractor in a plowed field.

When specifying the size of a matrix, you always list the number of rows before the number of columns.You might remember that you always list the rows before the columns by using the phrase **Row**man **C**atholic.

Consider the following definition.

Definition 2.1.1: Square Matrix

A matrix A which has size $n \times n$ is called a **square matrix** . In other words, A is a square matrix if it has the same number of rows and columns.

There is some notation specific to matrices which we now introduce. We denote the columns of a matrix A by A_j as follows

$$A = \begin{bmatrix} A_1 & A_2 & \cdots & A_n \end{bmatrix}$$

Therefore, A_j is the j^{th} column of A, when counted from left to right.

The individual elements of the matrix are called **entries** or **components** of A. Elements of the matrix are identified according to their position. The $(\mathbf{i},\mathbf{j})$**-entry** of a matrix is the entry in the i^{th} row and j^{th} column. For example, in the matrix (2.1.1) above, 8 is in position $(2,3)$ (and is called the $(2,3)$-entry) because it is in the second row and the third column.

In order to remember which matrix we are speaking of, we will denote the entry in the i^{th} row and the j^{th} column of matrix A by a_{ij}. Then, we can write A in terms of its entries, as $A = [a_{ij}]$. Using this notation on the matrix in (2.1.1), $a_{23} = 8, a_{32} = -9, a_{12} = 2$, etc.

There are various operations which are done on matrices of appropriate sizes. Matrices can be added to and subtracted from other matrices, multiplied by a scalar, and multiplied by other matrices. We will never divide a matrix by another matrix, but we will see later how matrix inverses play a similar role.

In doing arithmetic with matrices, we often define the action by what happens in terms of the entries (or components) of the matrices. Before looking at these operations in depth, consider a few general definitions.

Definition 2.1.2: The Zero Matrix

The $m \times n$ **zero matrix** is the $m \times n$ matrix having every entry equal to zero. It is denoted by 0.

One possible zero matrix is shown in the following example.

Example 2.1.1: The Zero Matrix

The 2×3 zero matrix is $0 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$.

Note there is a 2×3 zero matrix, a 3×4 zero matrix, etc. In fact there is a zero matrix for every size!

Definition 2.1.3: Equality of Matrices

Let A and B be two $m \times n$ matrices. Then $A = B$ means that for $A = [a_{ij}]$ and $B = [b_{ij}]$, $a_{ij} = b_{ij}$ for all $1 \leq i \leq m$ and $1 \leq j \leq n$.

In other words, two matrices are equal exactly when they are the same size and the corresponding entries are identical. Thus

$$\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \neq \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

because they are different sizes. Also,

$$\begin{bmatrix} 0 & 1 \\ 3 & 2 \end{bmatrix} \neq \begin{bmatrix} 1 & 0 \\ 2 & 3 \end{bmatrix}$$

because, although they are the same size, their corresponding entries are not identical.

In the following section, we explore addition of matrices.

Addition of Matrices

When adding matrices, all matrices in the sum need have the same size. For example,

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 2 \end{bmatrix}$$

and

$$\begin{bmatrix} -1 & 4 & 8 \\ 2 & 8 & 5 \end{bmatrix}$$

cannot be added, as one has size 3×2 while the other has size 2×3.

However, the addition

$$\begin{bmatrix} 4 & 6 & 3 \\ 5 & 0 & 4 \\ 11 & -2 & 3 \end{bmatrix} + \begin{bmatrix} 0 & 5 & 0 \\ 4 & -4 & 14 \\ 1 & 2 & 6 \end{bmatrix}$$

is possible.

The formal definition is as follows.

Definition 2.1.4: Addition of Matrices

Let $A = [a_{ij}]$ and $B = [b_{ij}]$ be two $m \times n$ matrices. Then $A + B = C$ where C is the $m \times n$ matrix $C = [c_{ij}]$ defined by

$$c_{ij} = a_{ij} + b_{ij}$$

This definition tells us that when adding matrices, we simply add corresponding entries of the matrices. This is demonstrated in the next example.

Example 2.1.2: Addition of Matrices of Same Size

Add the following matrices, if possible.

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 1 & 0 & 4 \end{bmatrix}, B = \begin{bmatrix} 5 & 2 & 3 \\ -6 & 2 & 1 \end{bmatrix}$$

Solution

Notice that both A and B are of size 2×3. Since A and B are of the same size, the addition is possible. Using Definition 2.1.4 , the addition is done as follows.

$$A + B = \begin{bmatrix} 1 & 2 & 3 \\ 1 & 0 & 4 \end{bmatrix} + \begin{bmatrix} 5 & 2 & 3 \\ -6 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 1+5 & 2+2 & 3+3 \\ 1+-6 & 0+2 & 4+1 \end{bmatrix} = \begin{bmatrix} 6 & 4 & 6 \\ -5 & 2 & 5 \end{bmatrix}$$

Addition of matrices obeys very much the same properties as normal addition with numbers. Note that when we write for example $A + B$ then we assume that both matrices are of equal size so that the operation is indeed possible.

Proposition 2.1.1: Properties of Matrix Addition

Let A, B and C be matrices. Then, the following properties hold.

- Commutative Law of Addition

$$A + B = B + A \tag{2.1.2}$$

- Associative Law of Addition

$$(A + B) + C = A + (B + C) \tag{2.1.3}$$

- Existence of an Additive Identity

$$\text{There exists a zero matrix } 0 \text{ such that } A + 0 = A \tag{2.1.4}$$

- Existence of an Additive Inverse

$$\text{There exists a matrix } -A \text{ such that } A + (-A) = 0 \tag{2.1.5}$$

Proof available at the end of this section.

We call the zero matrix in (2.1.4) the **additive identity**. Similarly, we call the matrix $-A$ in (2.1.5) the **additive inverse**. $-A$ is defined to equal $(-1)\, A = [-a_{ij}]$. In other words, every entry of A is multiplied by -1.

In the next section we will study scalar multiplication in more depth to understand what is meant by $(-1)\, A$.

Scalar Multiplication of Matrices

Recall that we use the word *scalar* when referring to numbers. Therefore, *scalar multiplication of a matrix* is the multiplication of a matrix by a number. To illustrate this concept, consider the following example in which a matrix is multiplied by the scalar 3.

$$3\begin{bmatrix} 1 & 2 & 3 & 4 \\ 5 & 2 & 8 & 7 \\ 6 & -9 & 1 & 2 \end{bmatrix} = \begin{bmatrix} 3 & 6 & 9 & 12 \\ 15 & 6 & 24 & 21 \\ 18 & -27 & 3 & 6 \end{bmatrix}$$

The new matrix is obtained by multiplying every entry of the original matrix by the given scalar.

The formal definition of scalar multiplication is as follows.

Definition 2.1.5: Scalar Multiplication of Matrices

If $A = [a_{ij}]$ and k is a scalar, then $kA = [ka_{ij}]$.

Consider the following example.

Example 2.1.3: Effect of Multiplication by a Scalar

Find the result of multiplying the following matrix A by 7.

$$A = \begin{bmatrix} 2 & 0 \\ 1 & -4 \end{bmatrix}$$

Solution

By Definition 2.1.5, we multiply each element of A by 7. Therefore,

$$7A = 7\begin{bmatrix} 2 & 0 \\ 1 & -4 \end{bmatrix} = \begin{bmatrix} 7(2) & 7(0) \\ 7(1) & 7(-4) \end{bmatrix} = \begin{bmatrix} 14 & 0 \\ 7 & -28 \end{bmatrix}$$

Similarly to addition of matrices, there are several properties of scalar multiplication which hold.

Proposition 2.1.2: Properties of Scalar Multiplication

Let A, B be matrices, and k, p be scalars. Then, the following properties hold.

- Distributive Law over Matrix Addition
$$k(A+B) = kA + kB$$
- Distributive Law over Scalar Addition
$$(k+p)A = kA + pA$$
- Associative Law for Scalar Multiplication
$$k(pA) = (kp)A$$
- Rule for Multiplication by 1
$$1A = A$$

Proof available at the end of this section.

Answers

Proposition 2.1.1**: Properties of Matrix Addition**

Consider the Commutative Law of Addition given in (2.1.2). Let A, B, C, and D be matrices such that $A + B = C$ and $B + A = D$. We want to show that $D = C$. To do so, we will use the definition of matrix addition given in Definition 2.1.4. Now,

$$c_{ij} = a_{ij} + b_{ij} = b_{ij} + a_{ij} = d_{ij}$$

Therefore, $C = D$ because the ij^{th} entries are the same for all i and j. Note that the conclusion follows from the commutative law of addition of numbers, which says that if a and b are two numbers, then $a + b = b + a$. The proof of the other results are similar, and are left as an exercise.

Proposition 2.1.2**: Properties of Scalar Multiplication**

The proof of this proposition is similar to the proof of Proposition 2.1.1 and is left an exercise to the reader.

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2.2: MULTIPLICATION OF MATRICES

The next important matrix operation we will explore is multiplication of matrices. The operation of matrix multiplication is one of the most important and useful of the matrix operations. Throughout this section, we will also demonstrate how matrix multiplication relates to linear systems of equations.

First, we provide a formal definition of row and column vectors.

Definition 2.2.1: Row and Column Vectors

Matrices of size $n \times 1$ or $1 \times n$ are called **vectors**. If X is such a matrix, then we write x_i to denote the entry of X in the i^{th} row of a column matrix, or the i^{th} column of a row matrix.

The $n \times 1$ matrix

$$X = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

is called a **column vector.** The $1 \times n$ matrix

$$X = \begin{bmatrix} x_1 & \cdots & x_n \end{bmatrix}$$

is called a **row vector**.

We may simply use the term **vector** throughout this text to refer to either a column or row vector. If we do so, the context will make it clear which we are referring to.

In this chapter, we will again use the notion of linear combination of vectors as in Definition 9.2.2. In this context, a linear combination is a sum consisting of vectors multiplied by scalars. For example,

$$\begin{bmatrix} 50 \\ 122 \end{bmatrix} = 7 \begin{bmatrix} 1 \\ 4 \end{bmatrix} + 8 \begin{bmatrix} 2 \\ 5 \end{bmatrix} + 9 \begin{bmatrix} 3 \\ 6 \end{bmatrix}$$

is a linear combination of three vectors.

It turns out that we can express any system of linear equations as a linear combination of vectors. In fact, the vectors that we will use are just the columns of the corresponding augmented matrix!

Definition 2.2.2: The Vector Form of a System of Linear Equations

Suppose we have a system of equations given by

$$\begin{aligned} a_{11}x_1 + \cdots + a_{1n}x_n &= b_1 \\ &\vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n &= b_m \end{aligned}$$

We can express this system in **vector form** which is as follows:

$$x_1 \begin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{m1} \end{bmatrix} + x_2 \begin{bmatrix} a_{12} \\ a_{22} \\ \vdots \\ a_{m2} \end{bmatrix} + \cdots + x_n \begin{bmatrix} a_{1n} \\ a_{2n} \\ \vdots \\ a_{mn} \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

Notice that each vector used here is one column from the corresponding augmented matrix. There is one vector for each variable in the system, along with the constant vector.

The first important form of matrix multiplication is multiplying a matrix by a vector. Consider the product given by

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \begin{bmatrix} 7 \\ 8 \\ 9 \end{bmatrix}$$

We will soon see that this equals

$$7\begin{bmatrix} 1 \\ 4 \end{bmatrix} + 8\begin{bmatrix} 2 \\ 5 \end{bmatrix} + 9\begin{bmatrix} 3 \\ 6 \end{bmatrix} = \begin{bmatrix} 50 \\ 122 \end{bmatrix}$$

In general terms,

$$\begin{aligned} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} &= x_1 \begin{bmatrix} a_{11} \\ a_{21} \end{bmatrix} + x_2 \begin{bmatrix} a_{12} \\ a_{22} \end{bmatrix} + x_3 \begin{bmatrix} a_{13} \\ a_{23} \end{bmatrix} \\ &= \begin{bmatrix} a_{11}x_1 + a_{12}x_2 + a_{13}x_3 \\ a_{21}x_1 + a_{22}x_2 + a_{23}x_3 \end{bmatrix} \end{aligned} \tag{2.2.1}$$

Thus you take x_1 times the first column, add to x_2 times the second column, and finally x_3 times the third column. The above sum is a linear combination of the columns of the matrix. When you multiply a matrix on the left by a vector on the right, the numbers making up the vector are just the scalars to be used in the linear combination of the columns as illustrated above.

Here is the formal definition of how to multiply an $m \times n$ matrix by an $n \times 1$ column vector.

Definition 2.2.3: Multiplication of Vector by Matrix

Let $A = [a_{ij}]$ be an $m \times n$ matrix and let X be an $n \times 1$ matrix given by

$$A = [A_1 \cdots A_n], X = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

Then the product AX is the $m \times 1$ column vector which equals the following linear combination of the columns of A:

$$x_1A_1 + x_2A_2 + \cdots + x_nA_n = \sum_{j=1}^{n} x_jA_j$$

If we write the columns of A in terms of their entries, they are of the form

$$A_j = \begin{bmatrix} a_{1j} \\ a_{2j} \\ \vdots \\ a_{mj} \end{bmatrix}$$

Then, we can write the product AX as

$$AX = x_1 \begin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{m1} \end{bmatrix} + x_2 \begin{bmatrix} a_{12} \\ a_{22} \\ \vdots \\ a_{m2} \end{bmatrix} + \cdots + x_n \begin{bmatrix} a_{1n} \\ a_{2n} \\ \vdots \\ a_{mn} \end{bmatrix}$$

Note that multiplication of an $m \times n$ matrix and an $n \times 1$ vector produces an $m \times 1$ vector.

Here is an example.

Example 2.2.1: A Vector Multiplied by a Matrix

Compute the product AX for

$$A = \begin{bmatrix} 1 & 2 & 1 & 3 \\ 0 & 2 & 1 & -2 \\ 2 & 1 & 4 & 1 \end{bmatrix}, X = \begin{bmatrix} 1 \\ 2 \\ 0 \\ 1 \end{bmatrix}$$

Solution

We will use Definition 2.2.3 to compute the product. Therefore, we compute the product AX as follows.

$$\begin{aligned} & 1\begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix} + 2\begin{bmatrix} 2 \\ 2 \\ 1 \end{bmatrix} + 0\begin{bmatrix} 1 \\ 1 \\ 4 \end{bmatrix} + 1\begin{bmatrix} 3 \\ -2 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix} + \begin{bmatrix} 4 \\ 4 \\ 2 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 3 \\ -2 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} 8 \\ 2 \\ 5 \end{bmatrix} \end{aligned} \tag{2.2.2}$$

Using the above operation, we can also write a system of linear equations in **matrix form**. In this form, we express the system as a matrix multiplied by a vector. Consider the following definition.

Definition 2.2.4: The Matrix Form of a System of Linear Equations

Suppose we have a system of equations given by

$$\begin{aligned} a_{11}x_1 + \cdots + a_{1n}x_n &= b_1 \\ a_{21}x_1 + \cdots + a_{2n}x_n &= b_2 \\ &\vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n &= b_m \end{aligned}$$

Then we can express this system in **matrix form** as follows.

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

The expression $AX = B$ is also known as the **Matrix Form** of the corresponding system of linear equations. The matrix A is simply the coefficient matrix of the system, the vector X is the column vector constructed from the variables of the system, and finally the vector B is the column vector constructed from the constants of the system. It is important to note that any system of linear equations can be written in this form.

Notice that if we write a homogeneous system of equations in matrix form, it would have the form $AX = 0$, for the zero vector 0.

You can see from this definition that a vector

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

will satisfy the equation $AX = B$ only when the entries $x_1, x_2, \cdots, x_n$ of the vector X are solutions to the original system.

Now that we have examined how to multiply a matrix by a vector, we wish to consider the case where we multiply two matrices of more general sizes, although these sizes still need to be appropriate as we will see. For example, in Example 2.2.1, we multiplied a 3×4 matrix by a 4×1 vector. We want to investigate how to multiply other sizes of matrices.

We have not yet given any conditions on when matrix multiplication is possible! For matrices A and B, in order to form the product AB, the number of columns of A must equal the number of rows of B. Consider a product AB where A has size $m \times n$ and B has size $n \times p$. Then, the product in terms of size of matrices is given by

$$(m \times \overbrace{n)\,(n}^{\text{these must match!}} \times p\ ) = m \times p$$

Note the two outside numbers give the size of the product. One of the most important rules regarding matrix multiplication is the following. If the two middle numbers don't match, you can't multiply the matrices!

When the number of columns of A equals the number of rows of B the two matrices are said to be **conformable** and the product AB is obtained as follows.

Definition 2.2.5: Multiplication of Two Matrices

Let A be an $m \times n$ matrix and let B be an $n \times p$ matrix of the form

$$B = [B_1 \cdots B_p]$$

where $B_1, \ldots, B_p$ are the $n \times 1$ columns of B. Then the $m \times p$ matrix AB is defined as follows:

$$AB = A\,[B_1 \cdots B_p] = [(AB)_1 \cdots (AB)_p]$$

where $(AB)_k$ is an $m \times 1$ matrix or column vector which gives the k^{th} column of AB.

Consider the following example.

Example 2.2.2: Multiplying Two Matrices

Find AB if possible.

$$A = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 2 & 1 \end{bmatrix}, B = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 3 & 1 \\ -2 & 1 & 1 \end{bmatrix}$$

Solution

The first thing you need to verify when calculating a product is whether the multiplication is possible. The first matrix has size 2×3 and the second matrix has size 3×3. The inside numbers are equal, so A and B are conformable matrices. According to the above discussion AB will be a 2×3 matrix. Definition 2.2.5 gives us a way to calculate each column of AB, as follows.

$$\begin{bmatrix} \overbrace{\begin{bmatrix} 1 & 2 & 1 \\ 0 & 2 & 1 \end{bmatrix}\begin{bmatrix} 1 \\ 0 \\ -2 \end{bmatrix}}^{\text{First column}}, & \overbrace{\begin{bmatrix} 1 & 2 & 1 \\ 0 & 2 & 1 \end{bmatrix}\begin{bmatrix} 2 \\ 3 \\ 1 \end{bmatrix}}^{\text{Second column}}, & \overbrace{\begin{bmatrix} 1 & 2 & 1 \\ 0 & 2 & 1 \end{bmatrix}\begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}}^{\text{Third column}} \end{bmatrix}$$

You know how to multiply a matrix times a vector, using Definition 2.2.3 for each of the three columns. Thus

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 2 & 1 \end{bmatrix}\begin{bmatrix} 1 & 2 & 0 \\ 0 & 3 & 1 \\ -2 & 1 & 1 \end{bmatrix} = \begin{bmatrix} -1 & 9 & 3 \\ -2 & 7 & 3 \end{bmatrix}$$

Since vectors are simply $n \times 1$ or $1 \times m$ matrices, we can also multiply a vector by another vector.

Example 2.2.3: Vector Times Vector Multiplication

Multiply if possible $\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 1 & 0 \end{bmatrix}$.

Solution

In this case we are multiplying a matrix of size 3×1 by a matrix of size 1×4. The inside numbers match so the product is defined. Note that the product will be a matrix of size 3×4. Using Definition 2.2.5, we can compute this product as follows

$$\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 1 & 0 \end{bmatrix} = \begin{bmatrix} \overbrace{\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} 1 \end{bmatrix}}^{\text{First column}}, \overbrace{\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} 2 \end{bmatrix}}^{\text{Second column}}, \overbrace{\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} 1 \end{bmatrix}}^{\text{Third column}}, \overbrace{\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} 0 \end{bmatrix}}^{\text{Fourth column}} \end{bmatrix}$$

You can use Definition 2.2.3 to verify that this product is

$$\begin{bmatrix} 1 & 2 & 1 & 0 \\ 2 & 4 & 2 & 0 \\ 1 & 2 & 1 & 0 \end{bmatrix}$$

Example 2.2.4: A Multiplication Which is Not Defined

Find BA if possible.

$$B = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 3 & 1 \\ -2 & 1 & 1 \end{bmatrix}, A = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 2 & 1 \end{bmatrix}$$

Solution

First check if it is possible. This product is of the form $(3 \times 3)(2 \times 3)$. The inside numbers do not match and so you can't do this multiplication.

In this case, we say that the multiplication is not defined. Notice that these are the same matrices which we used in Example 2.2.2. In this example, we tried to calculate BA instead of AB. This demonstrates another property of matrix multiplication. While the product AB maybe be defined, we cannot assume that the product BA will be possible. Therefore, it is important to always check that the product is defined before carrying out any calculations.

Earlier, we defined the zero matrix 0 to be the matrix (of appropriate size) containing zeros in all entries. Consider the following example for multiplication by the zero matrix.

Example 2.2.5: Multiplication by the Zero Matrix

Compute the product $A0$ for the matrix

$$A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$$

and the 2×2 zero matrix given by

$$0 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Solution

In this product, we compute

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Hence, $A0 = 0$.

Notice that we could also multiply A by the 2×1 zero vector given by $\begin{bmatrix} 0 \\ 0 \end{bmatrix}$. The result would be the 2×1 zero vector. Therefore, it is always the case that $A0 = 0$, for an appropriately sized zero matrix or vector.

Matrix Operations GeoGebra Demo by Kevin Hopkins

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2.3: The ijth Entry of a Product

In previous sections, we used the entries of a matrix to describe the action of matrix addition and scalar multiplication. We can also study matrix multiplication using the entries of matrices.

What is the ij^{th} entry of AB? It is the entry in the i^{th} row and the j^{th} column of the product AB.

Now if A is $m \times n$ and B is $n \times p$, then we know that the product AB has the form

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1j} & \cdots & b_{1p} \\ b_{21} & b_{22} & \cdots & b_{2j} & \cdots & b_{2p} \\ \vdots & \vdots & & \vdots & & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nj} & \cdots & b_{np} \end{bmatrix}$$

The j^{th} column of AB is of the form

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} b_{1j} \\ b_{2j} \\ \vdots \\ b_{nj} \end{bmatrix}$$

which is an $m \times 1$ column vector. It is calculated by

$$b_{1j} \begin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{m1} \end{bmatrix} + b_{2j} \begin{bmatrix} a_{12} \\ a_{22} \\ \vdots \\ a_{m2} \end{bmatrix} + \cdots + b_{nj} \begin{bmatrix} a_{1n} \\ a_{2n} \\ \vdots \\ a_{mn} \end{bmatrix}$$

Therefore, the ij^{th} entry is the entry in row i of this vector. This is computed by

$$a_{i1}b_{1j} + a_{i2}b_{2j} + \cdots + a_{in}b_{nj} = \sum_{k=1}^{n} a_{ik}b_{kj}$$

The following is the formal definition for the ij^{th} entry of a product of matrices.

Definition 2.3.1: The ij^{th} Entry of a Product

Let $A = [a_{ij}]$ be an $m \times n$ matrix and let $B = [b_{ij}]$ be an $n \times p$ matrix. Then AB is an $m \times p$ matrix and the (i, j)-entry of AB is defined as

$$(AB)_{ij} = \sum_{k=1}^{n} a_{ik}b_{kj}$$

Another way to write this is

$$(AB)_{ij} = \begin{bmatrix} a_{i1} & a_{i2} & \cdots & a_{in} \end{bmatrix} \begin{bmatrix} b_{1j} \\ b_{2j} \\ \vdots \\ b_{nj} \end{bmatrix} = a_{i1}b_{1j} + a_{i2}b_{2j} + \cdots + a_{in}b_{nj}$$

In other words, to find the (i, j)-entry of the product AB, or $(AB)_{ij}$, you multiply the i^{th} row of A, on the left by the j^{th} column of B. To express AB in terms of its entries, we write $AB = [(AB)_{ij}]$.

Consider the following example.

Example 2.3.1: The Entries of a Product

Compute AB if possible. If it is, find the $(3,2)$-entry of AB using Definition 2.3.1.

$$A = \begin{bmatrix} 1 & 2 \\ 3 & 1 \\ 2 & 6 \end{bmatrix}, B = \begin{bmatrix} 2 & 3 & 1 \\ 7 & 6 & 2 \end{bmatrix}$$

Solution

First check if the product is possible. It is of the form $(3 \times 2)(2 \times 3)$ and since the inside numbers match, it is possible to do the multiplication. The result should be a 3×3 matrix. We can first compute AB:

$$\left[\begin{bmatrix} 1 & 2 \\ 3 & 1 \\ 2 & 6 \end{bmatrix} \begin{bmatrix} 2 \\ 7 \end{bmatrix}, \begin{bmatrix} 1 & 2 \\ 3 & 1 \\ 2 & 6 \end{bmatrix} \begin{bmatrix} 3 \\ 6 \end{bmatrix}, \begin{bmatrix} 1 & 2 \\ 3 & 1 \\ 2 & 6 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} \right]$$

where the commas separate the columns in the resulting product. Thus the above product equals

$$\begin{bmatrix} 16 & 15 & 5 \\ 13 & 15 & 5 \\ 46 & 42 & 14 \end{bmatrix}$$

which is a 3×3 matrix as desired. Thus, the $(3,2)$-entry equals 42.

Now using Definition 2.3.1, we can find that the $(3,2)$-entry equals

$$\begin{aligned} \sum_{k=1}^{2} a_{3k} b_{k2} &= a_{31} b_{12} + a_{32} b_{22} \\ &= 2 \times 3 + 6 \times 6 = 42 \end{aligned} \tag{2.3.1}$$

Consulting our result for AB above, this is correct!

You may wish to use this method to verify that the rest of the entries in AB are correct.

Here is another example.

Example 2.3.2: Finding the Entries of a Product

Determine if the product AB is defined. If it is, find the $(2,1)$-entry of the product.

$$A = \begin{bmatrix} 2 & 3 & 1 \\ 7 & 6 & 2 \\ 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 1 & 2 \\ 3 & 1 \\ 2 & 6 \end{bmatrix}$$

Solution

This product is of the form $(3 \times 3)(3 \times 2)$. The middle numbers match so the matrices are conformable and it is possible to compute the product.

We want to find the $(2,1)$-entry of AB, that is, the entry in the second row and first column of the product. We will use Definition 2.3.1, which states

$$(AB)_{ij} = \sum_{k=1}^{n} a_{ik} b_{kj}$$

In this case, $n = 3$, $i = 2$ and $j = 1$. Hence the $(2,1)$-entry is found by computing

$$(AB)_{21} = \sum_{k=1}^{3} a_{2k} b_{k1} = \begin{bmatrix} a_{21} & a_{22} & a_{23} \end{bmatrix} \begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \end{bmatrix}$$

Substituting in the appropriate values, this product becomes

$$\begin{bmatrix} a_{21} & a_{22} & a_{23} \end{bmatrix} \begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \end{bmatrix} = \begin{bmatrix} 7 & 6 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} = 1 \times 7 + 3 \times 6 + 2 \times 2 = 29$$

Hence, $(AB)_{21} = 29$.

You should take a moment to find a few other entries of AB. You can multiply the matrices to check that your answers are correct. The product AB is given by

$$AB = \begin{bmatrix} 13 & 13 \\ 29 & 32 \\ 0 & 0 \end{bmatrix}$$

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2.4: Properties of Matrix Multiplication

As pointed out above, it is sometimes possible to multiply matrices in one order but not in the other order. However, even if both AB and BA are defined, they may not be equal.

Example 2.4.1: Matrix Multiplication is Not Commutative

Compare the products AB and BA, for matrices $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}, B = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$

Solution

First, notice that A and B are both of size 2×2. Therefore, both products AB and BA are defined. The first product, AB is

$$AB = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 4 & 3 \end{bmatrix}$$

The second product, BA is

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} = \begin{bmatrix} 3 & 4 \\ 1 & 2 \end{bmatrix}$$

Therefore, $AB \neq BA$.

This example illustrates that you cannot assume $AB = BA$ even when multiplication is defined in both orders. If for some matrices A and B it is true that $AB = BA$, then we say that A and B **commute**. This is one important property of matrix multiplication.

The following are other important properties of matrix multiplication. Notice that these properties hold only when the size of matrices are such that the products are defined.

Proposition 2.4.1: Properties of Matrix Multiplication

The following hold for matrices A, B, and C and for scalars r and s,

$$A(rB + sC) = r(AB) + s(AC) \tag{2.4.1}$$
$$(B + C)A = BA + CA \tag{2.4.2}$$
$$A(BC) = (AB)C \tag{2.4.3}$$

Proof available at the end of this section.

Answers

Proposition 2.4.1: Properties of Matrix Multiplication

First we will prove (2.4.1). We will use Definition 2.3.1 and prove this statement using the ij^{th} entries of a matrix. Therefore,

$$\begin{aligned} (A(rB + sC))_{ij} &= \sum_k a_{ik} (rB + sC)_{kj} \\ &= \sum_k a_{ik} (rb_{kj} + sc_{kj}) \\ &= r \sum_k a_{ik} b_{kj} + s \sum_k a_{ik} c_{kj} \\ &= r(AB)_{ij} + s(AC)_{ij} \\ &= (r(AB) + s(AC))_{ij} \end{aligned} \tag{2.4.4}$$

Thus $A(rB + sC) = r(AB) + s(AC)$ as claimed.

The proof of Equation (2.4.2) follows the same pattern and is left as an exercise.

Statement Equation (2.4.3) is the **associative law of multiplication**. Using Definition 2.3.1,

$$\begin{aligned}(A(BC))_{ij} &= \sum_k a_{ik}(BC)_{kj} \\ &= \sum_k a_{ik}\sum_l b_{kl}c_{lj} \\ &= \sum_l (AB)_{il}c_{lj} = ((AB)C)_{ij}.\end{aligned}$$

This proves (2.4.3).

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2.5: The Transpose

Another important operation on matrices is that of taking the **transpose**. For a matrix A, we denote the **transpose** of A by A^T. Before formally defining the transpose, we explore this operation on the following matrix.

$$\begin{bmatrix} 1 & 4 \\ 3 & 1 \\ 2 & 6 \end{bmatrix}^T = \begin{bmatrix} 1 & 3 & 2 \\ 4 & 1 & 6 \end{bmatrix}$$

What happened? The first column became the first row and the second column became the second row. Thus the 3×2 matrix became a 2×3 matrix. The number 4 was in the first row and the second column and it ended up in the second row and first column.

The definition of the transpose is as follows.

Definition 2.5.1: The Transpose of a Matrix

Let A be an $m \times n$ matrix. Then A^T, the **transpose** of A, denotes the $n \times m$ matrix given by

$$A^T = [a_{ij}]^T = [a_{ji}]$$

The (i, j)-entry of A becomes the (j, i)-entry of A^T.

Consider the following example.

Example 2.5.1: The Transpose of a Matrix

Calculate A^T for the following matrix

$$A = \begin{bmatrix} 1 & 2 & -6 \\ 3 & 5 & 4 \end{bmatrix}$$

Solution

By Definition 2.5.1, we know that for $A = [a_{ij}]$, $A^T = [a_{ji}]$. In other words, we switch the row and column location of each entry. The $(1, 2)$-entry becomes the $(2, 1)$-entry.

Thus,

$$A^T = \begin{bmatrix} 1 & 3 \\ 2 & 5 \\ -6 & 4 \end{bmatrix}$$

Notice that A is a 2×3 matrix, while A^T is a 3×2 matrix.

The transpose of a matrix has the following important properties.

Lemma 2.5.1: Properties of the Transpose of a Matrix

Let A be an $m \times n$ matrix, B an $n \times p$ matrix, and r and s scalars. Then

1. $$\left(A^T\right)^T = A$$

2. $$(AB)^T = B^T A^T$$
3. $$(rA + sB)^T = rA^T + sB^T$$

Proof available at the end of this section.

The transpose of a matrix is related to other important topics. Consider the following definition.

Definition 2.5.2: Symmetric and Skew Symmetric Matrices

An $n \times n$ matrix A is said to be **symmetric** if $A = A^T$. It is said to be **skew symmetric** if $A = -A^T$.

We will explore these definitions in the following examples.

Example 2.5.2: Symmetric Matrices

Let

$$A = \begin{bmatrix} 2 & 1 & 3 \\ 1 & 5 & -3 \\ 3 & -3 & 7 \end{bmatrix}$$

Use Definition 2.5.2 to show that A is symmetric.

Solution

By Definition 2.5.2, we need to show that $A = A^T$. Now, using Definition 2.5.1,

$$A^T = \begin{bmatrix} 2 & 1 & 3 \\ 1 & 5 & -3 \\ 3 & -3 & 7 \end{bmatrix}$$

Hence, $A = A^T$, so A is symmetric.

Example 2.5.3: A Skew Symmetric Matrix

Let

$$A = \begin{bmatrix} 0 & 1 & 3 \\ -1 & 0 & 2 \\ -3 & -2 & 0 \end{bmatrix}$$

Show that A is skew symmetric.

Solution

By Definition 2.5.2,

$$A^T = \begin{bmatrix} 0 & -1 & -3 \\ 1 & 0 & -2 \\ 3 & 2 & 0 \end{bmatrix}$$

You can see that each entry of A^T is equal to -1 times the same entry of A. Hence, $A^T = -A$ and so by Definition 2.5.2, A is skew symmetric.

Answers

Lemma 2.5.1: Properties of the Transpose of a Matrix

First we prove 2. From Definition 2.5.1,

$$\begin{aligned}(AB)^T = [(AB)_{ij}]^T = [(AB)_{ji}] = \sum_k a_{jk}b_{ki} = \sum_k b_{ki}a_{jk} \\ = \sum_k [b_{ik}]^T [a_{kj}]^T = [b_{ij}]^T [a_{ij}]^T = B^T A^T\end{aligned} \tag{2.5.1}$$

The proof of Formula 3 is left as an exercise.

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2.6: The Identity and Inverses

There is a special matrix, denoted I, which is called to as the **identity matrix**. The identity matrix is always a square matrix, and it has the property that there are ones down the main diagonal and zeroes elsewhere. Here are some identity matrices of various sizes.

$$[1], \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

The first is the 1×1 identity matrix, the second is the 2×2 identity matrix, and so on. By extension, you can likely see what the $n \times n$ identity matrix would be. When it is necessary to distinguish which size of identity matrix is being discussed, we will use the notation I_n for the $n \times n$ identity matrix.

The identity matrix is so important that there is a special symbol to denote the ij^{th} entry of the identity matrix. This symbol is given by $I_{ij} = \delta_{ij}$ where δ_{ij} is the **Kronecker symbol** defined by

$$\delta_{ij} = \begin{cases} 1 \text{ if } i = j \\ 0 \text{ if } i \neq j \end{cases}$$

I_n is called the **identity matrix** because it is a **multiplicative identity** in the following sense.

Lemma 2.6.1: Multiplication by the Identity Matrix

Suppose A is an $m \times n$ matrix and I_n is the $n \times n$ identity matrix**.** Then $AI_n = A$. If I_m is the $m \times m$ identity matrix, it also follows that $I_m A = A$.

Proof available at the end of this section.

We now define the matrix operation which in some ways plays the role of division.

Definition 2.6.1: The Inverse of a Matrix

A square $n \times n$ matrix A is said to have an **inverse** A^{-1} if and only if

$$AA^{-1} = A^{-1}A = I_n$$

In this case, the matrix A is called **invertible**.

Such a matrix A^{-1} will have the same size as the matrix A. It is very important to observe that the inverse of a matrix, if it exists, is unique. Another way to think of this is that if it acts like the inverse, then it is the inverse.

Theorem 2.6.1: Uniqueness of Inverse

Suppose A is an $n \times n$ matrix such that an inverse A^{-1} exists. Then there is only one such inverse matrix. That is, given any matrix B such that $AB = BA = I$, $B = A^{-1}$.

Proof available at the end of this section.

The next example demonstrates how to check the inverse of a matrix.

Example 2.6.1: Verifying the Inverse of a Matrix

Let $A = \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix}$. Show $\begin{bmatrix} 2 & -1 \\ -1 & 1 \end{bmatrix}$ is the inverse of A.

Solution

To check this, multiply

$$\begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 2 & -1 \\ -1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = I$$

and

$$\begin{bmatrix} 2 & -1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = I$$

showing that this matrix is indeed the inverse of A.

Unlike ordinary multiplication of numbers, it can happen that $A \neq 0$ but A may fail to have an inverse. This is illustrated in the following example.

Example 2.6.2: A Nonzero Matrix With No Inverse

Let $A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$. Show that A does not have an inverse.

Solution

One might think A would have an inverse because it does not equal zero. However, note that

$$\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

If A^{-1} existed, we would have the following

$$\begin{aligned} \begin{bmatrix} 0 \\ 0 \end{bmatrix} &= A^{-1}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}\right) \\ &= A^{-1}\left(A\begin{bmatrix} -1 \\ 1 \end{bmatrix}\right) \\ &= \left(A^{-1}A\right)\begin{bmatrix} -1 \\ 1 \end{bmatrix} \\ &= I\begin{bmatrix} -1 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} -1 \\ 1 \end{bmatrix} \end{aligned} \tag{2.6.1}$$

This says that

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

which is impossible! Therefore, A does not have an inverse.

In the next section, we will explore how to find the inverse of a matrix, if it exists.

Answers

Lemma 2.6.1: Multiplication by the Identity Matrix

The (i,j)-entry of AI_n is given by:

$$\sum_k a_{ik}\delta_{kj} = a_{ij}$$

and so $AI_n = A$. The other case is left as an exercise for you.

Theorem 2.6.1**: Uniqueness of Inverse**

In this proof, it is assumed that I is the $n \times n$ identity matrix. Let A, B be $n \times n$ matrices such that A^{-1} exists and $AB = BA = I$. We want to show that $A^{-1} = B$. Now using properties we have seen, we get:

$$A^{-1} = A^{-1}I = A^{-1}(AB) = \left(A^{-1}A\right)B = IB = B$$

Hence, $A^{-1} = B$ which tells us that the inverse is unique.

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2.7: Finding the Inverse of a Matrix

In Example 2.6.1, we were given A^{-1} and asked to verify that this matrix was in fact the inverse of A. In this section, we explore how to find A^{-1}.

Let

$$A = \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix}$$

as in Example 2.6.1. In order to find A^{-1}, we need to find a matrix $\begin{bmatrix} x & z \\ y & w \end{bmatrix}$ such that

$$\begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x & z \\ y & w \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

We can multiply these two matrices, and see that in order for this equation to be true, we must find the solution to the systems of equations,

$$\begin{aligned} x + y &= 1 \\ x + 2y &= 0 \end{aligned}$$

and

$$\begin{aligned} z + w &= 0 \\ z + 2w &= 1 \end{aligned}$$

Writing the augmented matrix for these two systems gives

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 0 \end{bmatrix}$$

for the first system and

$$\begin{bmatrix} 1 & 1 & 0 \\ 1 & 2 & 1 \end{bmatrix} \tag{2.7.1}$$

for the second.

Let's solve the first system. Take -1 times the first row and add to the second to get

$$\begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & -1 \end{bmatrix}$$

Now take -1 times the second row and add to the first to get

$$\begin{bmatrix} 1 & 0 & 2 \\ 0 & 1 & -1 \end{bmatrix}$$

Writing in terms of variables, this says $x = 2$ and $y = -1$.

Now solve the second system, (2.7.1) to find z and w. You will find that $z = -1$ and $w = 1$.

If we take the values found for x, y, z, and w and put them into our inverse matrix, we see that the inverse is

$$A^{-1} = \begin{bmatrix} x & z \\ y & w \end{bmatrix} = \begin{bmatrix} 2 & -1 \\ -1 & 1 \end{bmatrix}$$

After taking the time to solve the second system, you may have noticed that exactly the same row operations were used to solve both systems. In each case, the end result was something of the form $[I|X]$ where I is the identity and X gave a column of the inverse. In the above,

$$\begin{bmatrix} x \\ y \end{bmatrix}$$

the first column of the inverse was obtained by solving the first system and then the second column

$$\begin{bmatrix} z \\ w \end{bmatrix}$$

To simplify this procedure, we could have solved both systems at once! To do so, we could have written

$$\begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 2 & 0 & 1 \end{bmatrix}$$

and row reduced until we obtained

$$\begin{bmatrix} 1 & 0 & 2 & -1 \\ 0 & 1 & -1 & 1 \end{bmatrix}$$

and read off the inverse as the 2×2 matrix on the right side.

This exploration motivates the following important algorithm.

Algorithm 2.7.1: Matrix Inverse Algorithm

Suppose A is an $n \times n$ matrix. To find A^{-1} if it exists, form the augmented $n \times 2n$ matrix

$$[A|I]$$

If possible do row operations until you obtain an $n \times 2n$ matrix of the form

$$[I|B]$$

When this has been done, $B = A^{-1}$. In this case, we say that A is **invertible**. If it is impossible to row reduce to a matrix of the form $[I|B]$, then A has no inverse.

This algorithm shows how to find the inverse if it exists. It will also tell you if A does not have an inverse.

Consider the following example.

Example 2.7.1: Finding the Inverse

Let $A = \begin{bmatrix} 1 & 2 & 2 \\ 1 & 0 & 2 \\ 3 & 1 & -1 \end{bmatrix}$. Find A^{-1} if it exists.

Solution

Set up the augmented matrix

$$[A|I] = \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 1 & 0 & 2 & 0 & 1 & 0 \\ 3 & 1 & -1 & 0 & 0 & 1 \end{bmatrix}$$

Now we row reduce, with the goal of obtaining the 3×3 identity matrix on the left hand side. First, take -1 times the first row and add to the second followed by -3 times the first row added to the third row. This yields

$$\begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 0 & -2 & 0 & -1 & 1 & 0 \\ 0 & -5 & -7 & -3 & 0 & 1 \end{bmatrix}$$

Then take 5 times the second row and add to -2 times the third row.

$$\begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 0 & -10 & 0 & -5 & 5 & 0 \\ 0 & 0 & 14 & 1 & 5 & -2 \end{bmatrix}$$

Next take the third row and add to -7 times the first row. This yields

$$\begin{bmatrix} -7 & -14 & 0 & -6 & 5 & -2 \\ 0 & -10 & 0 & -5 & 5 & 0 \\ 0 & 0 & 14 & 1 & 5 & -2 \end{bmatrix}$$

Now take $-\frac{7}{5}$ times the second row and add to the first row.

$$\begin{bmatrix} -7 & 0 & 0 & 1 & -2 & -2 \\ 0 & -10 & 0 & -5 & 5 & 0 \\ 0 & 0 & 14 & 1 & 5 & -2 \end{bmatrix}$$

Finally divide the first row by -7, the second row by -10 and the third row by 14 which yields

$$\begin{bmatrix} 1 & 0 & 0 & -\frac{1}{7} & \frac{2}{7} & \frac{2}{7} \\ 0 & 1 & 0 & \frac{1}{2} & -\frac{1}{2} & 0 \\ 0 & 0 & 1 & \frac{1}{14} & \frac{5}{14} & -\frac{1}{7} \end{bmatrix}$$

Notice that the left hand side of this matrix is now the 3×3 identity matrix I_3. Therefore, the inverse is the 3×3 matrix on the right hand side, given by

$$\begin{bmatrix} -\frac{1}{7} & \frac{2}{7} & \frac{2}{7} \\ \frac{1}{2} & -\frac{1}{2} & 0 \\ \frac{1}{14} & \frac{5}{14} & -\frac{1}{7} \end{bmatrix}$$

It may happen that through this algorithm, you discover that the left hand side cannot be row reduced to the identity matrix. Consider the following example of this situation.

Example 2.7.2: A Matrix Which Has No Inverse

Let $A = \begin{bmatrix} 1 & 2 & 2 \\ 1 & 0 & 2 \\ 2 & 2 & 4 \end{bmatrix}$. Find A^{-1} if it exists.

Solution

Write the augmented matrix $[A|I]$

$$\begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 1 & 0 & 2 & 0 & 1 & 0 \\ 2 & 2 & 4 & 0 & 0 & 1 \end{bmatrix}$$

and proceed to do row operations attempting to obtain $[I|A^{-1}]$. Take -1 times the first row and add to the second. Then take -2 times the first row and add to the third row.

$$\begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 0 & -2 & 0 & -1 & 1 & 0 \\ 0 & -2 & 0 & -2 & 0 & 1 \end{bmatrix}$$

Next add -1 times the second row to the third row.

$$\begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 0 & -2 & 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & -1 & -1 & 1 \end{bmatrix}$$

At this point, you can see there will be no way to obtain I on the left side of this augmented matrix. Hence, there is no way to complete this algorithm, and therefore the inverse of A does not exist. In this case, we say that A is not invertible.

If the algorithm provides an inverse for the original matrix, it is always possible to check your answer. To do so, use the method demonstrated in Example 2.6.1. Check that the products AA^{-1} and $A^{-1}A$ both equal the identity matrix. Through this method, you can always be sure that you have calculated A^{-1} properly!

One way in which the inverse of a matrix is useful is to find the solution of a system of linear equations. Recall from Definition 2.2.4 that we can write a system of equations in matrix form, which is of the form $AX = B$. Suppose you find the inverse of the matrix A^{-1}. Then you could multiply both sides of this equation on the left by A^{-1} and simplify to obtain

$$\begin{aligned} \left(A^{-1}\right) AX &= A^{-1}B \\ \left(A^{-1}A\right) X &= A^{-1}B \\ IX &= A^{-1}B \\ X &= A^{-1}B \end{aligned}$$

Therefore we can find X, the solution to the system, by computing $X = A^{-1}B$. Note that once you have found A^{-1}, you can easily get the solution for different right hand sides (different B). It is always just $A^{-1}B$.

We will explore this method of finding the solution to a system in the following example.

Example 2.7.3: Using the Inverse to Solve a System of Equations

Consider the following system of equations. Use the inverse of a suitable matrix to give the solutions to this system.

$$\begin{aligned} x + z &= 1 \\ x - y + z &= 3 \\ x + y - z &= 2 \end{aligned}$$

Solution

First, we can write the system of equations in matrix form

$$AX = \begin{bmatrix} 1 & 0 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} = B \tag{2.7.2}$$

The inverse of the matrix

$$A = \begin{bmatrix} 1 & 0 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & -1 \end{bmatrix}$$

is

$$A^{-1} = \begin{bmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & -1 & 0 \\ 1 & -\frac{1}{2} & -\frac{1}{2} \end{bmatrix}$$

Verifying this inverse is left as an exercise.

From here, the solution to the given system (2.7.2) is found by

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = A^{-1}B = \begin{bmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & -1 & 0 \\ 1 & -\frac{1}{2} & -\frac{1}{2} \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} = \begin{bmatrix} \frac{5}{2} \\ -2 \\ -\frac{3}{2} \end{bmatrix}$$

What if the right side, B, of (2.7.2) had been $\begin{bmatrix} 0 \\ 1 \\ 3 \end{bmatrix}$? In other words, what would be the solution to

$$\begin{bmatrix} 1 & 0 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 3 \end{bmatrix}?$$

By the above discussion, the solution is given by

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = A^{-1}B = \begin{bmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & -1 & 0 \\ 1 & -\frac{1}{2} & -\frac{1}{2} \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 2 \\ -1 \\ -2 \end{bmatrix}$$

This illustrates that for a system $AX = B$ where A^{-1} exists, it is easy to find the solution when the vector B is changed.

We conclude this section with some important properties of the inverse.

Theorem 2.7.1: Inverses of Transposes and Products

Let A, B, and A_i for $i = 1, ..., k$ be $n \times n$ matrices.

1. If A is an invertible matrix, then $(A^T)^{-1} = (A^{-1})^T$
2. If A and B are invertible matrices, then AB is invertible and $(AB)^{-1} = B^{-1}A^{-1}$
3. If $A_1, A_2, ..., A_k$ are invertible, then the product $A_1A_2 \cdots A_k$ is invertible, and $(A_1A_2 \cdots A_k)^{-1} = A_k^{-1}A_{k-1}^{-1} \cdots A_2^{-1}A_1^{-1}$

Consider the following theorem.

Theorem 2.7.2: Properties of the Inverse

Let A be an $n \times n$ matrix and I the usual identity matrix.

1. I is invertible and $I^{-1} = I$
2. If A is invertible then so is A^{-1}, and $(A^{-1})^{-1} = A$
3. If A is invertible then so is A^k, and $(A^k)^{-1} = (A^{-1})^k$
4. If A is invertible and p is a nonzero real number, then pA is invertible and $(pA)^{-1} = \frac{1}{p}A^{-1}$

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2.8: Elementary Matrices

We now turn our attention to a special type of matrix called an **elementary matrix**. An elementary matrix is always a square matrix. Recall the row operations given in Definition 1.3.2. Any elementary matrix, which we often denote by E, is obtained from applying *one* row operation to the identity matrix of the same size.

For example, the matrix

$$E = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

is the elementary matrix obtained from switching the two rows. The matrix

$$E = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

is the elementary matrix obtained from multiplying the second row of the 3×3 identity matrix by 3. The matrix

$$E = \begin{bmatrix} 1 & 0 \\ -3 & 1 \end{bmatrix}$$

is the elementary matrix obtained from adding -3 times the first row to the third row.

You may construct an elementary matrix from any row operation, but remember that you can only apply one operation.

Consider the following definition.

Definition 2.8.1: Elementary Matrices and Row Operations

Let E be an $n \times n$ matrix. Then E is an **elementary matrix** if it is the result of applying one row operation to the $n \times n$ identity matrix I_n.

Those which involve switching rows of the identity matrix are called permutation matrices.

Therefore, E constructed above by switching the two rows of I_2 is called a permutation matrix.

Elementary matrices can be used in place of row operations and therefore are very useful. It turns out that multiplying (on the left hand side) by an elementary matrix E will have the same effect as doing the row operation used to obtain E.

The following theorem is an important result which we will use throughout this text.

Theorem 2.8.1: Multiplication by an Elementary Matrix and Row Operations

To perform any of the three row operations on a matrix A it suffices to take the product EA, where E is the elementary matrix obtained by using the desired row operation on the identity matrix.

Therefore, instead of performing row operations on a matrix A, we can row reduce through matrix multiplication with the appropriate elementary matrix. We will examine this theorem in detail for each of the three row operations given in Definition 1.3.2.

First, consider the following lemma.

Lemma 2.8.1: Action of Permutation Matrix

Let P^{ij} denote the elementary matrix which involves switching the i^{th} and the j^{th} rows. Then P^{ij} is a permutation matrix and

$$P^{ij}A = B$$

where B is obtained from A by switching the i^{th} and the j^{th} rows.

We will explore this idea more in the following example.

Example 2.8.1: Switching Rows with an Elementary Matrix

Let

$$P^{12} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, A = \begin{bmatrix} a & b \\ g & d \\ e & f \end{bmatrix}$$

Find B where $B = P^{12}A$.

Solution

You can see that the matrix P^{12} is obtained by switching the first and second rows of the 3×3 identity matrix I.

Using our usual procedure, compute the product $P^{12}A = B$. The result is given by

$$B = \begin{bmatrix} g & d \\ a & b \\ e & f \end{bmatrix}$$

Notice that B is the matrix obtained by switching rows 1 and 2 of A. Therefore by multiplying A by P^{12}, the row operation which was applied to I to obtain P^{12} is applied to A to obtain B.

Theorem 2.8.1 applies to all three row operations, and we now look at the row operation of multiplying a row by a scalar. Consider the following lemma.

Lemma 2.8.2: Multiplication by a Scalar and Elementary Matrices

Let $E(k,i)$ denote the elementary matrix corresponding to the row operation in which the i^{th} row is multiplied by the nonzero scalar, k. Then

$$E(k,i)A = B$$

where B is obtained from A by multiplying the i^{th} row of A by k.

We will explore this lemma further in the following example.

Example 2.8.2: Multiplication of a Row by 5 Using Elementary Matrix

Let

$$E(5,2) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 0 & 1 \end{bmatrix}, A = \begin{bmatrix} a & b \\ c & d \\ e & f \end{bmatrix}$$

Find the matrix B where $B = E(5,2)\,A$

Solution

You can see that $E(5,2)$ is obtained by multiplying the second row of the identity matrix by 5.

Using our usual procedure for multiplication of matrices, we can compute the product $E(5,2)\,A$. The resulting matrix is given by

$$B = \begin{bmatrix} a & b \\ 5c & 5d \\ e & f \end{bmatrix}$$

Notice that B is obtained by multiplying the second row of A by the scalar 5.

There is one last row operation to consider. The following lemma discusses the final operation of adding a multiple of a row to another row.

Lemma 2.8.3: Adding Multiples of Rows and Elementary Matrices

Let $E(k \times i + j)$ denote the elementary matrix obtained from I by adding k times the i^{th} row to the j^{th}. Then

$$E(k \times i + j)\,A = B$$

where B is obtained from A by adding k times the i^{th} row to the j^{th} row of A.

Consider the following example.

Example 2.8.3: Adding Two Times the First Row to the Last

Let

$$E(2 \times 1 + 3) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix}, A = \begin{bmatrix} a & b \\ c & d \\ e & f \end{bmatrix}$$

Find B where $B = E(2 \times 1 + 3)\,A$.

Solution

You can see that the matrix $E(2 \times 1 + 3)$ was obtained by adding 2 times the first row of I to the third row of I.

Using our usual procedure, we can compute the product $E(2 \times 1 + 3)\,A$. The resulting matrix B is given by

$$B = \begin{bmatrix} a & b \\ c & d \\ 2a + e & 2b + f \end{bmatrix}$$

You can see that B is the matrix obtained by adding 2 times the first row of A to the third row.

Suppose we have applied a row operation to a matrix A. Consider the row operation required to return A to its original form, to undo the row operation. It turns out that this action is how we find the inverse of an elementary matrix E.

Consider the following theorem.

Theorem 2.8.2: Elementary Matrices and Inverses

Every elementary matrix is invertible and its inverse is also an elementary matrix.

In fact, the inverse of an elementary matrix is constructed by doing the *reverse* row operation on I. E^{-1} will be obtained by performing the row operation which would carry E back to I.

- If E is obtained by switching rows i and j, then E^{-1} is also obtained by switching rows i and j.
- If E is obtained by multiplying row i by the scalar k, then E^{-1} is obtained by multiplying row i by the scalar $\frac{1}{k}$.
- If E is obtained by adding k times row i to row j, then E^{-1} is obtained by subtracting k times row i from row j.

Consider the following example.

Example 2.8.4: Inverse of an Elementary Matrix

Let

$$E = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$$

Find E^{-1}.

Solution

Consider the elementary matrix E given by

$$E = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$$

Here, E is obtained from the 2×2 identity matrix by multiplying the second row by 2. In order to carry E back to the identity, we need to multiply the second row of E by $\frac{1}{2}$. Hence,

E^{-1} is given by

$$E^{-1} = \begin{bmatrix} 1 & 0 \\ 0 & \frac{1}{2} \end{bmatrix}$$

We can verify that $EE^{-1} = I$. Take the product EE^{-1}, given by

$$EE^{-1} = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & \frac{1}{2} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

This equals I so we know that we have compute E^{-1} properly.

Suppose an $m \times n$ matrix A is row reduced to its reduced row-echelon form. By tracking each row operation completed, this row reduction can be completed through multiplication by elementary matrices.

Consider the following definition.

Definition 2.8.2: The Form $B = UA$

Let A be an $m \times n$ matrix and let B be the reduced row-echelon form of A. Then we can write $B = UA$ where U is the product of all elementary matrices representing the row operations done to A to obtain B.

Consider the following example.

Example 2.8.5: The Form $B = UA$

Let $A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 2 & 0 \end{bmatrix}$. Find B, the reduced row-echelon form of A and write it in the form $B = UA$.

Solution

To find B, row reduce A. For each step, we will record the appropriate elementary matrix. First, switch rows 1 and 2.

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 2 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 2 & 0 \end{bmatrix}$$

The resulting matrix is equivalent to finding the product of $P^{12} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ and A.

Next, add (-2) times row 1 to row 3.

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 2 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}$$

This is equivalent to multiplying by the matrix $E(-2 \times 1 + 3) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -2 & 0 & 1 \end{bmatrix}$. Notice that the resulting matrix is B, the required reduced row-echelon form of A.

We can then write

$$\begin{aligned} B &= E(-2 \times 1 + 2)\left(P^{12}A\right) \\ &= \left(E(-2 \times 1 + 2)P^{12}\right)A \\ &= UA \end{aligned} \tag{2.8.1}$$

It remains to find the matrix U.

$$\begin{aligned} U &= E(-2 \times 1 + 2)P^{12} \\ &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -2 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \\ &= \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & -2 & 1 \end{bmatrix} \end{aligned} \tag{2.8.2}$$

We can verify that $B = UA$ holds for this matrix U:

$$\begin{aligned} UA &= \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & -2 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 2 & 0 \end{bmatrix} \\ &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \\ &= B \end{aligned} \tag{2.8.3}$$

While the process used in the above example is reliable and simple when only a few row operations are used, it becomes

cumbersome in a case where many row operations are needed to carry A to B. The following theorem provides an alternate way to find the matrix U.

Theorem 2.8.3: Finding the Matrix U

Let A be an $m \times n$ matrix and let B be its reduced row-echelon form. Then $B = UA$ where U is an invertible $m \times m$ matrix found by forming the matrix $[A|I_m]$ and row reducing to $[B|U]$.

Let's revisit the above example using the process outlined in Theorem 2.8.3.

Example 2.8.6: The Form $B = UA$, Revisited

Let $A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 2 & 0 \end{bmatrix}$. Using the process outlined in Theorem 2.8.3, find U such that $B = UA$.

Solution

First, set up the matrix $[A|I_m]$.

$$\begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 2 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Now, row reduce this matrix until the left side equals the reduced row-echelon form of A.

$$\begin{aligned} \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 2 & 0 & 0 & 0 & 1 \end{bmatrix} &\rightarrow \begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 2 & 0 & 0 & 0 & 1 \end{bmatrix} \\ &\rightarrow \begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & -2 & 1 \end{bmatrix} \end{aligned} \tag{2.8.4}$$

The left side of this matrix is B, and the right side is U. Comparing this to the matrix U found above in Example 2.8.5, you can see that the same matrix is obtained regardless of which process is used.

Recall from Algorithm 2.7.1 that an $n \times n$ matrix A is invertible if and only if A can be carried to the $n \times n$ identity matrix using the usual row operations. This leads to an important consequence related to the above discussion.

Suppose A is an $n \times n$ invertible matrix. Then, set up the matrix $[A|I_n]$ as done above, and row reduce until it is of the form $[B|U]$. In this case, $B = I_n$ because A is invertible.

$$\begin{aligned} B &= UA \\ I_n &= UA \\ U^{-1} &= A \end{aligned} \tag{2.8.5}$$

Now suppose that $U = E_1 E_2 \cdots E_k$ where each E_i is an elementary matrix representing a row operation used to carry A to I. Then,

$$U^{-1} = (E_1 E_2 \cdots E_k)^{-1} = E_k^{-1} \cdots E_2^{-1} E_1^{-1}$$

Remember that if E_i is an elementary matrix, so too is E_i^{-1}. It follows that

$$\begin{aligned} A &= U^{-1} \\ &= E_k^{-1} \cdots E_2^{-1} E_1^{-1} \end{aligned} \tag{2.8.6}$$

and A can be written as a product of elementary matrices.

Theorem 2.8.4: Product of Elementary Matrices

Let A be an $n \times n$ matrix. Then A is invertible if and only if it can be written as a product of elementary matrices.

Consider the following example.

Example 2.8.7: Product of Elementary Matrices

Let $A = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & -2 & 1 \end{bmatrix}$. Write A as a product of elementary matrices.

Solution

We will use the process outlined in Theorem 2.8.3 to write A as a product of elementary matrices. We will set up the matrix $[A|I]$ and row reduce, recording each row operation as an elementary matrix.

First:

$$\begin{bmatrix} 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & -2 & 1 & 0 & 0 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & -2 & 1 & 0 & 0 & 1 \end{bmatrix}$$

represented by the elementary matrix $E_1 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$.

Secondly:

$$\begin{bmatrix} 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & -2 & 1 & 0 & 0 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 0 & -1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & -2 & 1 & 0 & 0 & 1 \end{bmatrix}$$

represented by the elementary matrix $E_2 = \begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$.

Finally:

$$\begin{bmatrix} 1 & 0 & 0 & -1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & -2 & 1 & 0 & 0 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 0 & -1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 2 & 0 & 1 \end{bmatrix}$$

represented by the elementary matrix $E_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 2 & 1 \end{bmatrix}$.

Notice that the reduced row-echelon form of A is I. Hence $I = UA$ where U is the product of the above elementary matrices. It follows that $A = U^{-1}$. Since we want to write A as a product of elementary matrices, we wish to express U^{-1} as a product of elementary matrices.

$$\begin{aligned} U^{-1} &= (E_3E_2E_1)^{-1} \\ &= E_1^{-1}E_2^{-1}E_3^{-1} \\ &= \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -2 & 1 \end{bmatrix} \\ &= A \end{aligned} \tag{2.8.7}$$

This gives A written as a product of elementary matrices. By Theorem 2.8.4 it follows that A is invertible.

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2.9: More on Matrix Inverses

In this section, we will prove three theorems which will clarify the concept of matrix inverses. In order to do this, first recall some important properties of elementary matrices.

Recall that an elementary matrix is a square matrix obtained by performing an elementary operation on an identity matrix. Each elementary matrix is invertible, and its inverse is also an elementary matrix. If E is an $m \times m$ elementary matrix and A is an $m \times n$ matrix, then the product EA is the result of applying to A the same elementary row operation that was applied to the $m \times m$ identity matrix in order to obtain E.

Let R be the reduced row-echelon form of an $m \times n$ matrix A. R is obtained by iteratively applying a sequence of elementary row operations to A. Denote by $E_1, E_2, \cdots, E_k$ the elementary matrices associated with the elementary row operations which were applied, in order, to the matrix A to obtain the resulting R. We then have that $R = (E_k \cdots (E_2 (E_1 A))) = E_k \cdots E_2 E_1 A$. Let E denote the product matrix $E_k \cdots E_2 E_1$ so that we can write $R = EA$ where E is an invertible matrix whose inverse is the product $(E_1)^{-1}(E_2)^{-1} \cdots (E_k)^{-1}$.

Now, we will consider some preliminary lemmas.

Lemma 2.9.1: Invertible Matrix and Zeros

Suppose that A and B are matrices such that the product AB is an identity matrix. Then the reduced row-echelon form of A does not have a row of zeros.

Proof available at the end of this section.

We now consider a second important lemma.

Lemma 2.9.2: Size of Invertible Matrix

Suppose that A and B are matrices such that the product AB is an identity matrix. Then A has at least as many columns as it has rows.

Proof available at the end of this section.

An important theorem follows from this lemma.

Theorem 2.9.1: Invertible Matrices are Square

Only square matrices can be invertible.

Proof available at the end of this section.

Of course, not all square matrices are invertible. In particular, zero matrices are not invertible, along with many other square matrices.

The following proposition will be useful in proving the next theorem.

Proposition 2.9.1: Reduced Row-Echelon Form of a Square Matrix

If R is the reduced row-echelon form of a square matrix, then either R has a row of zeros or R is an identity matrix.

The proof of this proposition is left as an exercise to the reader. We now consider the second important theorem of this section.

Theorem 2.9.2: Unique Inverse of a Matrix

Suppose A and B are square matrices such that $AB = I$ where I is an identity matrix. Then it follows that $BA = I$. Further, both A and B are invertible and $B = A^{-1}$ and $A = B^{-1}$.

Proof available at the end of this section.

This theorem is very useful, since with it we need only test one of the products AB or BA in order to check that B is the inverse of A. The hypothesis that A and B are square matrices is very important, and without this the theorem does not hold.

We will now consider an example.

Example 2.9.1: Non Square Matrices

Let

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix},$$

Show that $A^T A = I$ but $AA^T \neq 0$.

Solution

Consider the product $A^T A$ given by

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{2.9.1}$$

Therefore, $A^T A = I_2$, where I_2 is the 2×2 identity matrix. However, the product AA^T is

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{2.9.2}$$

Hence AA^T is not the 3×3 identity matrix. This shows that for Theorem 2.9.2, it is essential that both matrices be square and of the same size.

Is it possible to have matrices A and B such that $AB = I$, while $BA = 0$? This question is left to the reader to answer, and you should take a moment to consider the answer.

We conclude this section with an important theorem.

Theorem 2.9.3: The reduced row-echelon form of an Invertible Matrix

For any matrix A the following conditions are equivalent:

- A is invertible
- The reduced row-echelon form of A is an identity matrix

Proof available at the end of this section.

Theorem 2.9.3 corresponds to Algorithm 2.7.1, which claims that A^{-1} is found by row reducing the augmented matrix $[A|I]$ to the form $[I|A^{-1}]$. This will be a matrix product $E[A|I]$ where E is a product of elementary matrices. By the rules of matrix

multiplication, we have that $E[A|I] = [EA|EI] = [EA|E]$.

It follows that the reduced row-echelon form of $[A|I]$ is $[EA|E]$, where EA gives the reduced row-echelon form of A. By Theorem 2.9.3, if $EA \neq I$, then A is not invertible, and if $EA = I$, A is invertible. If $EA = I$, then by Theorem 2.9.2, $E = A^{-1}$. This proves that Algorithm 2.7.1 does in fact find A^{-1}.

Answers

Lemma 2.9.1: Invertible Matrix and Zeros

Let R be the reduced row-echelon form of A. Then $R = EA$ for some invertible square matrix E as described above. By hypothesis $AB = I$ where I is an identity matrix, so we have a chain of equalities

$$R(BE^{-1}) = (EA)(BE^{-1}) = E(AB)E^{-1} = EIE^{-1} = EE^{-1} = I$$

If R would have a row of zeros, then so would the product $R(BE^{-1})$. But since the identity matrix I does not have a row of zeros, neither can R have one.

Lemma 2.9.2: Size of Invertible Matrix

Let R be the reduced row-echelon form of A. By Lemma 2.9.1, we know that R does not have a row of zeros, and therefore each row of R has a leading 1. Since each column of R contains at most one of these leading 1s, R must have at least as many columns as it has rows.

Theorem 2.9.1: Invertible Matrices are Square

Suppose that A and B are matrices such that both products AB and BA are identity matrices. We will show that A and B must be square matrices of the same size. Let the matrix A have m rows and n columns, so that A is an $m \times n$ matrix. Since the product AB exists, B must have n rows, and since the product BA exists, B must have m columns so that B is an $n \times m$ matrix. To finish the proof, we need only verify that $m = n$.

We first apply Lemma 2.9.2 with A and B, to obtain the inequality $m \leq n$. We then apply Lemma 2.9.2 again (switching the order of the matrices), to obtain the inequality $n \leq m$. It follows that $m = n$, as we wanted.

Theorem 2.9.2: Unique Inverse of a Matrix

Let R be the reduced row-echelon form of a square matrix A. Then, $R = EA$ where E is an invertible matrix. Since $AB = I$, Lemma 2.9.1 gives us that R does not have a row of zeros. By noting that R is a square matrix and applying Proposition 2.9.1, we see that $R = I$. Hence, $EA = I$.

Using both that $EA = I$ and $AB = I$, we can finish the proof with a chain of equalities as given by

$$\begin{aligned} BA = IBIA &= (EA)B(E^{-1}E)A \\ &= E(AB)E^{-1}(EA) \\ &= EIE^{-1}I \\ &= EE^{-1} = I \end{aligned} \tag{2.9.3}$$

It follows from the definition of the inverse of a matrix that $B = A^{-1}$ and $A = B^{-1}$.

Theorem 2.9.3: The reduced row-echelon form of an Invertible Matrix

In order to prove this, we show that for any given matrix A, each condition implies the other. We first show that if A is invertible, then its reduced row-echelon form is an identity matrix, then we show that if the reduced row-echelon form of A is an identity matrix, then A is invertible.

If A is invertible, there is some matrix B such that $AB = I$. By Lemma 2.9.1, we get that the of A does not have a row of zeros. Then by Theorem 2.9.1, it follows that A and the reduced row-echelon form of A are square matrices. Finally, by Proposition 2.9.1, this reduced row-echelon form of A must be an identity matrix. This proves the first implication.

Now suppose the reduced row-echelon form of A is an identity matrix I. Then $I = EA$ for some product E of elementary matrices. By Theorem 2.9.2, we can conclude that A is invertible.

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2.10: LU Factorization

An LU factorization of a matrix involves writing the given matrix as the product of a lower triangular matrix L which has the main diagonal consisting entirely of ones, and an upper triangular matrix U in the indicated order. This is the version discussed here but it is sometimes the case that the L has numbers other than 1 down the main diagonal. It is still a useful concept. The L goes with "lower" and the U with "upper".

It turns out many matrices can be written in this way and when this is possible, people get excited about slick ways of solving the system of equations, $AX = B$. It is for this reason that you want to study the LU factorization. It allows you to work only with triangular matrices. It turns out that it takes about half as many operations to obtain an LU factorization as it does to find the row reduced echelon form.

First it should be noted not all matrices have an LU factorization and so we will emphasize the techniques for achieving it rather than formal proofs.

Example 2.10.1: A Matrix with NO LU factorization

Can you write $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$ in the form LU as just described?

Solution

To do so you would need

$$\begin{bmatrix} 1 & 0 \\ x & 1 \end{bmatrix} \begin{bmatrix} a & b \\ 0 & c \end{bmatrix} = \begin{bmatrix} a & b \\ xa & xb+c \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}.$$

Therefore, $b = 1$ and $a = 0$. Also, from the bottom rows, $xa = 1$ which can't happen and have $a = 0$. Therefore, you can't write this matrix in the form It has no LU factorization. This is what we mean above by saying the method lacks generality.

Nevertheless the method is often extremely useful, and we will describe below one the many methods used to produce an LU factorization when possible.

Finding An LU Factorization By Inspection

Which matrices have an LU factorization? It turns out it is those whose row-echelon form can be achieved without switching rows. In other words matrices which only involve using row operations of type 2 or 3 to obtain the row-echelon form.

Example 2.10.2: An LU factorization

Find an LU factorization of $A = \begin{bmatrix} 1 & 2 & 0 & 2 \\ 1 & 3 & 2 & 1 \\ 2 & 3 & 4 & 0 \end{bmatrix}$.

Solution

One way to find the LU factorization is to simply look for it directly. You need

$$\begin{bmatrix} 1 & 2 & 0 & 2 \\ 1 & 3 & 2 & 1 \\ 2 & 3 & 4 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ x & 1 & 0 \\ y & z & 1 \end{bmatrix} \begin{bmatrix} a & d & h & j \\ 0 & b & e & i \\ 0 & 0 & c & f \end{bmatrix}.$$

Then multiplying these you get

$$\begin{bmatrix} a & d & h & j \\ xa & xd+b & xh+e & xj+i \\ ya & yd+zb & yh+ze+c & yj+iz+f \end{bmatrix}$$

and so you can now tell what the various quantities equal. From the first column, you need $a=1, x=1, y=2$. Now go to the second column. You need $d=2, xd+b=3$ so $b=1, yd+zb=3$ so $z=-1$. From the third column, $h=0, e=2, c=6$. Now from the fourth column, $j=2, i=-1, f=-5$. Therefore, an LU factorization is

$$\begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 2 & -1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 0 & 2 \\ 0 & 1 & 2 & -1 \\ 0 & 0 & 6 & -5 \end{bmatrix}.$$

You can check whether you got it right by simply multiplying these two.

LU Factorization, Multiplier Method

Remember that for a matrix A to be written in the form $A=LU$, you must be able to reduce it to its row-echelon form without interchanging rows. The following method gives a process for calculating the LU factorization of such a matrix A.

Example 2.10.3: LU factorization

Find an LU factorization for

$$\begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ -2 & 3 & -2 \end{bmatrix}$$

Solution

Write the matrix as the following product.

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ -2 & 3 & -2 \end{bmatrix}$$

In the matrix on the right, begin with the left row and zero out the entries below the top using the row operation which involves adding a multiple of a row to another row. You do this and also update the matrix on the left so that the product will be unchanged. Here is the first step. Take -2 times the top row and add to the second. Then take 2 times the top row and add to the second in the matrix on the left.

$$\begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 3 \\ 0 & -1 & -5 \\ -2 & 3 & -2 \end{bmatrix}$$

The next step is to take 2 times the top row and add to the bottom in the matrix on the right. To ensure that the product is unchanged, you place a in the bottom left in the matrix on the left. Thus the next step yields

$$\begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ -2 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 3 \\ 0 & -1 & -5 \\ 0 & 7 & 4 \end{bmatrix}$$

Next take 7 times the middle row on right and add to bottom row. Updating the matrix on the left in a similar manner to what was done earlier,

$$\begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ -2 & -7 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 3 \\ 0 & -1 & -5 \\ 0 & 0 & -31 \end{bmatrix}$$

At this point, stop. You are done.

The method just described is called the multiplier method.

Solving Systems using LU Factorization

One reason people care about the LU factorization is it allows the quick solution of systems of equations. Here is an example.

Example 2.10.4: LU factorization to Solve Equations

Suppose you want to find the solutions to

$$\begin{bmatrix} 1 & 2 & 3 & 2 \\ 4 & 3 & 1 & 1 \\ 1 & 2 & 3 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}.$$

Solution

Of course one way is to write the augmented matrix and grind away. However, this involves more row operations than the computation of the LU factorization and it turns out that the LU factorization can give the solution quickly. Here is how. The following is an LU factorization for the matrix.

$$\begin{bmatrix} 1 & 2 & 3 & 2 \\ 4 & 3 & 1 & 1 \\ 1 & 2 & 3 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 4 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 3 & 2 \\ 0 & -5 & -11 & -7 \\ 0 & 0 & 0 & -2 \end{bmatrix}.$$

Let $UX = Y$ and consider $LY = B$ where in this case, $B = [1, 2, 3]^T$. Thus

$$\begin{bmatrix} 1 & 0 & 0 \\ 4 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

which yields very quickly that $Y = \begin{bmatrix} 1 \\ -2 \\ 2 \end{bmatrix}$.

Now you can find X by solving $UX = Y$. Thus in this case,

$$\begin{bmatrix} 1 & 2 & 3 & 2 \\ 0 & -5 & -11 & -7 \\ 0 & 0 & 0 & -2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 1 \\ -2 \\ 2 \end{bmatrix}$$

which yields

$$X = \begin{bmatrix} -\frac{3}{5} + \frac{7}{5}t \\ \frac{9}{5} - \frac{11}{5}t \\ t \\ -1 \end{bmatrix}, \quad t \in \mathbb{R}.$$

Justification for the Multiplier Method

Why does the multiplier method work for finding the LU factorization? Suppose A is a matrix which has the property that the row-echelon form for A may be achieved without switching rows. Thus every row which is replaced using this row operation in obtaining the row-echelon form may be modified by using a row which is above it.

Lemma 2.10.1: Multiplier Method and Triangular Matrices

Let L be a lower (upper) triangular matrix $m \times m$ which has ones down the main diagonal. Then L^{-1} also is a lower (upper) triangular matrix which has ones down the main diagonal. In the case that L is of the form

$$L = \begin{bmatrix} 1 & & & \\ a_1 & 1 & & \\ \vdots & & \ddots & \\ a_n & & & 1 \end{bmatrix} \tag{2.10.1}$$

where all entries are zero except for the left column and main diagonal, it is also the case that L^{-1} is obtained from L by simply multiplying each entry below the main diagonal in L with -1. The same is true if the single nonzero column is in another position.

Proof available at the end of this section.

For a simple illustration of the last claim,

$$\begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & a & 1 & 0 & 0 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & -a & 1 \end{bmatrix}$$

Now let A be an $m \times n$ matrix, say

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

and assume A can be row reduced to an upper triangular form using only row operation 3. Thus, in particular, $a_{11} \neq 0$. Multiply on the left by $E_1 =$

$$\begin{bmatrix} 1 & 0 & \cdots & 0 \\ -\frac{a_{21}}{a_{11}} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -\frac{a_{m1}}{a_{11}} & 0 & \cdots & 1 \end{bmatrix}$$

This is the product of elementary matrices which make modifications in the first column only. It is equivalent to taking $-a_{21}/a_{11}$ times the first row and adding to the second. Then taking $-a_{31}/a_{11}$ times the first row and adding to the third and so forth. The quotients in the first column of the above matrix are the multipliers. Thus the result is of the form

$$E_1 A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a'_{1n} \\ 0 & a'_{22} & \cdots & a'_{2n} \\ \vdots & \vdots & & \vdots \\ 0 & a'_{m2} & \cdots & a'_{mn} \end{bmatrix}$$

By assumption, $a'_{22} \neq 0$ and so it is possible to use this entry to zero out all the entries below it in the matrix on the right by multiplication by a matrix of the form $E_2 = \begin{bmatrix} 1 & \mathbf{0} \\ \mathbf{0} & E \end{bmatrix}$ where E is an $[m-1] \times [m-1]$ matrix of the form

$$E = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ -\frac{a'_{32}}{a'_{22}} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -\frac{a'_{m2}}{a'_{22}} & 0 & \cdots & 1 \end{bmatrix}$$

Again, the entries in the first column below the 1 are the multipliers. Continuing this way, zeroing out the entries below the diagonal entries, finally leads to

$$E_{m-1} E_{n-2} \cdots E_1 A = U$$

where U is upper triangular. Each E_j has all ones down the main diagonal and is lower triangular. Now multiply both sides by the

inverses of the E_j in the reverse order. This yields

$$A = E_1^{-1}E_2^{-1}\cdots E_{m-1}^{-1}U$$

By Lemma 2.10.1, this implies that the product of those E_j^{-1} is a lower triangular matrix having all ones down the main diagonal.

The above discussion and lemma gives the justification for the multiplier method. The expressions

$$\frac{-a_{21}}{a_{11}}, \frac{-a_{31}}{a_{11}}, \cdots, \frac{-a_{m1}}{a_{11}}$$

denoted respectively by $M_{21}, \cdots, M_{m1}$ to save notation which were obtained in building E_1 are the multipliers. Then according to the lemma, to find E_1^{-1} you simply write

$$\begin{bmatrix} 1 & 0 & \cdots & 0 \\ -M_{21} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -M_{m1} & 0 & \cdots & 1 \end{bmatrix}$$

Similar considerations apply to the other E_j^{-1}. Thus L is a product of the form

$$\begin{bmatrix} 1 & 0 & \cdots & 0 \\ -M_{21} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -M_{m1} & 0 & \cdots & 1 \end{bmatrix} \cdots \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & \cdots & -M_{m[m-1]} & 1 \end{bmatrix}$$

each factor having at most one nonzero column, the position of which moves from left to right in scanning the above product of matrices from left to right. It follows from what we know about the effect of multiplying on the left by an elementary matrix that the above product is of the form

$$\begin{bmatrix} 1 & 0 & \cdots & 0 & 0 \\ -M_{21} & 1 & \cdots & 0 & 0 \\ \vdots & -M_{32} & \ddots & \vdots & \vdots \\ -M_{[m-1]1} & \vdots & \cdots & 1 & 0 \\ -M_{m1} & -M_{m2} & \cdots & -M_{m[m-1]} & 1 \end{bmatrix}$$

In words, beginning at the left column and moving toward the right, you simply insert, into the corresponding position in the identity matrix, -1 times the multiplier which was used to zero out an entry in that position below the main diagonal in A, while retaining the main diagonal which consists entirely of ones. This is L.

Answers

Lemma 2.10.1: Multiplier Method and Triangular Matrices

Consider the usual setup for finding the inverse $\begin{bmatrix} L & I \end{bmatrix}$. Then each row operation done to L to reduce to row reduced echelon form results in changing only the entries in I below the main diagonal. In the special case of L given in (2.10.1) or the single nonzero column is in another position, multiplication by -1 as described in the lemma clearly results in L^{-1}.

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2.E: Exercises

Exercise $2.E.1$

For the following pairs of matrices, determine if the sum $A+B$ is defined. If so, find the sum.

a. $A=\begin{bmatrix}1&0\\0&1\end{bmatrix}, B=\begin{bmatrix}0&1\\1&0\end{bmatrix}$

b. $A=\begin{bmatrix}2&1&2\\1&1&0\end{bmatrix}, B=\begin{bmatrix}-1&0&3\\0&1&4\end{bmatrix}$

c. $A=\begin{bmatrix}1&0\\-2&3\\4&2\end{bmatrix}, B=\begin{bmatrix}2&7&-1\\0&3&4\end{bmatrix}$

Exercise $2.E.2$

For each matrix A, find the matrix $-A$ such that $A+(-A)=0$.

a. $A=\begin{bmatrix}1&2\\2&1\end{bmatrix}$

b. $A=\begin{bmatrix}-2&3\\0&2\end{bmatrix}$

c. $A=\begin{bmatrix}0&1&2\\1&-1&3\\4&2&0\end{bmatrix}$

Exercise $2.E.3$

In the context of Proposition 2.1.1, describe $-A$ and 0.

Answer available at the end of this section.

2.1.2: Scalar Multiplication of Matrices

Exercise $2.E.4$

For each matrix A, find the product $(-2)A, 0A$, and $3A$.

a. $A=\begin{bmatrix}1&2\\2&1\end{bmatrix}$

b. $A=\begin{bmatrix}-2&3\\0&2\end{bmatrix}$

c. $A=\begin{bmatrix}0&1&2\\1&-1&3\\4&2&0\end{bmatrix}$

Exercise $2.E.5$

Using only the properties given in Proposition 2.1.1 and Proposition 2.1.2, show $-A$ is unique.

Answer available at the end of this section.

Exercise $2.E.6$

Using only the properties given in Proposition 2.1.1 and Proposition 2.1.2, show 0 is unique.

Answer available at the end of this section.

Exercise $2.E.7$

Using only the properties given in Proposition 2.1.1 and Proposition 2.1.2 show $0A = 0$. Here the 0 on the left is the scalar 0 and the 0 on the right is the zero matrix of appropriate size.

Answer available at the end of this section.

Exercise $2.E.8$

Using only the properties given in Proposition 2.1.1 and Proposition 2.1.2, as well as previous problems show $(-1)\,A = -A$.

Answer available at the end of this section.

2.2

Exercise $2.E.9$

Consider the matrices $A = \begin{bmatrix} 1 & 2 & 3 \\ 2 & 1 & 7 \end{bmatrix}, B = \begin{bmatrix} 3 & -1 & 2 \\ -3 & 2 & 1 \end{bmatrix}, C = \begin{bmatrix} 1 & 2 \\ 3 & 1 \end{bmatrix}, D = \begin{bmatrix} -1 & 2 \\ 2 & -3 \end{bmatrix}, E = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$.

Find the following if possible. If it is not possible explain why.

a. $-3A$
b. $3B - A$
c. AC
d. CB
e. AE
f. EA

Answer available at the end of this section.

Exercise $2.E.10$

Consider the matrices $A = \begin{bmatrix} 1 & 2 \\ 3 & 2 \\ 1 & -1 \end{bmatrix}, B = \begin{bmatrix} 2 & -5 & 2 \\ -3 & 2 & 1 \end{bmatrix}, C = \begin{bmatrix} 1 & 2 \\ 5 & 0 \end{bmatrix}, D = \begin{bmatrix} -1 & 1 \\ 4 & -3 \end{bmatrix}, E = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$

Find the following if possible. If it is not possible explain why.

a. $-3A$
b. $3B - A$
c. AC
d. CA
e. AE
f. EA
g. BE
h. DE

Answer available at the end of this section.

Exercise $2.E.11$

Let $A = \begin{bmatrix} 1 & 1 \\ -2 & -1 \\ 1 & 2 \end{bmatrix}$, $B = \begin{bmatrix} 1 & -1 & -2 \\ 2 & 1 & -2 \end{bmatrix}$, and $C = \begin{bmatrix} 1 & 1 & -3 \\ -1 & 2 & 0 \\ -3 & -1 & 0 \end{bmatrix}$. Find the following if possible.

a. AB
b. BA
c. AC
d. CA
e. CB
f. BC

Answer available at the end of this section.

Exercise $2.E.12$

Let $A = \begin{bmatrix} -1 & -1 \\ 3 & 3 \end{bmatrix}$. Find all 2×2 matrices, B such that $AB = 0$.

Answer available at the end of this section.

Exercise $2.E.13$

Let $X = \begin{bmatrix} -1 & -1 & 1 \end{bmatrix}$ and $Y = \begin{bmatrix} 0 & 1 & 2 \end{bmatrix}$. Find X^TY and XY^T if possible.

Answer available at the end of this section.

Exercise $2.E.14$

Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$, $B = \begin{bmatrix} 1 & 2 \\ 3 & k \end{bmatrix}$. Is it possible to choose k such that $AB = BA$? If so, what should k equal?

Answer available at the end of this section.

Exercise $2.E.15$

Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$, $B = \begin{bmatrix} 1 & 2 \\ 1 & k \end{bmatrix}$. Is it possible to choose k such that $AB = BA$? If so, what should k equal?

Answer available at the end of this section.

Exercise $2.E.16$

Find 2×2 matrices, A, B, and C such that $A \neq 0, C \neq B$, but $AC = AB$.

Answer available at the end of this section.

Exercise $2.E.17$

Give an example of matrices (of any size), A, B, C such that $B \neq C$, $A \neq 0$, and yet $AB = AC$.

Exercise $2.E.18$

Find 2×2 matrices A and B such that $A \neq 0$ and $B \neq 0$ but $AB = 0$.

Answer available at the end of this section.

Exercise $2.E.19$

Give an example of matrices (of any size), A, B such that $A \neq 0$ and $B \neq 0$ but $AB = 0$.

Exercise $2.E.20$

Find 2×2 matrices A and B such that $A \neq 0$ and $B \neq 0$ with $AB \neq BA$.

Answer available at the end of this section.

Exercise $2.E.21$

Write the system

$$\begin{array}{c} x_1 - x_2 + 2x_3 \\ 2x_3 + x_1 \\ 3x_3 \\ 3x_4 + 3x_2 + x_1 \end{array}$$

in the form $A \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$ where A is an appropriate matrix.

Answer available at the end of this section.

Exercise $2.E.22$

Write the system

$$x_1 + 3x_2 + 2x_3$$
$$2x_3 + x_1$$
$$6x_3$$
$$x_4 + 3x_2 + x_1$$

in the form $A \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$ where A is an appropriate matrix.

Answer available at the end of this section.

Exercise $2.E.23$

Write the system

$$x_1 + x_2 + x_3$$
$$2x_3 + x_1 + x_2$$
$$x_3 - x_1$$
$$3x_4 + x_1$$

in the form $A \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$ where A is an appropriate matrix.

Answer available at the end of this section.

Exercise $2.E.24$

A matrix A is called *idempotent* if $A^2 = A$. Let

$$A = \begin{bmatrix} 2 & 0 & 2 \\ 1 & 1 & 2 \\ -1 & 0 & -1 \end{bmatrix}$$

and show that A is idempotent.

2.3

Exercise $2.E.25$

For each pair of matrices, find the $(1,2)$-entry and $(2,3)$-entry of the product AB.

1. $A = \begin{bmatrix} 1 & 2 & -1 \\ 3 & 4 & 0 \\ 2 & 5 & 1 \end{bmatrix}, B = \begin{bmatrix} 4 & 6 & -2 \\ 7 & 2 & 1 \\ -1 & 0 & 0 \end{bmatrix}$
2. $A = \begin{bmatrix} 1 & 3 & 1 \\ 0 & 2 & 4 \\ 1 & 0 & 5 \end{bmatrix}, B = \begin{bmatrix} 2 & 3 & 0 \\ -4 & 16 & 1 \\ 0 & 2 & 2 \end{bmatrix}$

2.4

Exercise $2.E.26$

Suppose A and B are square matrices of the same size. Which of the following are necessarily true?

a. $(A-B)^2 = A^2 - 2AB + B^2$
b. $(AB)^2 = A^2B^2$
c. $(A+B)^2 = A^2 + 2AB + B^2$
d. $(A+B)^2 = A^2 + AB + BA + B^2$
e. $A^2B^2 = A(AB)B$
f. $(A+B)^3 = A^3 + 3A^2B + 3AB^2 + B^3$
g. $(A+B)(A-B) = A^2 - B^2$

Answer available at the end of this section.

2.5

Exercise $2.E.27$

Consider the matrices $A = \begin{bmatrix} 1 & 2 \\ 3 & 2 \\ 1 & -1 \end{bmatrix}, B = \begin{bmatrix} 2 & -5 & 2 \\ -3 & 2 & 1 \end{bmatrix}, C = \begin{bmatrix} 1 & 2 \\ 5 & 0 \end{bmatrix}, D = \begin{bmatrix} -1 & 1 \\ 4 & -3 \end{bmatrix}, E = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$

Find the following if possible. If it is not possible explain why.

a. $-3A^T$
b. $3B - A^T$
c. E^TB
d. EE^T
e. B^TB
f. CA^T
g. D^TBE

Answer available at the end of this section.

Exercise $2.E.28$

Let A be an $n \times n$ matrix. Show A equals the sum of a symmetric and a skew symmetric matrix.

Hint available at the end of this section.

Exercise $2.E.29$

Show that the main diagonal of every skew symmetric matrix consists of only zeros. Recall that the main diagonal consists of every entry of the matrix which is of the form a_{ii}.

Answer available at the end of this section.

Exercise 2.E.30

Prove 3 from Lemma 2.5.1. That is, show that for an $m \times n$ matrix A, an $m \times n$ matrix B, and scalars r, s, the following holds:

$$(rA + sB)^T = rA^T + sB^T$$

2.6

Exercise 2.E.31

Prove that $I_m A = A$ where A is an $m \times n$ matrix.

Answer available at the end of this section.

Exercise 2.E.32

Suppose $AB = AC$ and A is an invertible $n \times n$ matrix. Does it follow that $B = C$? Explain why or why not.

Answer available at the end of this section.

Exercise 2.E.33

Suppose $AB = AC$ and A is a non invertible $n \times n$ matrix. Does it follow that $B = C$? Explain why or why not.

Exercise 2.E.34

Give an example of a matrix A such that $A^2 = I$ and yet $A \neq I$ and $A \neq -I$.

Answer available at the end of this section.

2.7

Exercise 2.E.35

Let

$$A = \begin{bmatrix} 2 & 1 \\ -1 & 3 \end{bmatrix}$$

Find A^{-1} if possible. If A^{-1} does not exist, explain why.

Answer available at the end of this section.

Exercise 2.E.36

Let

$$A = \begin{bmatrix} 0 & 1 \\ 5 & 3 \end{bmatrix}$$

Find A^{-1} if possible. If A^{-1} does not exist, explain why.

Answer available at the end of this section.

Exercise $2.E.37$

Add exercises text here.Let

$$A = \begin{bmatrix} 2 & 1 \\ 3 & 0 \end{bmatrix}$$

Find A^{-1} if possible. If A^{-1} does not exist, explain why.

Answer available at the end of this section.

Exercise $2.E.38$

Let

$$A = \begin{bmatrix} 2 & 1 \\ 4 & 2 \end{bmatrix}$$

Find A^{-1} if possible. If A^{-1} does not exist, explain why.

Answer available at the end of this section.

Exercise $2.E.39$

Let A be a 2×2 invertible matrix, with $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$. Find a formula for A^{-1} in terms of a, b, c, d.

Answer available at the end of this section.

Exercise $2.E.40$

Let

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 2 & 1 & 4 \\ 1 & 0 & 2 \end{bmatrix}$$

Find A^{-1} if possible. If A^{-1} does not exist, explain why.

Answer available at the end of this section.

Exercise $2.E.41$

Let

$$A = \begin{bmatrix} 1 & 0 & 3 \\ 2 & 3 & 4 \\ 1 & 0 & 2 \end{bmatrix}$$

Find A^{-1} if possible. If A^{-1} does not exist, explain why.

Answer available at the end of this section.

Exercise $2.E.42$

Let

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 2 & 1 & 4 \\ 4 & 5 & 10 \end{bmatrix}$$

Find A^{-1} if possible. If A^{-1} does not exist, explain why.

Answer available at the end of this section.

Exercise $2.E.43$

Let

$$A = \begin{bmatrix} 1 & 2 & 0 & 2 \\ 1 & 1 & 2 & 0 \\ 2 & 1 & -3 & 2 \\ 1 & 2 & 1 & 2 \end{bmatrix}$$

Find A^{-1} if possible. If A^{-1} does not exist, explain why.

Answer available at the end of this section.

Exercise $2.E.44$

Using the inverse of the matrix, find the solution to the systems:

a. $$\begin{bmatrix} 2 & 4 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

b. $$\begin{bmatrix} 2 & 4 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \end{bmatrix}$$

Now give the solution in terms of a and b to

$$\begin{bmatrix} 2 & 4 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a \\ b \end{bmatrix}$$

Exercise $2.E.45$

Using the inverse of the matrix, find the solution to the systems:

a. $$\begin{bmatrix} 1 & 0 & 3 \\ 2 & 3 & 4 \\ 1 & 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

b. $$\begin{bmatrix} 1 & 0 & 3 \\ 2 & 3 & 4 \\ 1 & 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 3 \\ -1 \\ -2 \end{bmatrix}$$

Now give the solution in terms of $a, b,$ and c to the following:

$$\begin{bmatrix} 1 & 0 & 3 \\ 2 & 3 & 4 \\ 1 & 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

Answer available at the end of this section.

Exercise $2.E.46$

Show that if A is an $n \times n$ invertible matrix and X is a $n \times 1$ matrix such that $AX = B$ for B an $n \times 1$ matrix, then $X = A^{-1}B$.

Answer available at the end of this section.

Exercise $2.E.47$

Prove that if A^{-1} exists and $AX = 0$ then $X = 0$.

Answer available at the end of this section.

Exercise $2.E.48$: Inverse Product

Show that if A^{-1} exists for an $n \times n$ matrix, then it is unique. That is, if $BA = I$ and $AB = I$, then $B = A^{-1}$.

Answer available at the end of this section.

Exercise $2.E.49$

Show that if A is an invertible $n \times n$ matrix, then so is A^T and $\left(A^T\right)^{-1} = \left(A^{-1}\right)^T$.

Answer available at the end of this section.

Exercise $2.E.50$

Show $(AB)^{-1} = B^{-1}A^{-1}$ by verifying that

$$AB\left(B^{-1}A^{-1}\right) = I$$

and

$$B^{-1}A^{-1}(AB) = I$$

Hint: Use Problem $2.E.48$.

Answer available at the end of this section.

Exercise $2.E.51$

Show that $(ABC)^{-1} = C^{-1}B^{-1}A^{-1}$ by verifying that

$$(ABC)\left(C^{-1}B^{-1}A^{-1}\right) = I$$

and

$$\left(C^{-1}B^{-1}A^{-1}\right)(ABC) = I$$

Hint: Use Problem $2.E.48$.

Answer available at the end of this section.

Exercise $2.E.52$

If A is invertible, show $\left(A^2\right)^{-1} = \left(A^{-1}\right)^2$. **Hint:** Use Problem $2.E.48$.

Answer available at the end of this section.

Exercise $2.E.53$

If A is invertible, show $\left(A^{-1}\right)^{-1} = A$. **Hint:** Use Problem $2.E.48$.

Answer available at the end of this section.

2.8

Exercise $2.E.54$

Let $A = \begin{bmatrix} 2 & 3 \\ 1 & 2 \end{bmatrix}$. Suppose a row operation is applied to A and the result is $B = \begin{bmatrix} 1 & 2 \\ 2 & 3 \end{bmatrix}$. Find the elementary matrix E that represents this row operation.

Exercise $2.E.55$

Let $A = \begin{bmatrix} 4 & 0 \\ 2 & 1 \end{bmatrix}$. Suppose a row operation is applied to A and the result is $B = \begin{bmatrix} 8 & 0 \\ 2 & 1 \end{bmatrix}$. Find the elementary matrix E that represents this row operation.

Exercise $2.E.56$

Let $A = \begin{bmatrix} 1 & -3 \\ 0 & 5 \end{bmatrix}$. Suppose a row operation is applied to A and the result is $B = \begin{bmatrix} 1 & -3 \\ 2 & -1 \end{bmatrix}$. Find the elementary matrix E that represents this row operation.

Exercise $2.E.57$

Let $A = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 5 & 1 \\ 2 & -1 & 4 \end{bmatrix}$. Suppose a row operation is applied to A and the result is $B = \begin{bmatrix} 1 & 2 & 1 \\ 2 & -1 & 4 \\ 0 & 5 & 1 \end{bmatrix}$.

a. Find the elementary matrix E such that $EA = B$.
b. Find the inverse of E, E^{-1}, such that $E^{-1}B = A$.

Exercise 2.E.58

Let $A = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 5 & 1 \\ 2 & -1 & 4 \end{bmatrix}$. Suppose a row operation is applied to A and the result is $B = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 10 & 2 \\ 2 & -1 & 4 \end{bmatrix}$.

a. Find the elementary matrix E such that $EA = B$.
b. Find the inverse of E, E^{-1}, such that $E^{-1}B = A$.

Exercise 2.E.59

Let $A = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 5 & 1 \\ 2 & -1 & 4 \end{bmatrix}$. Suppose a row operation is applied to A and the result is $B = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 5 & 1 \\ 1 & -\frac{1}{2} & 2 \end{bmatrix}$.

a. Find the elementary matrix E such that $EA = B$.
b. Find the inverse of E, E^{-1}, such that $E^{-1}B = A$.

Exercise 2.E.60

Let $A = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 5 & 1 \\ 2 & -1 & 4 \end{bmatrix}$. Suppose a row operation is applied to A and the result is $B = \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 5 \\ 2 & -1 & 4 \end{bmatrix}$.

a. Find the elementary matrix E such that $EA = B$.
b. Find the inverse of E, E^{-1}, such that $E^{-1}B = A$.

2.10

Exercise 2.E.61

Find an LU factorization of $\begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 3 \\ 1 & 2 & 3 \end{bmatrix}$.

Answer available at the end of this section.

Exercise 2.E.62

Find an LU factorization of $\begin{bmatrix} 1 & 2 & 3 & 2 \\ 1 & 3 & 2 & 1 \\ 5 & 0 & 1 & 3 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $2.E.63$

Find an LU factorization of the matrix $\begin{bmatrix} 1 & -2 & -5 & 0 \\ -2 & 5 & 11 & 3 \\ 3 & -6 & -15 & 1 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $2.E.64$

Find an LU factorization of the matrix $\begin{bmatrix} 1 & -1 & -3 & -1 \\ -1 & 2 & 4 & 3 \\ 2 & -3 & -7 & -3 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $2.E.65$

Find an LU factorization of the matrix $\begin{bmatrix} 1 & -3 & -4 & -3 \\ -3 & 10 & 10 & 10 \\ 1 & -6 & 2 & -5 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $2.E.66$

Find an LU factorization of the matrix $\begin{bmatrix} 1 & 3 & 1 & -1 \\ 3 & 10 & 8 & -1 \\ 2 & 5 & -3 & -3 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $2.E.67$

Find an LU factorization of the matrix $\begin{bmatrix} 3 & -2 & 1 \\ 9 & -8 & 6 \\ -6 & 2 & 2 \\ 3 & 2 & -7 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $2.E.68$

Find an LU factorization of the matrix $\begin{bmatrix} -3 & -1 & 3 \\ 9 & 9 & -12 \\ 3 & 19 & -16 \\ 12 & 40 & -26 \end{bmatrix}$.

Exercise 2.E.69

Find an LU factorization of the matrix $\begin{bmatrix} -1 & -3 & -1 \\ 1 & 3 & 0 \\ 3 & 9 & 0 \\ 4 & 12 & 16 \end{bmatrix}$.

Answer available at the end of this section.

Exercise 2.E.70

Find the LU factorization of the coefficient matrix using Dolittle's method and use it to solve the system of equations.

$$x + 2y = 5$$
$$2x + 3y = 6$$

Answer available at the end of this section.

Exercise 2.E.71

Find the LU factorization of the coefficient matrix using Dolittle's method and use it to solve the system of equations.

$$x + 2y + z = 1$$
$$y + 3z = 2$$
$$2x + 3y = 6$$

Answer available at the end of this section.

Exercise 2.E.72

Find the LU factorization of the coefficient matrix using Dolittle's method and use it to solve the system of equations.

$$x + 2y + 3z = 5$$
$$2x + 3y + z = 6$$
$$x - y + z = 2$$

Exercise 2.E.73

Find the LU factorization of the coefficient matrix using Dolittle's method and use it to solve the system of equations.

$$x + 2y + 3z = 5$$
$$2x + 3y + z = 6$$
$$3x + 5y + 4z = 11$$

Answer available at the end of this section.

Exercise 2.E.74

Is there only one LU factorization for a given matrix? **Hint:** Consider the equation

$$\begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}.$$

Look for all possible LU factorizations.

Answer available at the end of this section.

Answers

Exercise $2.E.3$

To get $-A$, just replace every entry of A with its additive inverse. The $\mathbb{0}$ matrix is the one which has all zeros in it.

Exercise $2.E.5$

Suppose B also works. Then

$$-A = -A + (A + B) = (-A + A) + B = 0 + B = B$$

Exercise $2.E.6$

Suppose $0'$ also works. Then $0' = 0' + 0 = 0$.

Exercise $2.E.7$

$0A = (0 + 0)\, A = 0A + 0A$. Now add $-(0A)$ to both sides. Then $0 = 0A$.

Exercise $2.E.8$

$A + (-1)\, A = (1 + (-1))\, A = 0A = 0$. Therefore, from the uniqueness of the additive inverse proved in the above Problem $2.E.7$, it follows that $-A = (-1)\, A$.

Exercise $2.E.9$

a. $\begin{bmatrix} -3 & -6 & -9 \\ -6 & -3 & -21 \end{bmatrix}$

b. $\begin{bmatrix} 8 & -5 & 3 \\ -11 & 5 & -4 \end{bmatrix}$

c. Not possible

d. $\begin{bmatrix} -3 & 3 & 4 \\ 6 & -1 & 7 \end{bmatrix}$

e. Not possible

f. Not possible

Exercise $2.E.10$

a. $\begin{bmatrix} -3 & -6 \\ -9 & -6 \\ -3 & 3 \end{bmatrix}$

b. Not possible.

c. $\begin{bmatrix} 11 & 2 \\ 13 & 6 \\ -4 & 2 \end{bmatrix}$

d. Not possible.

e. $\begin{bmatrix} 7 \\ 9 \\ -2 \end{bmatrix}$

f. Not possible.

g. Not possible.

h. $\begin{bmatrix} 2 \\ -5 \end{bmatrix}$

Exercise $2.E.11$

a. $\begin{bmatrix} 3 & 0 & -4 \\ -4 & 1 & 6 \\ 5 & 1 & -6 \end{bmatrix}$

b. $\begin{bmatrix} 1 & -2 \\ -2 & -3 \end{bmatrix}$

c. Not possible

d. $\begin{bmatrix} -4 & -6 \\ -5 & -3 \\ -1 & -2 \end{bmatrix}$

e. $\begin{bmatrix} 8 & 1 & -3 \\ 7 & 6 & -6 \end{bmatrix}$

Exercise $2.E.12$

$$\begin{aligned} \begin{bmatrix} -1 & -1 \\ 3 & 3 \end{bmatrix} \begin{bmatrix} x & y \\ z & w \end{bmatrix} &= \begin{bmatrix} -x - z & -w - y \\ 3x + 3z & 3w + 3y \end{bmatrix} \\ &= \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \end{aligned} \tag{2.E.1}$$

Solution is: $w = -y, x = -z$ so the matrices are of the form $\begin{bmatrix} x & y \\ -x & -y \end{bmatrix}$.

Exercise $2.E.13$

$$X^TY = \begin{bmatrix} 0 & -1 & -2 \\ 0 & -1 & -2 \\ 0 & 1 & 2 \end{bmatrix}, XY^T = 1$$

Exercise $2.E.14$

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}\begin{bmatrix} 1 & 2 \\ 3 & k \end{bmatrix} = \begin{bmatrix} 7 & 2k+2 \\ 15 & 4k+6 \end{bmatrix}$$
$$\begin{bmatrix} 1 & 2 \\ 3 & k \end{bmatrix}\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} = \begin{bmatrix} 7 & 10 \\ 3k+3 & 4k+6 \end{bmatrix} \tag{2.E.2}$$

Thus you must have $\begin{matrix} 3k+3=15 \\ 2k+2=10 \end{matrix}$, Solution is: $[k=4]$

Exercise $2.E.15$

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}\begin{bmatrix} 1 & 2 \\ 1 & k \end{bmatrix} = \begin{bmatrix} 3 & 2k+2 \\ 7 & 4k+6 \end{bmatrix}$$
$$\begin{bmatrix} 1 & 2 \\ 1 & k \end{bmatrix}\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} = \begin{bmatrix} 7 & 10 \\ 3k+1 & 4k+2 \end{bmatrix} \tag{2.E.3}$$

However, $7 \neq 3$ and so there is no possible choice of k which will make these matrices commute.

Exercise $2.E.16$

Let $A = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$, $B = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$, $C = \begin{bmatrix} 2 & 2 \\ 2 & 2 \end{bmatrix}$.

$$\begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$
$$\begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}\begin{bmatrix} 2 & 2 \\ 2 & 2 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{2.E.4}$$

Exercise $2.E.18$

Let $A = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$, $B = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$.

$$\begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Exercise $2.E.20$

Let $A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$, $B = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$.

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} = \begin{bmatrix} 3 & 4 \\ 1 & 2 \end{bmatrix}$$
$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 4 & 3 \end{bmatrix} \tag{2.E.5}$$

Exercise $2.E.21$

$$A = \begin{bmatrix} 1 & -1 & 2 & 0 \\ 1 & 0 & 2 & 0 \\ 0 & 0 & 3 & 0 \\ 1 & 3 & 0 & 3 \end{bmatrix}$$

Exercise $2.E.22$

$$A = \begin{bmatrix} 1 & 3 & 2 & 0 \\ 1 & 0 & 2 & 0 \\ 0 & 0 & 6 & 0 \\ 1 & 3 & 0 & 1 \end{bmatrix}$$

Exercise $2.E.23$

$$A = \begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 1 & 2 & 0 \\ -1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 3 \end{bmatrix}$$

Exercise $2.E.26$

a. Not necessarily true.
b. Not necessarily true.
c. Not necessarily true.
d. Necessarily true.
e. Necessarily true.
f. Not necessarily true.
g. Not necessarily true.

Exercise $2.E.27$

a. $\begin{bmatrix} -3 & -9 & -3 \\ -6 & -6 & 3 \end{bmatrix}$
b. $\begin{bmatrix} 5 & -18 & 5 \\ -11 & 4 & 4 \end{bmatrix}$

c. $\begin{bmatrix} -7 & 1 & 5 \end{bmatrix}$

d. $\begin{bmatrix} 1 & 3 \\ 3 & 9 \end{bmatrix}$

e. $\begin{bmatrix} 13 & -16 & 1 \\ -16 & 29 & -8 \\ 1 & -8 & 5 \end{bmatrix}$

f. $\begin{bmatrix} 5 & 7 & -1 \\ 5 & 15 & 5 \end{bmatrix}$

g. Not possible.

Exercise $2.E.28$

Show that $\frac{1}{2}\left(A^T + A\right)$ is symmetric and then consider using this as one of the matrices.

Exercise $2.E.29$

If A is symmetric then $A = -A^T$. It follows that $a_{ii} = -a_{ii}$ and so each $a_{ii} = 0$.

Exercise $2.E.31$

$(I_m A)_{ij} \equiv \sum_j \delta_{ik} A_{kj} = A_{ij}$

Exercise $2.E.32$

Yes $B = C$. Multiply $AB = AC$ on the left by A^{-1}.

Exercise $2.E.34$

$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

Exercise $2.E.35$

$\begin{bmatrix} 2 & 1 \\ -1 & 3 \end{bmatrix}^{-1} = \begin{bmatrix} \frac{3}{7} & -\frac{1}{7} \\ \frac{1}{7} & \frac{2}{7} \end{bmatrix}$

Exercise $2.E.36$

$\begin{bmatrix} 0 & 1 \\ 5 & 3 \end{bmatrix}^{-1} = \begin{bmatrix} -\frac{3}{5} & \frac{1}{5} \\ 1 & 0 \end{bmatrix}$

Exercise $2.E.37$

$\begin{bmatrix} 2 & 1 \\ 3 & 0 \end{bmatrix}^{-1} = \begin{bmatrix} 0 & \frac{1}{3} \\ 1 & -\frac{2}{3} \end{bmatrix}$

Exercise $2.E.38$

$\begin{bmatrix} 2 & 1 \\ 4 & 2 \end{bmatrix}^{-1}$ does not exist. The of this matrix is $\begin{bmatrix} 1 & \frac{1}{2} \\ 0 & 0 \end{bmatrix}$

Exercise $2.E.39$

$\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \begin{bmatrix} \frac{d}{ad-bc} & -\frac{b}{ad-bc} \\ -\frac{c}{ad-bc} & \frac{a}{ad-bc} \end{bmatrix}$

Exercise $2.E.40$

$\begin{bmatrix} 1 & 2 & 3 \\ 2 & 1 & 4 \\ 1 & 0 & 2 \end{bmatrix}^{-1} = \begin{bmatrix} -2 & 4 & -5 \\ 0 & 1 & -2 \\ 1 & -2 & 3 \end{bmatrix}$

Exercise $2.E.41$

$\begin{bmatrix} 1 & 0 & 3 \\ 2 & 3 & 4 \\ 1 & 0 & 2 \end{bmatrix}^{-1} = \begin{bmatrix} -2 & 0 & 3 \\ 0 & \frac{1}{3} & -\frac{2}{3} \\ 1 & 0 & -1 \end{bmatrix}$

Exercise $2.E.42$

The reduced row-echelon form is $\begin{bmatrix} 1 & 0 & \frac{5}{3} \\ 0 & 1 & \frac{2}{3} \\ 0 & 0 & 0 \end{bmatrix}$. There is no inverse.

Exercise $2.E.43$

$\begin{bmatrix} 1 & 2 & 0 & 2 \\ 1 & 1 & 2 & 0 \\ 2 & 1 & -3 & 2 \\ 1 & 2 & 1 & 2 \end{bmatrix}^{-1} = \begin{bmatrix} -1 & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ 3 & \frac{1}{2} & -\frac{1}{2} & -\frac{5}{2} \\ -1 & 0 & 0 & 1 \\ -2 & -\frac{3}{4} & \frac{1}{4} & \frac{9}{4} \end{bmatrix}$

Exercise $2.E.45$

a. $\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ -\frac{2}{3} \\ 0 \end{bmatrix}$

b. $\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} -12 \\ 1 \\ 5 \end{bmatrix}$

c. $\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 3c-2a \\ \frac{1}{3}b - \frac{2}{3}c \\ a-c \end{bmatrix}$

Exercise $2.E.46$

Multiply both sides of $AX = B$ on the left by A^{-1}.

Exercise $2.E.47$

Multiply on both sides on the left by A^{-1}. Thus

$$0 = A^{-1}0 = A^{-1}(AX) = \left(A^{-1}A\right)X = IX = X$$

Exercise $2.E.48$**: Inverse Product**

$A^{-1} = A^{-1}I = A^{-1}(AB) = \left(A^{-1}A\right)B = IB = B.$

Exercise $2.E.49$

You need to show that $\left(A^{-1}\right)^T$ acts like the inverse of A^T because from uniqueness in the above problem, this will imply it is the inverse. From properties of the transpose,

$$\begin{aligned} A^T\left(A^{-1}\right)^T &= \left(A^{-1}A\right)^T = I^T = I \\ \left(A^{-1}\right)^T A^T &= \left(AA^{-1}\right)^T = I^T = I \end{aligned} \tag{2.E.6}$$

Hence $\left(A^{-1}\right)^T = \left(A^T\right)^{-1}$ and this last matrix exists.

Exercise $2.E.50$

$(AB)B^{-1}A^{-1} = A\left(BB^{-1}\right)A^{-1} = AA^{-1} = I$ $B^{-1}A^{-1}(AB) = B^{-1}\left(A^{-1}A\right)B = B^{-1}IB = B^{-1}B = I$

Exercise $2.E.51$

The proof of this exercise follows from the previous one.

Exercise $2.E.52$

$A^2\left(A^{-1}\right)^2 = AAA^{-1}A^{-1} = AIA^{-1} = AA^{-1} = I$ $\left(A^{-1}\right)^2A^2 = A^{-1}A^{-1}AA = A^{-1}IA = A^{-1}A = I$

Exercise $2.E.53$

$A^{-1}A = AA^{-1} = I$ and so by uniqueness, $\left(A^{-1}\right)^{-1} = A$.

Exercise $2.E.61$

$$\begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 3 \\ 1 & 2 & 3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 0 \\ 0 & -3 & 3 \\ 0 & 0 & 3 \end{bmatrix}$$

Exercise $2.E.62$

$$\begin{bmatrix} 1 & 2 & 3 & 2 \\ 1 & 3 & 2 & 1 \\ 5 & 0 & 1 & 3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 5 & -10 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 3 & 2 \\ 0 & 1 & -1 & -1 \\ 0 & 0 & -24 & -17 \end{bmatrix}$$

Exercise $2.E.63$

$$\begin{bmatrix} 1 & -2 & -5 & 0 \\ -2 & 5 & 11 & 3 \\ 3 & -6 & -15 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ -2 & 1 & 0 \\ 3 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & -2 & -5 & 0 \\ 0 & 1 & 1 & 3 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Exercise $2.E.64$

$$\begin{bmatrix} 1 & -1 & -3 & -1 \\ -1 & 2 & 4 & 3 \\ 2 & -3 & -7 & -3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 2 & -1 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 & -3 & -1 \\ 0 & 1 & 1 & 2 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Exercise $2.E.65$

$$\begin{bmatrix} 1 & -3 & -4 & -3 \\ -3 & 10 & 10 & 10 \\ 1 & -6 & 2 & -5 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ -3 & 1 & 0 \\ 1 & -3 & 1 \end{bmatrix} \begin{bmatrix} 1 & -3 & -4 & -3 \\ 0 & 1 & -2 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Exercise $2.E.66$

$$\begin{bmatrix} 1 & 3 & 1 & -1 \\ 3 & 10 & 8 & -1 \\ 2 & 5 & -3 & -3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 3 & 1 & 0 \\ 2 & -1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 3 & 1 & -1 \\ 0 & 1 & 5 & 2 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Exercise $2.E.67$

$$\begin{bmatrix} 3 & -2 & 1 \\ 9 & -8 & 6 \\ -6 & 2 & 2 \\ 3 & 2 & -7 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 3 & 1 & 0 & 0 \\ -2 & 1 & 1 & 0 \\ 1 & -2 & -2 & 1 \end{bmatrix} \begin{bmatrix} 3 & -2 & 1 \\ 0 & -2 & 3 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

Exercise $2.E.69$

$$\begin{bmatrix} -1 & -3 & -1 \\ 1 & 3 & 0 \\ 3 & 9 & 0 \\ 4 & 12 & 16 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -1 & 1 & 0 & 0 \\ -3 & 0 & 1 & 0 \\ -4 & 0 & -4 & 1 \end{bmatrix} \begin{bmatrix} -1 & -3 & -1 \\ 0 & 0 & -1 \\ 0 & 0 & -3 \\ 0 & 0 & 0 \end{bmatrix}$$

Exercise $2.E.70$

An LU factorization of the coefficient matrix is

$$\begin{bmatrix} 1 & 2 \\ 2 & 3 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 0 & -1 \end{bmatrix}$$

First solve

$$\begin{bmatrix} 1 & 0 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 5 \\ 6 \end{bmatrix}$$

which gives $\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 5 \\ -4 \end{bmatrix}$. Then solve

$$\begin{bmatrix} 1 & 2 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 5 \\ -4 \end{bmatrix}$$

which says that $y = 4$ and $x = -3$.

Exercise $2.E.71$

An LU factorization of the coefficient matrix is

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 1 & 3 \\ 2 & 3 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 2 & -1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 1 \\ 0 & 1 & 3 \\ 0 & 0 & 1 \end{bmatrix}$$

First solve

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 2 & -1 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 6 \end{bmatrix}$$

which yields $u = 1, v = 2, w = 6$. Next solve

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 1 & 3 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 6 \end{bmatrix}$$

This yields $z = 6, y = -16, x = 27$.

Exercise $2.E.73$

An LU factorization of the coefficient matrix is

$$\begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 5 & 4 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 3 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 3 \\ 0 & -1 & -5 \\ 0 & 0 & 0 \end{bmatrix}$$

First solve

$$\begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 3 & 1 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \end{bmatrix} = \begin{bmatrix} 5 \\ 6 \\ 11 \end{bmatrix}$$

Solution is: $\begin{bmatrix} u \\ v \\ w \end{bmatrix} = \begin{bmatrix} 5 \\ -4 \\ 0 \end{bmatrix}$. Next solve

$$\begin{bmatrix} 1 & 2 & 3 \\ 0 & -1 & -5 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 5 \\ -4 \\ 0 \end{bmatrix}$$

Solution is: $\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 7t - 3 \\ 4 - 5t \\ t \end{bmatrix}, t \in \mathbb{R}$.

Exercise $2.E.74$

Sometimes there is more than one LU factorization as is the case in this example. The given equation clearly gives an LU factorization. However, it appears that the following equation gives another LU factorization.

$$\begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}$$

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3: DETERMINANTS

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3.1: Basic Techniques

Cofactors and 2 x 2 Determinants

Outcomes

A. Evaluate the determinant of a square matrix using either Laplace Expansion or row operations.
B. Demonstrate the effects that row operations have on determinants.
C. Verify the following:
   a. The determinant of a product of matrices is the product of the determinants.
   b. The determinant of a matrix is equal to the determinant of its transpose.

Let A be an $n \times n$ matrix. That is, let A be a square matrix. The **determinant** of A, denoted by $\det(A)$ is a very important number which we will explore throughout this section.

If A is a 2×2 matrix, the determinant is given by the following formula.

Definition 3.1.1: Determinant of a Two By Two Matrix

Let $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$. Then

$$\det(A) = ad - cb$$

The determinant is also often denoted by enclosing the matrix with two vertical lines. Thus

$$\det \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{vmatrix} a & b \\ c & d \end{vmatrix} = ad - bc$$

The following is an example of finding the determinant of a 2×2 matrix.

Example 3.1.1: A Two by Two Determinant

Find $\det(A)$ for the matrix $A = \begin{bmatrix} 2 & 4 \\ -1 & 6 \end{bmatrix}$.

Solution

From Definition 3.1.1,

$$\det(A) = (2)(6) - (-1)(4) = 12 + 4 = 16$$

The 2×2 determinant can be used to find the determinant of larger matrices. We will now explore how to find the determinant of a 3×3 matrix, using several tools including the 2×2 determinant.

We begin with the following definition.

Definition 3.1.2: The ij^{th} Minor of a Matrix

Let A be a 3×3 matrix. The ij^{th} **minor** of A, denoted as $minor(A)_{ij}$, is the determinant of the 2×2 matrix which results from deleting the i^{th} row and the j^{th} column of A.

In general, if A is an $n \times n$ matrix, then the ij^{th} minor of A is the determinant of the $n-1 \times n-1$ matrix which results from deleting the i^{th} row and the j^{th} column of A.

Hence, there is a minor associated with each entry of A. Consider the following example which demonstrates this definition.

Example 3.1.2: Finding Minors of a Matrix

Let

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 3 & 2 \\ 3 & 2 & 1 \end{bmatrix}$$

Find $minor\,(A)_{12}$ and $minor\,(A)_{23}$.

Solution

First we will find $minor\,(A)_{12}$. By Definition 3.1.2, this is the determinant of the 2×2 matrix which results when you delete the first row and the second column. This minor is given by

$$minor\,(A)_{12} = \det \begin{bmatrix} 4 & 2 \\ 3 & 1 \end{bmatrix}$$

Using Definition 3.1.1, we see that

$$\det \begin{bmatrix} 4 & 2 \\ 3 & 1 \end{bmatrix} = (4)(1) - (3)(2) = 4 - 6 = -2$$

Therefore $minor\,(A)_{12} = -2$.

Similarly, $minor\,(A)_{23}$ is the determinant of the 2×2 matrix which results when you delete the second row and the third column. This minor is therefore

$$minor\,(A)_{23} = \det \begin{bmatrix} 1 & 2 \\ 3 & 2 \end{bmatrix} = -4$$

Finding the other minors of A is left as an exercise.

The ij^{th} minor of a matrix A is used in another important definition, given next.

Definition 3.1.3: The ij^{th} Cofactor of a Matrix

Suppose A is an $n \times n$ matrix. The ij^{th} **cofactor**, denoted by $\mathrm{cof}\,(A)_{ij}$ is defined to be

$$\mathrm{cof}\,(A)_{ij} = (-1)^{i+j}\, minor\,(A)_{ij}$$

It is also convenient to refer to the cofactor of an entry of a matrix as follows. If a_{ij} is the ij^{th} entry of the matrix, then its cofactor is just $\mathrm{cof}\,(A)_{ij}$.

Example 3.1.3: Finding Cofactors of a Matrix

Consider the matrix

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 3 & 2 \\ 3 & 2 & 1 \end{bmatrix}$$

Find $\mathrm{cof}\,(A)_{12}$ and $\mathrm{cof}\,(A)_{23}$.

Solution

We will use Definition 3.1.3 to compute these cofactors.

First, we will compute $\mathrm{cof}\,(A)_{12}$. Therefore, we need to find $minor\,(A)_{12}$. This is the determinant of the 2×2 matrix which results when you delete the first row and the second column. Thus $minor\,(A)_{12}$ is given by

$$\det \begin{bmatrix} 4 & 2 \\ 3 & 1 \end{bmatrix} = -2$$

Then,

$$\mathrm{cof}\,(A)_{12} = (-1)^{1+2}\, minor\,(A)_{12} = (-1)^{1+2}\,(-2) = 2$$

Hence, $\mathrm{cof}\,(A)_{12} = 2$.

Similarly, we can find $\mathrm{cof}\,(A)_{23}$. First, find $minor\,(A)_{23}$, which is the determinant of the 2×2 matrix which results when you delete the second row and the third column. This minor is therefore

$$\det \begin{bmatrix} 1 & 2 \\ 3 & 2 \end{bmatrix} = -4$$

Hence,

$$\mathrm{cof}\,(A)_{23} = (-1)^{2+3}\, minor\,(A)_{23} = (-1)^{2+3}\,(-4) = 4$$

You may wish to find the remaining cofactors for the above matrix. Remember that there is a cofactor for every entry in the matrix.

We have now established the tools we need to find the determinant of a 3×3 matrix.

Definition 3.1.4: The Determinant of a Three By Three Matrix

Let A be a 3×3 matrix. Then, $\det\,(A)$ is calculated by picking a row (or column) and taking the product of each entry in that row (column) with its cofactor and adding these products together.

This process when applied to the i^{th} row (column) is known as **expanding along the i^{th} row (column)** as is given by

$$\det\,(A) = a_{i1}\mathrm{cof}(A)_{i1} + a_{i2}\mathrm{cof}(A)_{i2} + a_{i3}\mathrm{cof}(A)_{i3}$$

When calculating the determinant, you can choose to expand any row or any column. Regardless of your choice, you will always get the same number which is the determinant of the matrix A. This method of evaluating a determinant by expanding along a row or a column is called **Laplace Expansion** or **Cofactor Expansion**.

Consider the following example.

Example 3.1.4: Finding the Determinant of a Three by Three Matrix

Let

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 3 & 2 \\ 3 & 2 & 1 \end{bmatrix}$$

Find $\det\,(A)$ using the method of Laplace Expansion.

Solution

First, we will calculate $\det\,(A)$ by expanding along the first column. Using Definition 3.1.4, we take the 1 in the first column and multiply it by its cofactor,

$$1\left(-1\right)^{1+1}\begin{vmatrix}3&2\\2&1\end{vmatrix}=\left(1\right)\left(1\right)\left(-1\right)=-1$$

Similarly, we take the 4 in the first column and multiply it by its cofactor, as well as with the 3 in the first column. Finally, we add these numbers together, as given in the following equation.

$$\det\left(A\right)=1\overbrace{\left(-1\right)^{1+1}\begin{vmatrix}3&2\\2&1\end{vmatrix}}^{\mathrm{cof}(A)_{11}}+4\overbrace{\left(-1\right)^{2+1}\begin{vmatrix}2&3\\2&1\end{vmatrix}}^{\mathrm{cof}(A)_{21}}+3\overbrace{\left(-1\right)^{3+1}\begin{vmatrix}2&3\\3&2\end{vmatrix}}^{\mathrm{cof}(A)_{31}}$$

Calculating each of these, we obtain

$$\det\left(A\right)=1\left(1\right)\left(-1\right)+4\left(-1\right)\left(-4\right)+3\left(1\right)\left(-5\right)=-1+16+-15=0$$

Hence, $\det\left(A\right)=0$.

As mentioned in Definition 3.1.4, we can choose to expand along any row or column. Let's try now by expanding along the second row. Here, we take the 4 in the second row and multiply it to its cofactor, then add this to the 3 in the second row multiplied by its cofactor, and the 2 in the second row multiplied by its cofactor. The calculation is as follows.

$$\det\left(A\right)=4\overbrace{\left(-1\right)^{2+1}\begin{vmatrix}2&3\\2&1\end{vmatrix}}^{\mathrm{cof}(A)_{21}}+3\overbrace{\left(-1\right)^{2+2}\begin{vmatrix}1&3\\3&1\end{vmatrix}}^{\mathrm{cof}(A)_{22}}+2\overbrace{\left(-1\right)^{2+3}\begin{vmatrix}1&2\\3&2\end{vmatrix}}^{\mathrm{cof}(A)_{23}}$$

Calculating each of these products, we obtain

$$\det\left(A\right)=4\left(-1\right)\left(-2\right)+3\left(1\right)\left(-8\right)+2\left(-1\right)\left(-4\right)=0$$

You can see that for both methods, we obtained $\det\left(A\right)=0$.

As mentioned above, we will always come up with the same value for $\det\left(A\right)$ regardless of the row or column we choose to expand along. You should try to compute the above determinant by expanding along other rows and columns. This is a good way to check your work, because you should come up with the same number each time!

We present this idea formally in the following theorem.

Theorem 3.1.1: The Determinant is Well Defined

Expanding the $n\times n$ matrix along any row or column always gives the same answer, which is the determinant.

We have now looked at the determinant of 2×2 and 3×3 matrices. It turns out that the method used to calculate the determinant of a 3×3 matrix can be used to calculate the determinant of any sized matrix. Notice that Definition 3.1.2, Definition 3.1.3 and Definition 3.1.4 can all be applied to a matrix of any size.

For example, the ij^{th} minor of a 4×4 matrix is the determinant of the 3×3 matrix you obtain when you delete the i^{th} row and the j^{th} column. Just as with the 3×3 determinant, we can compute the determinant of a 4×4 matrix by Laplace Expansion, along any row or column

Consider the following example.

Example 3.1.5: Determinant of a Four by Four Matrix

Find $\det\left(A\right)$ where

$$A=\begin{bmatrix}1&2&3&4\\5&4&2&3\\1&3&4&5\\3&4&3&2\end{bmatrix}$$

Solution

As in the case of a 3×3 matrix, you can expand this along any row or column. Lets pick the third column. Then, using Laplace Expansion,

$$\det(A) = 3(-1)^{1+3}\begin{vmatrix} 5 & 4 & 3 \\ 1 & 3 & 5 \\ 3 & 4 & 2 \end{vmatrix} + 2(-1)^{2+3}\begin{vmatrix} 1 & 2 & 4 \\ 1 & 3 & 5 \\ 3 & 4 & 2 \end{vmatrix} +$$
$$4(-1)^{3+3}\begin{vmatrix} 1 & 2 & 4 \\ 5 & 4 & 3 \\ 3 & 4 & 2 \end{vmatrix} + 3(-1)^{4+3}\begin{vmatrix} 1 & 2 & 4 \\ 5 & 4 & 3 \\ 1 & 3 & 5 \end{vmatrix}$$

Now, you can calculate each 3×3 determinant using Laplace Expansion, as we did above. You should complete these as an exercise and verify that $\det(A) = -12$.

The following provides a formal definition for the determinant of an $n \times n$ matrix. You may wish to take a moment and consider the above definitions for 2×2 and 3×3 determinants in context of this definition.

Definition 3.1.5: The Determinant of an $n \times n$ Matrix

Let A be an $n \times n$ matrix where $n \geq 2$ and suppose the determinant of an $(n-1) \times (n-1)$ has been defined. Then

$$\det(A) = \sum_{j=1}^{n} a_{ij}\text{cof}(A)_{ij} = \sum_{i=1}^{n} a_{ij}\text{cof}(A)_{ij}$$

The first formula consists of expanding the determinant along the i^{th} row and the second expands the determinant along the j^{th} column.

In the following sections, we will explore some important properties and characteristics of the determinant.

The Determinant of a Triangular Matrix

There is a certain type of matrix for which finding the determinant is a very simple procedure. Consider the following definition.

Definition 3.1.6: Triangular Matrices

A matrix A is upper triangular if $a_{ij} = 0$ whenever $i > j$. Thus the entries of such a matrix below the main diagonal equal 0, as shown. Here, $*$ refers to any nonzero number.

$$\begin{bmatrix} * & * & \cdots & * \\ 0 & * & \cdots & \vdots \\ \vdots & \vdots & \ddots & * \\ 0 & \cdots & 0 & * \end{bmatrix}$$

A lower triangular matrix is defined similarly as a matrix for which all entries above the main diagonal are equal to zero.

The following theorem provides a useful way to calculate the determinant of a triangular matrix.

Theorem 3.1.2: Determinant of a Triangular Matrix

Let A be an upper or lower triangular matrix. Then $\det(A)$ is obtained by taking the product of the entries on the main diagonal.

The verification of this Theorem can be done by computing the determinant using Laplace Expansion along the first row or column.

Consider the following example.

Example 3.1.6: Determinant of a Triangular Matrix

Let

$$A = \begin{bmatrix} 1 & 2 & 3 & 77 \\ 0 & 2 & 6 & 7 \\ 0 & 0 & 3 & 33.7 \\ 0 & 0 & 0 & -1 \end{bmatrix}$$

Find $\det(A)$.

Solution

From Theorem 3.1.2, it suffices to take the product of the elements on the main diagonal. Thus $\det(A) = 1 \times 2 \times 3 \times (-1) = -6$.

Without using Theorem 3.1.2, you could use Laplace Expansion. We will expand along the first column. This gives

$$\begin{aligned} \det(A) =& 1 \begin{vmatrix} 2 & 6 & 7 \\ 0 & 3 & 33.7 \\ 0 & 0 & -1 \end{vmatrix} + 0(-1)^{2+1} \begin{vmatrix} 2 & 3 & 77 \\ 0 & 3 & 33.7 \\ 0 & 0 & -1 \end{vmatrix} + \\ & 0(-1)^{3+1} \begin{vmatrix} 2 & 3 & 77 \\ 2 & 6 & 7 \\ 0 & 0 & -1 \end{vmatrix} + 0(-1)^{4+1} \begin{vmatrix} 2 & 3 & 77 \\ 2 & 6 & 7 \\ 0 & 3 & 33.7 \end{vmatrix} \end{aligned} \tag{3.1.1}$$

and the only nonzero term in the expansion is

$$1 \begin{vmatrix} 2 & 6 & 7 \\ 0 & 3 & 33.7 \\ 0 & 0 & -1 \end{vmatrix}$$

Now find the determinant of this 3×3 matrix, by expanding along the first column to obtain

$$\begin{aligned} \det(A) &= 1 \times \left(2 \times \begin{vmatrix} 3 & 33.7 \\ 0 & -1 \end{vmatrix} + 0(-1)^{2+1} \begin{vmatrix} 6 & 7 \\ 0 & -1 \end{vmatrix} + 0(-1)^{3+1} \begin{vmatrix} 6 & 7 \\ 3 & 33.7 \end{vmatrix} \right) \\ &= 1 \times 2 \times \begin{vmatrix} 3 & 33.7 \\ 0 & -1 \end{vmatrix} \end{aligned}$$

Next use Definition 3.1.1 to find the determinant of this 2×2 matrix, which is just $3 \times -1 - 0 \times 33.7 = -3$. Putting all these steps together, we have

$$\det(A) = 1 \times 2 \times 3 \times (-1) = -6$$

which is just the product of the entries down the main diagonal of the original matrix!

You can see that while both methods result in the same answer, Theorem 3.1.2 provides a much quicker method.

In the next section, we explore some important properties of determinants.

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3.2: Properties of Determinants

Properties of Determinants I: Examples

There are many important properties of determinants. Since many of these properties involve the row operations discussed in Chapter 1, we recall that definition now.

Definition 3.2.1: Row Operations

The row operations consist of the following

1. Switch two rows.
2. Multiply a row by a nonzero number.
3. Replace a row by a multiple of another row added to itself.

We will now consider the effect of row operations on the determinant of a matrix. In future sections, we will see that using the following properties can greatly assist in finding determinants. This section will use the theorems as motivation to provide various examples of the usefulness of the properties.

The first theorem explains the affect on the determinant of a matrix when two rows are switched.

Theorem 3.2.1: Switching Rows

Let A be an $n \times n$ matrix and let B be a matrix which results from switching two rows of A. Then $\det(B) = -\det(A)$.

When we switch two rows of a matrix, the determinant is multiplied by -1. Consider the following example.

Example 3.2.1: Switching Two Rows

Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ and let $B = \begin{bmatrix} 3 & 4 \\ 1 & 2 \end{bmatrix}$. Knowing that $\det(A) = -2$, find $\det(B)$.

Solution

By Definition 3.1.1, $\det(A) = 1 \times 4 - 3 \times 2 = -2$. Notice that the rows of B are the rows of A but switched. By Theorem 3.2.1 since two rows of A have been switched, $\det(B) = -\det(A) = -(-2) = 2$. You can verify this using Definition 3.1.1.

The next theorem demonstrates the effect on the determinant of a matrix when we multiply a row by a scalar.

Theorem 3.2.2: Multiplying a Row by a Scalar

Let A be an $n \times n$ matrix and let B be a matrix which results from multiplying some row of A by a scalar k. Then $\det(B) = k\det(A)$.

Notice that this theorem is true when we multiply *one* row of the matrix by k. If we were to multiply *two* rows of A by k to obtain B, we would have $\det(B) = k^2 \det(A)$. Suppose we were to multiply all n rows of A by k to obtain the matrix B, so that $B = kA$. Then, $\det(B) = k^n \det(A)$. This gives the next theorem.

Theorem 3.2.3: Scalar Multiplication

Let A and B be $n \times n$ matrices and k a scalar, such that $B = kA$. Then $\det(B) = k^n \det(A)$.

Consider the following example.

Example 3.2.2: Multiplying a Row by 5

Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$, $B = \begin{bmatrix} 5 & 10 \\ 3 & 4 \end{bmatrix}$. Knowing that $\det(A) = -2$, find $\det(B)$.

Solution

By Definition 3.1.1, $\det(A) = -2$. We can also compute $\det(B)$ using Definition 3.1.1, and we see that $\det(B) = -10$.

Now, let's compute $\det(B)$ using Theorem 3.2.2 and see if we obtain the same answer. Notice that the first row of B is 5 times the first row of A, while the second row of B is equal to the second row of A. By Theorem 3.2.2, $\det(B) = 5 \times \det(A) = 5 \times -2 = -10$.

You can see that this matches our answer above.

Finally, consider the next theorem for the last row operation, that of adding a multiple of a row to another row.

Theorem 3.2.4: Adding a Multiple of a Row to Another Row

Let A be an $n \times n$ matrix and let B be a matrix which results from adding a multiple of a row to another row. Then $\det(A) = \det(B)$.

Therefore, when we add a multiple of a row to another row, the determinant of the matrix is unchanged. Note that if a matrix A contains a row which is a multiple of another row, $\det(A)$ will equal 0. To see this, suppose the first row of A is equal to -1 times the second row. By Theorem 3.2.4, we can add the first row to the second row, and the determinant will be unchanged. However, this row operation will result in a row of zeros. Using Laplace Expansion along the row of zeros, we find that the determinant is 0.

Consider the following example.

Example 3.2.3: Adding a Row to Another Row

Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ and let $B = \begin{bmatrix} 1 & 2 \\ 5 & 8 \end{bmatrix}$. Find $\det(B)$.

Solution

By Definition 3.1.1, $\det(A) = -2$. Notice that the second row of B is two times the first row of A added to the second row. By Theorem 3.2.1, $\det(B) = \det(A) = -2$. As usual, you can verify this answer using Definition 3.1.1.

Example 3.2.4: Multiple of a Row

Let $A = \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$. Show that $\det(A) = 0$.

Solution

Using Definition 3.1.1, the determinant is given by

$$\det(A) = 1 \times 4 - 2 \times 2 = 0$$

However notice that the second row is equal to 2 times the first row. Then by the discussion above following Theorem 3.2.4 the determinant will equal 0.

Until now, our focus has primarily been on row operations. However, we can carry out the same operations with columns, rather than rows. The three operations outlined in Definition 3.2.1 can be done with columns instead of rows. In this case, in Theorems 3.2.1, 3.2.2, and 3.2.4 you can replace the word, "row" with the word "column".

There are several other major properties of determinants which do not involve row (or column) operations. The first is the determinant of a product of matrices.

Theorem 3.2.5: Determinant of a Product

Let A and B be two $n \times n$ matrices. Then

$$\det(AB) = \det(A)\det(B)$$

In order to find the determinant of a product of matrices, we can simply take the product of the determinants.

Consider the following example.

Example 3.2.5: The Determinant of a Product

Compare $\det(AB)$ and $\det(A)\det(B)$ for

$$A = \begin{bmatrix} 1 & 2 \\ -3 & 2 \end{bmatrix}, B = \begin{bmatrix} 3 & 2 \\ 4 & 1 \end{bmatrix}$$

Solution

First compute AB, which is given by

$$AB = \begin{bmatrix} 1 & 2 \\ -3 & 2 \end{bmatrix} \begin{bmatrix} 3 & 2 \\ 4 & 1 \end{bmatrix} = \begin{bmatrix} 11 & 4 \\ -1 & -4 \end{bmatrix}$$

and so by Definition 3.1.1

$$\det(AB) = \det \begin{bmatrix} 11 & 4 \\ -1 & -4 \end{bmatrix} = -40$$

Now

$$\det(A) = \det \begin{bmatrix} 1 & 2 \\ -3 & 2 \end{bmatrix} = 8$$

and

$$\det(B) = \det \begin{bmatrix} 3 & 2 \\ 4 & 1 \end{bmatrix} = -5$$

Computing $\det(A) \times \det(B)$ we have $8 \times -5 = -40$. This is the same answer as above and you can see that $\det(A)\det(B) = 8 \times (-5) = -40 = \det(AB)$.

Consider the next important property.

Theorem 3.2.6: Determinant of the Transpose

Let A be a matrix where A^T is the transpose of A. Then,

$$\det\left(A^T\right) = \det\left(A\right)$$

This theorem is illustrated in the following example.

Example 3.2.6: Determinant of the Transpose

Let

$$A = \begin{bmatrix} 2 & 5 \\ 4 & 3 \end{bmatrix}$$

Find $\det\left(A^T\right)$.

Solution

First, note that

$$A^T = \begin{bmatrix} 2 & 4 \\ 5 & 3 \end{bmatrix}$$

Using Definition 3.1.1, we can compute $\det\left(A\right)$ and $\det\left(A^T\right)$. It follows that $\det\left(A\right) = 2 \times 3 - 4 \times 5 = -14$ and $\det\left(A^T\right) = 2 \times 3 - 5 \times 4 = -14$. Hence, $\det\left(A\right) = \det\left(A^T\right)$.

The following provides an essential property of the determinant, as well as a useful way to determine if a matrix is invertible.

Theorem 3.2.7: Determinant of the Inverse

Let A be an $n \times n$ matrix. Then A is invertible if and only if $\det(A) \neq 0$. If this is true, it follows that

$$\det(A^{-1}) = \frac{1}{\det(A)}$$

Consider the following example.

Example 3.2.7: Determinant of an Invertible Matrix

Let $A = \begin{bmatrix} 3 & 6 \\ 2 & 4 \end{bmatrix}, B = \begin{bmatrix} 2 & 3 \\ 5 & 1 \end{bmatrix}$. For each matrix, determine if it is invertible. If so, find the determinant of the inverse.

Solution

Consider the matrix A first. Using Definition 3.1.1 we can find the determinant as follows:

$$\det\left(A\right) = 3 \times 4 - 2 \times 6 = 12 - 12 = 0$$

By Theorem 3.2.7 A is not invertible.

Now consider the matrix B. Again by Definition 3.1.1 we have

$$\det\left(B\right) = 2 \times 1 - 5 \times 3 = 2 - 15 = -13$$

By Theorem 3.2.7 B is invertible and the determinant of the inverse is given by

$$\begin{aligned}\det\left(A^{-1}\right) &= \frac{1}{\det(A)} \\ &= \frac{1}{-13} \\ &= -\frac{1}{13}\end{aligned} \tag{3.2.1}$$

Properties of Determinants II: Some Important Proofs

This section includes some important proofs on determinants and cofactors.

First we recall the definition of a determinant. If $A = [a_{ij}]$ is an $n \times n$ matrix, then $\det A$ is defined by computing the expansion along the first row:

$$\det A = \sum_{i=1}^{n} a_{1,i}\text{cof}(A)_{1,i}. \tag{3.2.2}$$

If $n = 1$ then $\det A = a_{1,1}$.

The following example is straightforward and strongly recommended as a means for getting used to definitions.

Example 3.2.8:

(1) Let E_{ij} be the elementary matrix obtained by interchanging ith and jth rows of I. Then $\det E_{ij} = -1$.

(2) Let E_{ik} be the elementary matrix obtained by multiplying the ith row of I by k. Then $\det E_{ik} = k$.

(3) Let E_{ijk} be the elementary matrix obtained by multiplying ith row of I by k and adding it to its jth row. Then $\det E_{ijk} = 1$.

(4) If C and B are such that CB is defined and the ith row of C consists of zeros, then the ith row of CB consists of zeros.

(5) If E is an elementary matrix, then $\det E = \det E^T$.

Many of the proofs in section use the Principle of Mathematical Induction. This concept is discussed in Appendix A.2 and is reviewed here for convenience. First we check that the assertion is true for $n = 2$ (the case $n = 1$ is either completely trivial or meaningless).

Next, we assume that the assertion is true for $n - 1$ (where $n \geq 3$) and prove it for n. Once this is accomplished, by the Principle of Mathematical Induction we can conclude that the statement is true for all $n \times n$ matrices for every $n \geq 2$.

If A is an $n \times n$ matrix and $1 \leq j \leq n$, then the matrix obtained by removing 1st column and jth row from A is an $n - 1 \times n - 1$ matrix (we shall denote this matrix by $A(j)$ below). Since these matrices are used in computation of cofactors $\text{cof}(A)_{1,i}$, for $1 \leq i \neq n$, the inductive assumption applies to these matrices.

Consider the following lemma.

Lemma 3.2.1:

If A is an $n \times n$ matrix such that one of its rows consists of zeros, then $\det A = 0$.

Proof available at the end of this section.

Lemma 3.2.2:

Assume A, B and C are $n \times n$ matrices that for some $1 \leq i \leq n$ satisfy the following.

1. jth rows of all three matrices are identical, for $j \neq i$.
2. Each entry in the jth row of A is the sum of the corresponding entries in jth rows of B and C.

Then $\det A = \det B + \det C$.

Proof available at the end of this section.

Theorem 3.2.8:

Let A and B be $n \times n$ matrices.

1. If A is obtained by interchanging ith and jth rows of B (with $i \neq j$), then $\det A = -\det B$.
2. If A is obtained by multiplying ith row of B by k then $\det A = k \det B$.
3. If two rows of A are identical then $\det A = 0$.
4. If A is obtained by multiplying ith row of B by k and adding it to jth row of B ($i \neq j$) then $\det A = \det B$.

Proof available at the end of this section.

Theorem 3.2.9:

Let A and B be two $n \times n$ matrices. Then

$$\det(AB) = \det(A) \det(B)$$

Proof available at the end of this section.

The same 'machine' used in the previous proof will be used again.

Theorem 3.2.10:

Let A be a matrix where A^T is the transpose of A. Then,

$$\det\left(A^T\right) = \det(A)$$

Proof available at the end of this section.

The above discussions allow us to now prove Theorem 3.1.1. It is restated below.

Theorem 3.2.11:

Expanding an $n \times n$ matrix along any row or column always gives the same result, which is the determinant.

Proof available at the end of this section.

Answers

Lemma 3.2.1:

We will prove this lemma using Mathematical Induction.

If $n = 2$ this is easy (check!).

Let $n \geq 3$ be such that every matrix of size $n-1 \times n-1$ with a row consisting of zeros has determinant equal to zero. Let i be such that the ith row of A consists of zeros. Then we have $a_{ij} = 0$ for $1 \leq j \leq n$.

Fix $j \in \{1, 2, \dots, n\}$ such that $j \neq i$. Then matrix $A(j)$ used in computation of $\operatorname{cof}(A)_{1,j}$ has a row consisting of zeros, and by our inductive assumption $\operatorname{cof}(A)_{1,j} = 0$.

On the other hand, if $j = i$ then $a_{1,j} = 0$. Therefore $a_{1,j}\operatorname{cof}(A)_{1,j} = 0$ for all j and by (3.2.2) we have

$$\det A = \sum_{j=1}^{n} a_{1,j}\operatorname{cof}(A)_{1,j} = 0$$

as each of the summands is equal to 0.

Lemma 3.2.2**:**

This is not difficult to check for $n = 2$ (do check it!).

Now assume that the statement of Lemma is true for $n-1 \times n-1$ matrices and fix A, B and C as in the statement. The assumptions state that we have $a_{l,j} = b_{l,j} = c_{l,j}$ for $j \neq i$ and for $1 \leq l \leq n$ and $a_{l,i} = b_{l,i} + c_{l,i}$ for all $1 \leq l \leq n$. Therefore $A(i) = B(i) = C(i)$, and $A(j)$ has the property that its ith row is the sum of ith rows of $B(j)$ and $C(j)$ for $j \neq i$ while the other rows of all three matrices are identical. Therefore by our inductive assumption we have $\operatorname{cof}(A)_{1j} = \operatorname{cof}(B)_{1j} + \operatorname{cof}(C)_{1j}$ for $j \neq i$.

By (3.2.2) we have (using all equalities established above)

$$\begin{aligned} \det A &= \sum_{l=1}^{n} a_{1,l}\operatorname{cof}(A)_{1,l} \\ &= \sum_{l \neq i} a_{1,l}(\operatorname{cof}(B)_{1,l} + \operatorname{cof}(C)_{1,l}) + (b_{1,i} + c_{1,i})\operatorname{cof}(A)_{1,i} \\ &= \det B + \det C \end{aligned} \tag{3.2.3}$$

This proves that the assertion is true for all n and completes the proof.

Theorem 3.2.8**:**

We prove all statements by induction. The case $n = 2$ is easily checked directly (and it is strongly suggested that you do check it).

We assume $n \geq 3$ and (1)–(4) are true for all matrices of size $n-1 \times n-1$.

(1) We prove the case when $j = i + 1$, i.e., we are interchanging two consecutive rows.

Let $l \in \{1, \dots, n\} \setminus \{i, j\}$. Then $A(l)$ is obtained from $B(l)$ by interchanging two of its rows (draw a picture) and by our assumption

$$\operatorname{cof}(A)_{1,l} = -\operatorname{cof}(B)_{1,l}. \tag{3.2.4}$$

Now consider $a_{1,i}\operatorname{cof}(A)_{1,l}$. We have that $a_{1,i} = b_{1,j}$ and also that $A(i) = B(j)$. Since $j = i + 1$, we have

$$(-1)^{1+j} = (-1)^{1+i+1} = -(-1)^{1+i}$$

and therefore $a_{1i}\operatorname{cof}(A)_{1i} = -b_{1j}\operatorname{cof}(B)_{1j}$ and $a_{1j}\operatorname{cof}(A)_{1j} = -b_{1i}\operatorname{cof}(B)_{1i}$. Putting this together with (3.2.4) into (3.2.2) we see that if in the formula for $\det A$ we change the sign of each of the summands we obtain the formula for $\det B$.

$$\det A = \sum_{l=1}^{n} a_{1l}\operatorname{cof}(A)_{1l} = -\sum_{l=1}^{n} b_{1l}B_{1l} = \det B.$$

We have therefore proved the case of (1) when $j = i + 1$. In order to prove the general case, one needs the following fact. If $i < j$, then in order to interchange i th and jth row one can proceed by interchanging two adjacent rows $2(j-i)+1$ times: First swap ith and $i+1$st, then $i+1$st and $i+2$nd, and so on. After one interchanges $j-1$st and jth row, we have ith row in position of jth and lth row in position of $l-1$st for $i+1 \leq l \leq j$. Then proceed backwards swapping adjacent rows until everything is in place.

Since $2(j-i)+1$ is an odd number $(-1)^{2(j-i)+1} = -1$ and we have that $\det A = -\det B$.

(2) This is like (1)... but much easier. Assume that (2) is true for all $n-1 \times n-1$ matrices. We have that $a_{ji} = kb_{ji}$ for $1 \leq j \leq n$. In particular $a_{1i} = kb_{1i}$, and for $l \neq i$ matrix $A(l)$ is obtained from $B(l)$ by multiplying one of its rows by k. Therefore $\operatorname{cof}(A)_{1l} = k\operatorname{cof}(B)_{1l}$ for $l \neq i$, and for all l we have $a_{1l}\operatorname{cof}(A)_{1l} = kb_{1l}\operatorname{cof}(B)_{1l}$. By (3.2.2), we have $\det A = k \det B$.

(3) This is a consequence of (1). If two rows of A are identical, then A is equal to the matrix obtained by interchanging those two rows and therefore by (1) $\det A = -\det A$. This implies $\det A = 0$.

(4) Assume (4) is true for all $n-1 \times n-1$ matrices and fix A and B such that A is obtained by multiplying ith row of B by k and adding it to jth row of B ($i \neq j$) then $\det A = \det B$. If $k = 0$ then $A = B$ and there is nothing to prove, so we may assume $k \neq 0$.

Let C be the matrix obtained by replacing the jth row of B by the ith row of B multiplied by k. By Lemma 3.2.2, we have that

$$\det A = \det B + \det C$$

and we 'only' need to show that $\det C = 0$. But ith and jth rows of C are proportional. If D is obtained by multiplying the jth row of C by $\frac{1}{k}$ then by (2) we have $\det C = \frac{1}{k}\det D$ (recall that $k \neq 0$!). But ith and jth rows of D are identical, hence by (3) we have $\det D = 0$ and therefore $\det C = 0$.

Theorem 3.2.9**:**

If A is an elementary matrix of either type, then multiplying by A on the left has the same effect as performing the corresponding elementary row operation. Therefore the equality $\det(AB) = \det A \det B$ in this case follows by Example 3.2.8 and Theorem 3.2.8.

If C is the reduced row-echelon form of A then we can write $A = E_1 \cdot E_2 \cdot \cdots \cdot E_m \cdot C$ for some elementary matrices $E_1, \dots, E_m$.

Now we consider two cases.

Assume first that $C = I$. Then $A = E_1 \cdot E_2 \cdot \cdots \cdot E_m$ and $AB = E_1 \cdot E_2 \cdot \cdots \cdot E_m B$. By applying the above equality m times, and then $m-1$ times, we have that

$$\begin{aligned} \det AB &= \det E_1 \det E_2 \cdot \det E_m \cdot \det B \\ &= \det(E_1 \cdot E_2 \cdot \cdots \cdot E_m) \det B \\ &= \det A \det B. \end{aligned} \tag{3.2.5}$$

Now assume $C \neq I$. Since it is in reduced row-echelon form, its last row consists of zeros and by (4) of Example 3.2.8 the last row of CB consists of zeros. By Lemma 3.2.1 we have $\det C = \det(CB) = 0$ and therefore

$$\det A = \det(E_1 \cdot E_2 \cdot E_m) \cdot \det(C) = \det(E_1 \cdot E_2 \cdot E_m) \cdot 0 = 0$$

and also

$$\det AB = \det(E_1 \cdot E_2 \cdot E_m) \cdot \det(CB) = \det(E_1 \cdot E_2 \cdot \cdots \cdot E_m)0 = 0$$

hence $\det AB = 0 = \det A \det B$.

Theorem 3.2.10**:**

Note first that the conclusion is true if A is elementary by (5) of Example 3.2.8.

Let C be the reduced row-echelon form of A. Then we can write $A = E_1 \cdot E_2 \cdot \cdots \cdot E_m C$. Then $A^T = C^T \cdot E_m^T \cdot \cdots \cdot E_2^T \cdot E_1$. By Theorem 3.2.9 we have

$$\det(A^T) = \det(C^T) \cdot \det(E_m^T) \cdot \cdots \cdot \det(E_2^T) \cdot \det(E_1).$$

By (5) of Example 3.2.8 we have that $\det E_j = \det E_j^T$ for all j. Also, $\det C$ is either 0 or 1 (depending on whether $C = I$ or not) and in either case $\det C = \det C^T$. Therefore $\det A = \det A^T$.

Theorem 3.2.11**:**

We first show that the determinant can be computed along any row. The case $n = 1$ does not apply and thus let $n \geq 2$.

Let Abe an $n \times n$ matrix and fix $j > 1$. We need to prove that

$$\det A = \sum_{i=1}^{n} a_{j,i} \text{cof}(A)_{j,i}.$$

Let us prove the case when $j = 2$.

Let B be the matrix obtained from A by interchanging its 1st and 2nd rows. Then by Theorem 3.2.8 we have

$$\det A = -\det B.$$

Now we have

$$\det B = \sum_{i=1}^{n} b_{1,i} \text{cof}(B)_{1,i}.$$

Since B is obtained by interchanging the 1st and 2nd rows of A we have that $b_{1,i} = a_{2,i}$ for all i and one can see that $minor(B)_{1,i} = minor(A)_{2,i}$.

Further,

$$\text{cof}(B)_{1,i} = (-1)^{1+i} minor B_{1,i} = -(-1)^{2+i} minor(A)_{2,i} = -\text{cof}(A)_{2,i}$$

hence $\det B = -\sum_{i=1}^{n} a_{2,i} \text{cof}(A)_{2,i}$, and therefore $\det A = -\det B = \sum_{i=1}^{n} a_{2,i} \text{cof}(A)_{2,i}$ as desired.

The case when $j > 2$ is very similar; we still have $minor(B)_{1,i} = minor(A)_{j,i}$ but checking that $\det B = -\sum_{i=1}^{n} a_{j,i} \text{cof}(A)_{j,i}$ is slightly more involved.

Now the cofactor expansion along column j of A is equal to the cofactor expansion along row j of A^T, which is by the above result just proved equal to the cofactor expansion along row 1 of A^T, which is equal to the cofactor expansion along column 1 of A. Thus the cofactor cofactor along any column yields the same result.

Finally, since $\det A = \det A^T$ by Theorem 3.2.10, we conclude that the cofactor expansion along row 1 of A is equal to the cofactor expansion along row 1 of A^T, which is equal to the cofactor expansion along column 1 of A. Thus the proof is complete.

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3.3: Finding Determinants using Row Operations

Theorems 3.2.1, 3.2.2 and 3.2.4 illustrate how row operations affect the determinant of a matrix. In this section, we look at two examples where row operations are used to find the determinant of a large matrix. Recall that when working with large matrices, Laplace Expansion is effective but timely, as there are many steps involved. This section provides useful tools for an alternative method. By first applying row operations, we can obtain a simpler matrix to which we apply Laplace Expansion.

While working through questions such as these, it is useful to record your row operations as you go along. Keep this in mind as you read through the next example.

Example 3.3.1: Finding a Determinant

Find the determinant of the matrix

$$A = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 5 & 1 & 2 & 3 \\ 4 & 5 & 4 & 3 \\ 2 & 2 & -4 & 5 \end{bmatrix}$$

Solution

We will use the properties of determinants outlined above to find $\det(A)$. First, add -5 times the first row to the second row. Then add -4 times the first row to the third row, and -2 times the first row to the fourth row. This yields the matrix

$$B = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 0 & -9 & -13 & -17 \\ 0 & -3 & -8 & -13 \\ 0 & -2 & -10 & -3 \end{bmatrix}$$

Notice that the only row operation we have done so far is adding a multiple of a row to another row. Therefore, by Theorem 3.2.4, $\det(B) = \det(A)$.

At this stage, you could use Laplace Expansion to find $\det(B)$. However, we will continue with row operations to find an even simpler matrix to work with.

Add -3 times the third row to the second row. By Theorem 3.2.4 this does not change the value of the determinant. Then, multiply the fourth row by -3. This results in the matrix

$$C = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 0 & 0 & 11 & 22 \\ 0 & -3 & -8 & -13 \\ 0 & 6 & 30 & 9 \end{bmatrix}$$

Here, $\det(C) = -3\det(B)$, which means that $\det(B) = \left(-\frac{1}{3}\right)\det(C)$

Since $\det(A) = \det(B)$, we now have that $\det(A) = \left(-\frac{1}{3}\right)\det(C)$. Again, you could use Laplace Expansion here to find $\det(C)$. However, we will continue with row operations.

Now replace the add 2 times the third row to the fourth row. This does not change the value of the determinant by Theorem 3.2.4. Finally switch the third and second rows. This causes the determinant to be multiplied by -1. Thus $\det(C) = -\det(D)$ where

$$D = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 0 & -3 & -8 & -13 \\ 0 & 0 & 11 & 22 \\ 0 & 0 & 14 & -17 \end{bmatrix}$$

Hence, $\det(A) = \left(-\frac{1}{3}\right)\det(C) = \left(\frac{1}{3}\right)\det(D)$

You could do more row operations or you could note that this can be easily expanded along the first column. Then, expand the resulting 3×3 matrix also along the first column. This results in

$$\det(D) = 1(-3)\begin{vmatrix} 11 & 22 \\ 14 & -17 \end{vmatrix} = 1485$$

and so $\det(A) = \left(\frac{1}{3}\right)(1485) = 495$.

You can see that by using row operations, we can simplify a matrix to the point where Laplace Expansion involves only a few steps. In Example 3.3.1, we also could have continued until the matrix was in upper triangular form, and taken the product of the entries on the main diagonal. Whenever computing the determinant, it is useful to consider all the possible methods and tools.

Consider the next example.

Example 3.3.2: Find the Determinant

Find the determinant of the matrix

$$A = \begin{bmatrix} 1 & 2 & 3 & 2 \\ 1 & -3 & 2 & 1 \\ 2 & 1 & 2 & 5 \\ 3 & -4 & 1 & 2 \end{bmatrix}$$

Solution

Once again, we will simplify the matrix through row operations. Add -1 times the first row to the second row. Next add -2 times the first row to the third and finally take -3 times the first row and add to the fourth row. This yields

$$B = \begin{bmatrix} 1 & 2 & 3 & 2 \\ 0 & -5 & -1 & -1 \\ 0 & -3 & -4 & 1 \\ 0 & -10 & -8 & -4 \end{bmatrix}$$

By Theorem 3.2.4, $\det(A) = \det(B)$.

Remember you can work with the columns also. Take -5 times the fourth column and add to the second column. This yields

$$C = \begin{bmatrix} 1 & -8 & 3 & 2 \\ 0 & 0 & -1 & -1 \\ 0 & -8 & -4 & 1 \\ 0 & 10 & -8 & -4 \end{bmatrix}$$

By Theorem 3.2.4 $\det(A) = \det(C)$.

Now take -1 times the third row and add to the top row. This gives.

$$D = \begin{bmatrix} 1 & 0 & 7 & 1 \\ 0 & 0 & -1 & -1 \\ 0 & -8 & -4 & 1 \\ 0 & 10 & -8 & -4 \end{bmatrix}$$

which by Theorem 3.2.4 has the same determinant as A.

Now, we can find $\det(D)$ by expanding along the first column as follows. You can see that there will be only one non zero term.

$$\det(D) = 1\det\begin{bmatrix} 0 & -1 & -1 \\ -8 & -4 & 1 \\ 10 & -8 & -4 \end{bmatrix} + 0 + 0 + 0$$

Expanding again along the first column, we have

$$\det(D) = 1\left(0 + 8\det\begin{bmatrix} -1 & -1 \\ -8 & -4 \end{bmatrix} + 10\det\begin{bmatrix} -1 & -1 \\ -4 & 1 \end{bmatrix}\right) = -82$$

Now since $\det(A) = \det(D)$, it follows that $\det(A) = -82$.

Remember that you can verify these answers by using Laplace Expansion on A. Similarly, if you first compute the determinant using Laplace Expansion, you can use the row operation method to verify.

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3.4: APPLICATIONS OF THE DETERMINANT

Outcomes

A. Use determinants to determine whether a matrix has an inverse, and evaluate the inverse using cofactors.
B. Apply Cramer's Rule to solve a 2×2 or a 3×3 linear system.
C. Given data points, find an appropriate interpolating polynomial and use it to estimate points.

A Formula for the Inverse

The determinant of a matrix also provides a way to find the inverse of a matrix. Recall the definition of the inverse of a matrix in Definition 2.6.1. We say that A^{-1}, an $n \times n$ matrix, is the inverse of A, also $n \times n$, if $AA^{-1} = I$ and $A^{-1}A = I$.

We now define a new matrix called the **cofactor matrix** of A. The cofactor matrix of A is the matrix whose ij^{th} entry is the ij^{th} cofactor of A. The formal definition is as follows.

Definition 3.4.1: The Cofactor Matrix

Let $A = [a_{ij}]$ be an $n \times n$ matrix. Then the **cofactor matrix of** A, denoted $\mathrm{cof}(A)$, is defined by $\mathrm{cof}(A) = \left[\mathrm{cof}(A)_{ij}\right]$ where $\mathrm{cof}(A)_{ij}$ is the ij^{th} cofactor of A.

Note that $\mathrm{cof}(A)_{ij}$ denotes the ij^{th} entry of the cofactor matrix.

We will use the cofactor matrix to create a formula for the inverse of A. First, we define the **adjugate** of A to be the transpose of the cofactor matrix. We can also call this matrix the **classical adjoint** of A, and we denote it by $adj(A)$.

In the specific case where A is a 2×2 matrix given by

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

then $adj(A)$ is given by

$$adj(A) = \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

In general, $adj(A)$ can always be found by taking the transpose of the cofactor matrix of A. The following theorem provides a formula for A^{-1} using the determinant and adjugate of A.

Theorem 3.4.1: The Inverse and the Determinant

Let A be an $n \times n$ matrix. Then

$$A\, adj(A) = adj(A)\, A = \det(A) I$$

Moreover A is invertible if and only if $\det(A) \neq 0$. In this case we have:

$$A^{-1} = \frac{1}{\det(A)} adj(A)$$

Notice that the first formula holds for any $n \times n$ matrix A, and in the case A is invertible we actually have a formula for A^{-1}.

Consider the following example.

Example 3.4.1: Find Inverse Using the Determinant

Find the inverse of the matrix

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 3 & 0 & 1 \\ 1 & 2 & 1 \end{bmatrix}$$

using the formula in Theorem 3.4.1.

Solution

According to Theorem 3.4.1,

$$A^{-1} = \frac{1}{\det(A)} adj(A)$$

First we will find the determinant of this matrix. Using Theorems 3.2.1, 3.2.2, and 3.2.4, we can first simplify the matrix through row operations. First, add -3 times the first row to the second row. Then add -1 times the first row to the third row to obtain

$$B = \begin{bmatrix} 1 & 2 & 3 \\ 0 & -6 & -8 \\ 0 & 0 & -2 \end{bmatrix}$$

By Theorem 3.2.4, $\det(A) = \det(B)$. By Theorem 3.1.2, $\det(B) = 1 \times -6 \times -2 = 12$. Hence, $\det(A) = 12$.

Now, we need to find $adj(A)$. To do so, first we will find the cofactor matrix of A. This is given by

$$\operatorname{cof}(A) = \begin{bmatrix} -2 & -2 & 6 \\ 4 & -2 & 0 \\ 2 & 8 & -6 \end{bmatrix}$$

Here, the ij^{th} entry is the ij^{th} cofactor of the original matrix A which you can verify. Therefore, from Theorem 3.4.1, the inverse of A is given by

$$A^{-1} = \frac{1}{12} \begin{bmatrix} -2 & -2 & 6 \\ 4 & -2 & 0 \\ 2 & 8 & -6 \end{bmatrix}^T = \begin{bmatrix} -\frac{1}{6} & \frac{1}{3} & \frac{1}{6} \\ -\frac{1}{6} & -\frac{1}{6} & \frac{2}{3} \\ \frac{1}{2} & 0 & -\frac{1}{2} \end{bmatrix}$$

Remember that we can always verify our answer for A^{-1}. Compute the product AA^{-1} and $A^{-1}A$ and make sure each product is equal to I.

Compute $A^{-1}A$ as follows

$$A^{-1}A = \begin{bmatrix} -\frac{1}{6} & \frac{1}{3} & \frac{1}{6} \\ -\frac{1}{6} & -\frac{1}{6} & \frac{2}{3} \\ \frac{1}{2} & 0 & -\frac{1}{2} \end{bmatrix} \begin{bmatrix} 1 & 2 & 3 \\ 3 & 0 & 1 \\ 1 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = I$$

You can verify that $AA^{-1} = I$ and hence our answer is correct.

We will look at another example of how to use this formula to find A^{-1}.

Example 3.4.2: Find the Inverse From a Formula

Find the inverse of the matrix

$$A = \begin{bmatrix} \frac{1}{2} & 0 & \frac{1}{2} \\ -\frac{1}{6} & \frac{1}{3} & -\frac{1}{2} \\ -\frac{5}{6} & \frac{2}{3} & -\frac{1}{2} \end{bmatrix}$$

using the formula given in Theorem 3.4.1.

Solution

First we need to find $\det(A)$. This step is left as an exercise and you should verify that $\det(A) = \frac{1}{6}$. The inverse is therefore equal to

$$A^{-1} = \frac{1}{(1/6)}\, adj(A) = 6\, adj(A)$$

We continue to calculate as follows. Here we show the 2×2 determinants needed to find the cofactors.

$$A^{-1} = 6 \begin{bmatrix} \begin{vmatrix} \frac{1}{3} & -\frac{1}{2} \\ \frac{2}{3} & -\frac{1}{2} \end{vmatrix} & -\begin{vmatrix} -\frac{1}{6} & -\frac{1}{2} \\ -\frac{5}{6} & -\frac{1}{2} \end{vmatrix} & \begin{vmatrix} -\frac{1}{6} & \frac{1}{3} \\ -\frac{5}{6} & \frac{2}{3} \end{vmatrix} \\ -\begin{vmatrix} 0 & \frac{1}{2} \\ \frac{2}{3} & -\frac{1}{2} \end{vmatrix} & \begin{vmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{5}{6} & -\frac{1}{2} \end{vmatrix} & -\begin{vmatrix} \frac{1}{2} & 0 \\ -\frac{5}{6} & \frac{2}{3} \end{vmatrix} \\ \begin{vmatrix} 0 & \frac{1}{2} \\ \frac{1}{3} & -\frac{1}{2} \end{vmatrix} & -\begin{vmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{1}{6} & -\frac{1}{2} \end{vmatrix} & \begin{vmatrix} \frac{1}{2} & 0 \\ -\frac{1}{6} & \frac{1}{3} \end{vmatrix} \end{bmatrix}^T$$

Expanding all the 2×2 determinants, this yields

$$A^{-1} = 6 \begin{bmatrix} \frac{1}{6} & \frac{1}{3} & \frac{1}{6} \\ \frac{1}{3} & \frac{1}{6} & -\frac{1}{3} \\ -\frac{1}{6} & \frac{1}{6} & \frac{1}{6} \end{bmatrix}^T = \begin{bmatrix} 1 & 2 & -1 \\ 2 & 1 & 1 \\ 1 & -2 & 1 \end{bmatrix}$$

Again, you can always check your work by multiplying $A^{-1}A$ and AA^{-1} and ensuring these products equal I.

$$A^{-1}A = \begin{bmatrix} 1 & 2 & -1 \\ 2 & 1 & 1 \\ 1 & -2 & 1 \end{bmatrix} \begin{bmatrix} \frac{1}{2} & 0 & \frac{1}{2} \\ -\frac{1}{6} & \frac{1}{3} & -\frac{1}{2} \\ -\frac{5}{6} & \frac{2}{3} & -\frac{1}{2} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

This tells us that our calculation for A^{-1} is correct. It is left to the reader to verify that $AA^{-1} = I$.

The verification step is very important, as it is a simple way to check your work! If you multiply $A^{-1}A$ and AA^{-1} and these products are not both equal to I, be sure to go back and double check each step. One common error is to forget to take the transpose of the cofactor matrix, so be sure to complete this step.

We will now prove Theorem 3.4.1.

Theorem 3.4.1: The Inverse and the Determinant

Proof available at the end of this section.

This method for finding the inverse of A is useful in many contexts. In particular, it is useful with complicated matrices where the entries are functions, rather than numbers.

Consider the following example.

Example 3.4.3: Inverse for Non-Constant Matrix

Suppose

$$A(t) = \begin{bmatrix} e^t & 0 & 0 \\ 0 & \cos t & \sin t \\ 0 & -\sin t & \cos t \end{bmatrix}$$

Show that $A(t)^{-1}$ exists and then find it.

Solution

First note $\det(A(t)) = e^t(\cos^2 t + \sin^2 t) = e^t \neq 0$ so $A(t)^{-1}$ exists.

The cofactor matrix is

$$C(t) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^t \cos t & e^t \sin t \\ 0 & -e^t \sin t & e^t \cos t \end{bmatrix}$$

and so the inverse is

$$\frac{1}{e^t}\begin{bmatrix} 1 & 0 & 0 \\ 0 & e^t \cos t & e^t \sin t \\ 0 & -e^t \sin t & e^t \cos t \end{bmatrix}^T = \begin{bmatrix} e^{-t} & 0 & 0 \\ 0 & \cos t & -\sin t \\ 0 & \sin t & \cos t \end{bmatrix}$$

Cramer's Rule

Another context in which the formula given in Theorem 3.4.1 is important is **Cramer's Rule**. Recall that we can represent a system of linear equations in the form $AX = B$, where the solutions to this system are given by X. Cramer's Rule gives a formula for the solutions X in the special case that A is a square invertible matrix. Note this rule does not apply if you have a system of equations in which there is a different number of equations than variables (in other words, when A is not square), or when A is not invertible.

Suppose we have a system of equations given by $AX = B$, and we want to find solutions X which satisfy this system. Then recall that if A^{-1} exists,

$$\begin{aligned} AX &= B \\ A^{-1}(AX) &= A^{-1}B \\ (A^{-1}A)X &= A^{-1}B \\ IX &= A^{-1}B \\ X &= A^{-1}B \end{aligned} \tag{3.4.1}$$

Hence, the solutions X to the system are given by $X = A^{-1}B$. Since we assume that A^{-1} exists, we can use the formula for A^{-1} given above. Substituting this formula into the equation for X, we have

$$X = A^{-1}B = \frac{1}{\det(A)} adj(A)\, B$$

Let x_i be the i^{th} entry of X and b_j be the j^{th} entry of B. Then this equation becomes

$$x_i = \sum_{j=1}^{n} [a_{ij}]^{-1} b_j = \sum_{j=1}^{n} \frac{1}{\det(A)} adj(A)_{ij}\, b_j$$

where $adj(A)_{ij}$ is the ij^{th} entry of $adj(A)$.

By the formula for the expansion of a determinant along a column,

$$x_i = \frac{1}{\det(A)} \det \begin{bmatrix} * & \cdots & b_1 & \cdots & * \\ \vdots & & \vdots & & \vdots \\ * & \cdots & b_n & \cdots & * \end{bmatrix}$$

where here the i^{th} column of A is replaced with the column vector $[b_1 \cdots, b_n]^T$. The determinant of this modified matrix is taken and divided by $\det(A)$. This formula is known as Cramer's rule.

We formally define this method now.

Procedure 3.4.1: Using Cramer's Rule

Suppose A is an $n \times n$ invertible matrix and we wish to solve the system $AX = B$ for $X = [x_1, \cdots, x_n]^T$. Then Cramer's rule says

$$x_i = \frac{\det(A_i)}{\det(A)}$$

where A_i is the matrix obtained by replacing the i^{th} column of A with the column matrix

$$B = \begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix}$$

We illustrate this procedure in the following example.

Example 3.4.4: Using Cramer's Rule

Find x, y, z if

$$\begin{bmatrix} 1 & 2 & 1 \\ 3 & 2 & 1 \\ 2 & -3 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

Solution

We will use method outlined in Procedure 3.4.1 to find the values for x, y, z which give the solution to this system. Let

$$B = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

In order to find x, we calculate

$$x = \frac{\det(A_1)}{\det(A)}$$

where A_1 is the matrix obtained from replacing the first column of A with B.

Hence, A_1 is given by

$$A_1 = \begin{bmatrix} 1 & 2 & 1 \\ 2 & 2 & 1 \\ 3 & -3 & 2 \end{bmatrix}$$

Therefore,

$$x = \frac{\det(A_1)}{\det(A)} = \frac{\begin{vmatrix} 1 & 2 & 1 \\ 2 & 2 & 1 \\ 3 & -3 & 2 \end{vmatrix}}{\begin{vmatrix} 1 & 2 & 1 \\ 3 & 2 & 1 \\ 2 & -3 & 2 \end{vmatrix}} = \frac{1}{2}$$

Similarly, to find y we construct A_2 by replacing the second column of A with B. Hence, A_2 is given by

$$A_2 = \begin{bmatrix} 1 & 1 & 1 \\ 3 & 2 & 1 \\ 2 & 3 & 2 \end{bmatrix}$$

Therefore,

$$y = \frac{\det(A_2)}{\det(A)} = \frac{\begin{vmatrix} 1 & 1 & 1 \\ 3 & 2 & 1 \\ 2 & 3 & 2 \end{vmatrix}}{\begin{vmatrix} 1 & 2 & 1 \\ 3 & 2 & 1 \\ 2 & -3 & 2 \end{vmatrix}} = -\frac{1}{7}$$

Similarly, A_3 is constructed by replacing the third column of A with B. Then, A_3 is given by

$$A_3 = \begin{bmatrix} 1 & 2 & 1 \\ 3 & 2 & 2 \\ 2 & -3 & 3 \end{bmatrix}$$

Therefore, z is calculated as follows.

$$z = \frac{\det(A_3)}{\det(A)} = \frac{\begin{vmatrix} 1 & 2 & 1 \\ 3 & 2 & 2 \\ 2 & -3 & 3 \end{vmatrix}}{\begin{vmatrix} 1 & 2 & 1 \\ 3 & 2 & 1 \\ 2 & -3 & 2 \end{vmatrix}} = \frac{11}{14}$$

Cramer's Rule gives you another tool to consider when solving a system of linear equations.

We can also use Cramer's Rule for systems of non linear equations. Consider the following system where the matrix A has functions rather than numbers for entries.

Using Cramer's Rule

Example 3.4.5: Use Cramer's Rule for Non-Constant Matrix

Solve for z if

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & e^t \cos t & e^t \sin t \\ 0 & -e^t \sin t & e^t \cos t \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ t \\ 0.05int^2 \end{bmatrix}$$

Solution

We are asked to find the value of z in the solution. We will solve using Cramer's rule. Thus

$$z = .05in \frac{\begin{vmatrix} 1 & 0 & 1 \\ 0 & e^t \cos t & t \\ 0 & -e^t \sin t & t^2 \end{vmatrix}}{\begin{vmatrix} 1 & 0 & 0 \\ 0 & e^t \cos t & e^t \sin t \\ 0 & -e^t \sin t & e^t \cos t \end{vmatrix}} = t\left((\cos t)\, t + \sin t\right) e^{-t}$$

Polynomial Interpolation

In studying a set of data that relates variables x and y, it may be the case that we can use a polynomial to "fit" to the data. If such a polynomial can be established, it can be used to estimate values of x and y which have not been provided.

Consider the following example.

Example 3.4.6: Polynomial Interpolation

Given data points $(1,4),(2,9),(3,12)$, find an interpolating polynomial $p(x)$ of degree at most 2 and then estimate the value corresponding to $x=\frac{1}{2}$.

Solution

We want to find a polynomial given by

$$p(x)=r_0+r_1x_1+r_2x_2^2$$

such that $p(1)=4, p(2)=9$ and $p(3)=12$. To find this polynomial, substitute the known values in for x and solve for r_0, r_1, and r_2.

$$\begin{aligned} p(1)&=r_0+r_1+r_2=4\\ p(2)&=r_0+2r_1+4r_2=9\\ p(3)&=r_0+3r_1+9r_2=12 \end{aligned} \tag{3.4.2}$$

Writing the augmented matrix, we have

$$\begin{bmatrix} 1 & 1 & 1 & 4\\ 1 & 2 & 4 & 9\\ 1 & 3 & 9 & 12 \end{bmatrix}$$

After row operations, the resulting matrix is

$$\begin{bmatrix} 1 & 0 & 0 & -3\\ 0 & 1 & 0 & 8\\ 0 & 0 & 1 & -1 \end{bmatrix}$$

Therefore the solution to the system is $r_0=-3, r_1=8, r_2=-1$ and the required interpolating polynomial is

$$p(x)=-3+8x-x^2$$

To estimate the value for $x=\frac{1}{2}$, we calculate $p(\frac{1}{2})$:

$$\begin{aligned} p(\frac{1}{2})&=-3+8(\frac{1}{2})-(\frac{1}{2})^2\\ &=-3+4-\frac{1}{4}\\ &=\frac{3}{4} \end{aligned} \tag{3.4.3}$$

This procedure can be used for any number of data points, and any degree of polynomial. The steps are outlined below.

Procedure 3.4.2: Finding an Interpolation Polynomial

Suppose that values of x and corresponding values of y are given, such that the actual relationship between x and y is unknown. Then, values of y can be estimated using an **interpolating polynomial** $p(x)$. If given $x_1,\ldots,x_n$ and the corresponding $y_1,\ldots,y_n$, the procedure to find $p(x)$ is as follows:

1. The desired polynomial $p(x)$ is given by
$$p(x)=r_0+r_1x+r_2x^2+\ldots+r_{n-1}x^{n-1}$$
2. $p(x_i)=y_i$ for all $i=1,2,\ldots,n$ so that

$$
\begin{aligned}
r_0 + r_1 x_1 + r_2 x_1^2 + \ldots + r_{n-1} x_1^{n-1} &= y_1 \\
r_0 + r_1 x_2 + r_2 x_2^2 + \ldots + r_{n-1} x_2^{n-1} &= y_2 \\
&\vdots \\
r_0 + r_1 x_n + r_2 x_n^2 + \ldots + r_{n-1} x_n^{n-1} &= y_n
\end{aligned}
$$

3. Set up the augmented matrix of this system of equations

$$
\begin{bmatrix}
1 & x_1 & x_1^2 & \cdots & x_1^{n-1} & y_1 \\
1 & x_2 & x_2^2 & \cdots & x_2^{n-1} & y_2 \\
\vdots & \vdots & \vdots & & \vdots & \vdots \\
1 & x_n & x_n^2 & \cdots & x_n^{n-1} & y_n
\end{bmatrix}
$$

4. Solving this system will result in a unique solution $r_0, r_1, \cdots, r_{n-1}$. Use these values to construct $p(x)$, and estimate the value of $p(a)$ for any $x = a$.

This procedure motivates the following theorem.

Theorem 3.4.2: Polynomial Interpolation

Given n data points $(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)$ with the x_i distinct, there is a unique polynomial $p(x) = r_0 + r_1 x + r_2 x^2 + \cdots + r_{n-1} x^{n-1}$ such that $p(x_i) = y_i$ for $i = 1, 2, \cdots, n$. The resulting polynomial $p(x)$ is called the **interpolating polynomial** for the data points.

We conclude this section with another example.

Example 3.4.7: Polynomial Interpolation

Consider the data points $(0, 1), (1, 2), (3, 22), (5, 66)$. Find an interpolating polynomial $p(x)$ of degree at most three, and estimate the value of $p(2)$.

Solution

The desired polynomial $p(x)$ is given by:

$$p(x) = r_0 + r_1 x + r_2 x^2 + r_3 x^3$$

Using the given points, the system of equations is

$$
\begin{aligned}
p(0) &= r_0 = 1 \\
p(1) &= r_0 + r_1 + r_2 + r_3 = 2 \\
p(3) &= r_0 + 3r_1 + 9r_2 + 27r_3 = 22 \\
p(5) &= r_0 + 5r_1 + 25r_2 + 125r_3 = 66
\end{aligned}
\tag{3.4.4}
$$

The augmented matrix is given by:

$$
\begin{bmatrix}
1 & 0 & 0 & 0 & 1 \\
1 & 1 & 1 & 1 & 2 \\
1 & 3 & 9 & 27 & 22 \\
1 & 5 & 25 & 125 & 66
\end{bmatrix}
$$

The resulting matrix is

$$
\begin{bmatrix}
1 & 0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0 & -2 \\
0 & 0 & 1 & 0 & 3 \\
0 & 0 & 0 & 1 & 0
\end{bmatrix}
$$

Therefore, $r_0 = 1, r_1 = -2, r_2 = 3, r_3 = 0$ and $p(x) = 1 - 2x + 3x^2$. To estimate the value of $p(2)$, we compute $p(2) = 1 - 2(2) + 3(2^2) = 1 - 4 + 12 = 9$.

Answers

Theorem 3.4.1**: The Inverse and the Determinant**

(of Theorem 3.4.1) Recall that the (i, j)-entry of $adj(A)$ is equal to $\text{cof}(A)_{ji}$. Thus the (i, j)-entry of $B = A \cdot adj(A)$ is :

$$B_{ij} = \sum_{k=1}^{n} a_{ik} adj(A)_{kj} = \sum_{k=1}^{n} a_{ik} \text{cof}(A)_{jk}$$

By the cofactor expansion theorem, we see that this expression for B_{ij} is equal to the determinant of the matrix obtained from A by replacing its jth row by $a_{i1}, a_{i2}, \ldots a_{in}$ — i.e., its ith row.

If $i = j$ then this matrix is A itself and therefore $B_{ii} = \det A$. If on the other hand $i \neq j$, then this matrix has its ith row equal to its jth row, and therefore $B_{ij} = 0$ in his case. Thus we obtain:

$$A\ adj\,(A) = \det(A) I$$

Similarly we can verify that:

$$adj\,(A)\, A = \det(A) I$$

And this proves the first part of the theorem.

Further if A is invertible, then by Theorem 3.2.5 we have:

$$1 = \det(I) = \det\left(AA^{-1}\right) = \det(A) \det\left(A^{-1}\right)$$

and thus $\det(A) \neq 0$. Equivalently, if $\det(A) = 0$, then A is not invertible.

Finally if $\det(A) \neq 0$, then the above formula shows that A is invertible and that:

$$A^{-1} = \frac{1}{\det(A)} adj\,(A)$$

This completes the proof.

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3.5: SUPPLEMENTARY NOTES - DETERMINANTS AND PERMUTATIONS

We can think of a determinant in terms of a permutation in order to obtain some properties of determinants.

3.5.1: The Determinant Formula

3.5.2: Elementary Matrices and Determinants

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3.5.1: The Determinant Formula

The determinant extracts a single number from a matrix that determines whether its *invertibility*. Lets see how this works for small matrices first.

Simple Examples

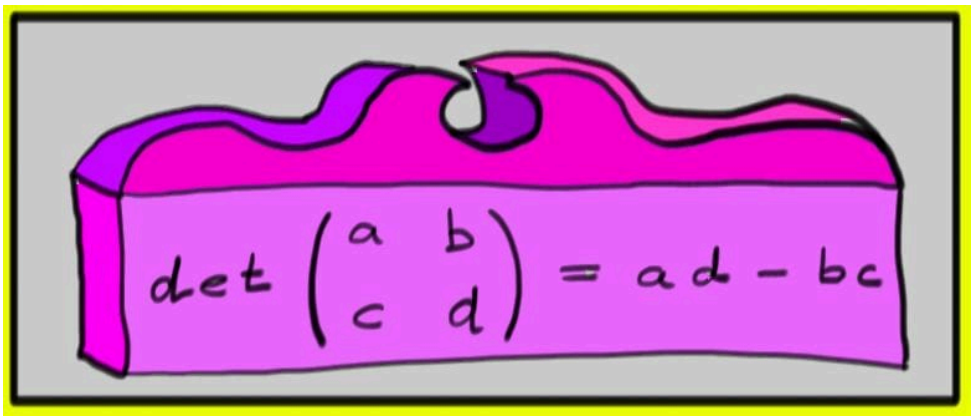
For small cases, we already know when a matrix is invertible. If M is a 1×1 matrix, then $M = (m) \Rightarrow M^{-1} = (1/m)$. Then M is invertible if and only if $m \neq 0$.

For M a 2×2 matrix, chapter 7 section 7.5 shows that if $M = \begin{pmatrix} m_1^1 & m_2^1 \\ m_1^2 & m_2^2 \end{pmatrix}$, then $M^{-1} = \frac{1}{m_1^1 m_2^2 - m_2^1 m_1^2} \begin{pmatrix} m_2^2 & -m_2^1 \\ -m_1^2 & m_1^1 \end{pmatrix}$. Thus M is invertible if and only if

$$m_1^1 m_2^2 - m_2^1 m_1^2 \neq 0\,. \tag{3.5.1.1}$$

For 2×2 matrices, this quantity is called the $determinant\ of\ M$.

$$\det M = \det \begin{pmatrix} m_1^1 & m_2^1 \\ m_1^2 & m_2^2 \end{pmatrix} = m_1^1 m_2^2 - m_2^1 m_1^2\,. \tag{3.5.1.2}$$



Example 3.5.1.1:

For a 3×3 matrix,

$$M = \begin{pmatrix} m_1^1 & m_2^1 & m_3^1 \\ m_1^2 & m_2^2 & m_3^2 \\ m_1^3 & m_2^3 & m_3^3 \end{pmatrix}, \tag{3.5.1.3}$$

then---see review question 1---M is non-singular if and only if

$$\det M = m_1^1 m_2^2 m_3^3 - m_1^1 m_3^2 m_2^3 + m_2^1 m_3^2 m_1^3 - m_2^1 m_1^2 m_3^3 + m_3^1 m_1^2 m_2^3 - m_3^1 m_2^2 m_1^3 \neq 0. \tag{3.5.1.4}$$

Notice that in the subscripts, each ordering of the numbers 1, 2, and 3 occurs exactly once. Each of these is a $permutation$ of the set $\{1, 2, 3\}$.

Permutations

Consider n objects labeled 1 through n and shuffle them. Each possible shuffle is called a $permutation$.
For example, here is an example of a permutation of 1--5:

$$\sigma = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 \\ 4 & 2 & 5 & 1 & 3 \end{bmatrix} \tag{3.5.1.5}$$

We can consider a permutation σ as an invertible function from the set of numbers $[n] := \{1, 2, \dots, n\}$ to $[n]$, so can write $\sigma(3) = 5$ in the above example. In general we can write

$$\begin{bmatrix} 1 & 2 & 3 & 4 & 5 \\ \sigma(1) & \sigma(2) & \sigma(3) & \sigma(4) & \sigma(5) \end{bmatrix}, \tag{3.5.1.6}$$

but since the top line of any permutation is always the same, we can omit it and just write:

$$\sigma = [\sigma(1) \quad \sigma(2) \quad \sigma(3) \quad \sigma(4) \quad \sigma(5)] \tag{3.5.1.7}$$

and so our example becomes simply $\sigma = [4\ 2\ 5\ 1\ 3]$. The mathematics of permutations is extensive; there are a few key properties of permutations that we'll need:

1. There are $n!$ permutations of n distinct objects, since there are n choices for the first object, $n-1$ choices for the second once the first has been chosen, and so on.
2. Every permutation can be built up by successively swapping pairs of objects. For example, to build up the permutation $[3 \quad 1 \quad 2]$ from the trivial permutation $[1 \quad 2 \quad 3]$, you can first swap 2 and 3, and then swap 1 and 3.
3. For any given permutation σ, there is some number of swaps it takes to build up the permutation. (It's simplest to use the minimum number of swaps, but you don't have to: it turns out that *any* way of building up the permutation from swaps will have have the same parity of swaps, either even or odd.) If this number happens to be even, then σ is called an *even permutation* if this number is odd, then σ is an *odd permutation*. In fact, $n!$ is even for all $n \geq 2$, and exactly half of the permutations are even and the other half are odd. It's worth noting that the trivial permutation (which sends $i \to i$ for every i) is an even permutation, since it uses zero swaps.

Definition

The *sign function* is a function sgn that sends permutations to the set $\{-1, 1\}$, defined by:

$$\operatorname{sgn}(\sigma) = \begin{cases} 1 & \text{if } \sigma \text{ is even;} \\ -1 & \text{if } \sigma \text{ is odd.} \end{cases} \tag{3.5.1.8}$$

We can use permutations to give a definition of the determinant.

Definition

For an $n \times n$ matrix M, the *determinant* of M (sometimes written $|M|$) is given by:

$$\det M = \sum_{\sigma} sgn(\sigma) m^1_{\sigma(1)} m^2_{\sigma(2)} \cdots m^n_{\sigma(n)} \tag{3.5.1.9}$$

The sum is over all permutations of n. Each summand is a product of a single entry from each row, but with the column numbers shuffled by the permutation σ. The last statement about the summands yields a nice property of the determinant:

Theorem

If $M = (m^i_j)$ has a row consisting entirely of zeros, then $m^i_{\sigma(i)} = 0$ for every σ and some i. Moreover $\det M = 0$.

Because there are many permutations of n, writing the determinant this way for a general matrix gives a very long sum. For $n = 4$, there are $24 = 4!$ permutations, and for $n = 5$, there are already $120 = 5!$ permutations.

For a 4×4 matrix, $M = \begin{pmatrix} m_1^1 & m_2^1 & m_3^1 & m_4^1 \\ m_1^2 & m_2^2 & m_3^2 & m_4^2 \\ m_1^3 & m_2^3 & m_3^3 & m_4^3 \\ m_1^4 & m_2^4 & m_3^4 & m_4^4 \end{pmatrix}$, then $\det M$ is:

$$\begin{aligned} \det M = & m_1^1 m_2^2 m_3^3 m_4^4 - m_1^1 m_3^2 m_2^3 m_4^4 - m_1^1 m_2^2 m_4^3 m_3^4 \\ & - m_2^1 m_1^2 m_3^3 m_4^4 + m_1^1 m_3^2 m_4^3 m_2^4 + m_1^1 m_4^2 m_2^3 m_3^4 \\ & + m_2^1 m_3^2 m_1^3 m_4^4 + m_2^1 m_1^2 m_4^3 m_3^4 \pm 16 \text{ more terms.} \end{aligned}$$

This is very cumbersome.

Luckily, it is very easy to compute the determinants of certain matrices. For example, if M is diagonal, then $M_j^i = 0$ whenever $i \neq j$. Then all summands of the determinant involving off-diagonal entries vanish, so:

$$\det M = \sum_\sigma \operatorname{sgn}(\sigma) m^1_{\sigma(1)} m^2_{\sigma(2)} \cdots m^n_{\sigma(n)} = m_1^1 m_2^2 \cdots m_n^n. \tag{3.5.1.10}$$

Thus: *The determinant of a diagonal matrix is the product of its diagonal entries.*

Since the identity matrix is diagonal with all diagonal entries equal to one, we have:

$$\det I = 1. \tag{3.5.1.11}$$

We would like to use the determinant to decide whether a matrix is invertible. Previously, we computed the inverse of a matrix by applying row operations. Therefore we ask what happens to the determinant when row operations are applied to a matrix.

Remark: Swapping rows

Lets swap rows i and j of a matrix M and then compute its determinant. For the permutation σ, let $\hat{\sigma}$ be the permutation obtained by swapping positions i and j. Clearly

$$\hat{\sigma} = -\sigma\,. \tag{3.5.1.12}$$

Let M' be the matrix M with rows i and j swapped. Then (assuming $i < j$):

$$\begin{aligned} \det M' &= \sum_\sigma \operatorname{sgn}(\sigma)\, m^1_{\sigma(1)} \cdots m^j_{\sigma(i)} \cdots m^i_{\sigma(j)} \cdots m^n_{\sigma(n)} \\ &= \sum_\sigma \operatorname{sgn}(\sigma)\, m^1_{\sigma(1)} \cdots m^i_{\sigma(j)} \cdots m^j_{\sigma(i)} \cdots m^n_{\sigma(n)} \\ &= \sum_\sigma (-\operatorname{sgn}(\hat{\sigma}))\, m^1_{\hat{\sigma}(1)} \cdots m^i_{\hat{\sigma}(i)} \cdots m^j_{\hat{\sigma}(j)} \cdots m^n_{\hat{\sigma}(n)} \\ &= -\sum_{\hat{\sigma}} \operatorname{sgn}(\hat{\sigma})\, m^1_{\hat{\sigma}(1)} \cdots m^i_{\hat{\sigma}(i)} \cdots m^j_{\hat{\sigma}(j)} \cdots m^n_{\hat{\sigma}(n)} \\ &= -\det M. \end{aligned} \tag{3.5.1.13}$$

The step replacing $\sum_\sigma$ by $\sum_{\hat{\sigma}}$ often causes confusion; it hold since we sum over all permutations (see review problem 3). Thus we see that swapping rows changes the sign of the determinant. *i.e.*,

$$M' = -\det M\,. \tag{3.5.1.14}$$

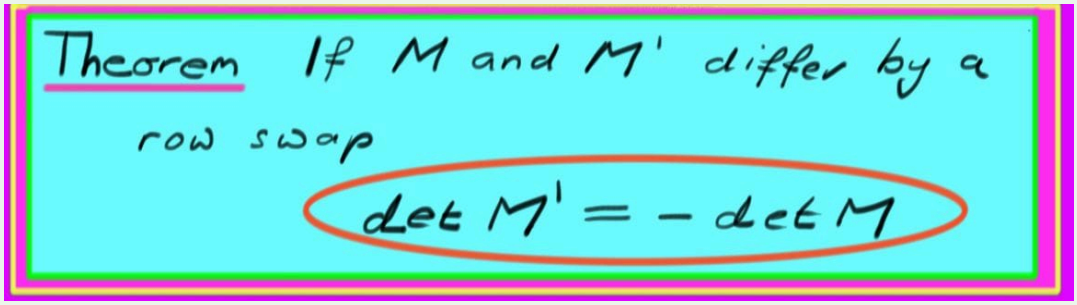
Applying this result to $M = I$ (the identity matrix) yields

$$\det E_j^i = -1\,, \tag{3.5.1.15}$$

where the matrix E_j^i is the identity matrix with rows i and j swapped. It is a row swap elementary matrix. This implies another nice property of the determinant. If two rows of the matrix are identical, then swapping the rows changes the sign of the matrix, but leaves the matrix unchanged. Then we see the following:

Theorem

If M has two identical rows, then $\det M = 0$.



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3.5.2: Elementary Matrices and Determinants

In chapter 2 we found the elementary matrices that perform the Gaussian row operations. In other words, for any matrix M, and a matrix M' equal to M after a row operation, multiplying by an elementary matrix E gave $M' = EM$. We now examine what the elementary matrices to do determinants.

Row Swap

Our first elementary matrix multiplies a matrix M by swapping rows i and j. Explicitly: let R^1 through R^n denote the rows of M, and let M' be the matrix M with rows i and j swapped. Then M and M' can be regarded as a block matrices (where the blocks are rows):

$$M = \begin{pmatrix} \vdots \\ R^i \\ \vdots \\ R^j \\ \vdots \end{pmatrix} \text{ and } M' = \begin{pmatrix} \vdots \\ R^j \\ \vdots \\ R^i \\ \vdots \end{pmatrix}. \tag{3.5.2.1}$$

Then notice that:

$$M' = \begin{pmatrix} \vdots \\ R^j \\ \vdots \\ R^i \\ \vdots \end{pmatrix} = \begin{pmatrix} 1 & & & & & \\ & \ddots & & & & \\ & & 0 & & 1 & \\ & & & \ddots & & \\ & & 1 & & 0 & \\ & & & & & \ddots \\ & & & & & & 1 \end{pmatrix} \begin{pmatrix} \vdots \\ R^i \\ \vdots \\ R^j \\ \vdots \end{pmatrix} \tag{3.5.2.2}$$

The matrix

$$\begin{pmatrix} 1 & & & & & \\ & \ddots & & & & \\ & & 0 & & 1 & \\ & & & \ddots & & \\ & & 1 & & 0 & \\ & & & & & \ddots \\ & & & & & & 1 \end{pmatrix} =: E^i_j \tag{3.5.2.3}$$

is just the identity matrix with rows i and j swapped. The matrix E^i_j is an $elementary\ matrix$ and

$$M' = E^i_j M\,. \tag{3.5.2.4}$$

Because $\det I = 1$ and swapping a pair of rows changes the sign of the determinant, we have found that

$$\det E^i_j = -1\,. \tag{3.5.2.5}$$

Now we know that swapping a pair of rows flips the sign of the determinant so $\det M' = -detM$. But $\det E^i_j = -1$ and $M' = E^i_j M$ so

$$\det E^i_j M = \det E^i_j \det M\,. \tag{3.5.2.6}$$

This result hints at a general rule for determinants of products of matrices.

Scalar Multiply

The next row operation is multiplying a row by a scalar. Consider

$$M = \begin{pmatrix} R^1 \\ \vdots \\ R^n \end{pmatrix} , \tag{3.5.2.7}$$

where R^i are row vectors. Let $R^i(\lambda)$ be the identity matrix, with the ith diagonal entry replaced by λ, not to be confused with the row vectors. $i.e.$,

$$R^i(\lambda) = \begin{pmatrix} 1 & & & & \\ & \ddots & & & \\ & & \lambda & & \\ & & & \ddots & \\ & & & & 1 \end{pmatrix} . \tag{3.5.2.8}$$

Then:

$$M' = R^i(\lambda)M = \begin{pmatrix} R^1 \\ \vdots \\ \lambda R^i \\ \vdots \\ R^n \end{pmatrix} , \tag{3.5.2.9}$$

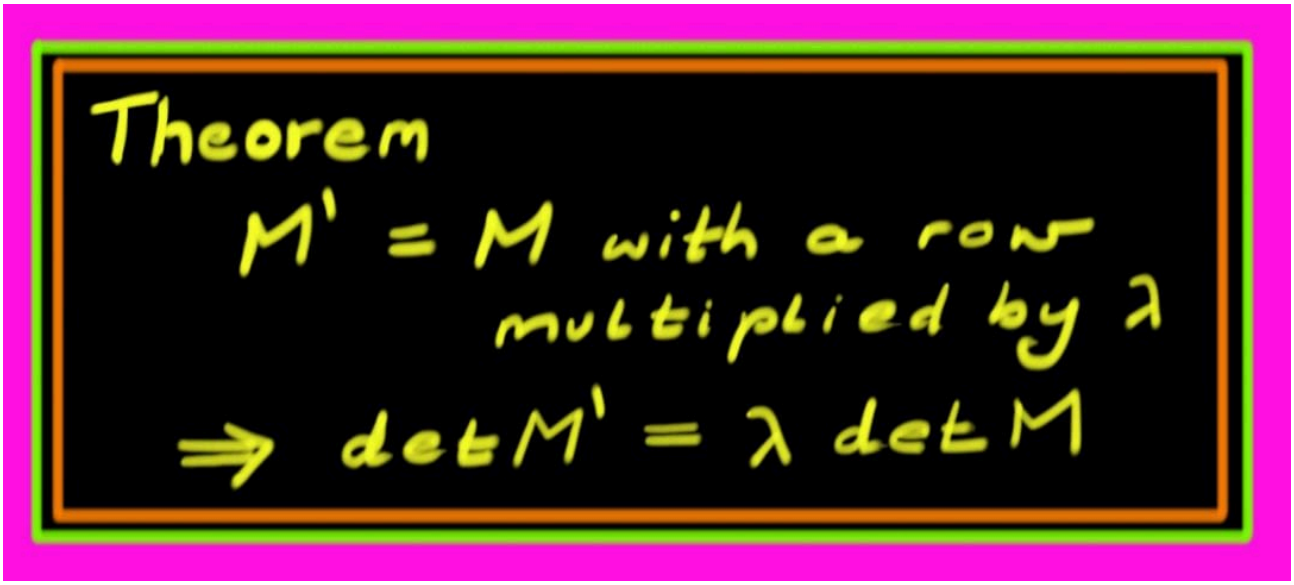
equals M with one row multiplied by λ.

What effect does multiplication by the elementary matrix $R^i(\lambda)$ have on the determinant?

$$\begin{aligned} \det M' &= \sum_\sigma sgn(\sigma) m^1_{\sigma(1)} \cdots \lambda m^i_{\sigma(i)} \cdots m^n_{\sigma(n)} \\ &= \lambda \sum_\sigma sgn(\sigma) m^1_{\sigma(1)} \cdots m^i_{\sigma(i)} \cdots m^n_{\sigma(n)} \\ &= \lambda \det M \end{aligned}$$

Thus, multiplying a row by λ multiplies the determinant by λ. $i.e.$,

$$\det R^i(\lambda)M = \lambda \det M \, . \tag{3.5.2.10}$$



Since $R^i(\lambda)$ is just the identity matrix with a single row multiplied by λ, then by the above rule, the determinant of $R^i(\lambda)$ is λ. Thus:

$$\det R^i(\lambda) = \det \begin{pmatrix} 1 & & & & \\ & \ddots & & & \\ & & \lambda & & \\ & & & \ddots & \\ & & & & 1 \end{pmatrix} = \lambda\,, \tag{3.5.2.11}$$

and once again we have a product of determinants formula:
$$
\det R^{i}(\lambda) M = \det R^{i}(\lambda) \det M
\]

Row Addition

The final row operation is adding μR^j to R^i. This is done with the elementary matrix $S^i_j(\mu)$, which is an identity matrix but with an additional μ in the i, j position:

$$S^i_j(\mu) = \begin{pmatrix} 1 & & & & & \\ & \ddots & & & & \\ & & 1 & & \mu & \\ & & & \ddots & & \\ & & & & 1 & \\ & & & & & \ddots \\ & & & & & & 1 \end{pmatrix}. \tag{3.5.2.12}$$

Then multiplying M by $S^i_j(\mu)$ performs a row addition:

$$\begin{pmatrix} 1 & & & & & \\ & \ddots & & & & \\ & & 1 & & \mu & \\ & & & \ddots & & \\ & & & & 1 & \\ & & & & & \ddots \\ & & & & & & 1 \end{pmatrix} \begin{pmatrix} \vdots \\ R^i \\ \vdots \\ R^j \\ \vdots \end{pmatrix} = \begin{pmatrix} \vdots \\ R^i + \mu R^j \\ \vdots \\ R^j \\ \vdots \end{pmatrix}. \tag{3.5.2.13}$$

What is the effect of multiplying by $S^i_j(\mu)$ on the determinant? Let $M' = S^i_j(\mu)M$, and let M'' be the matrix M but with R^i replaced by R^j. Then

$$\begin{aligned} \det M' &= \sum_\sigma sgn(\sigma) m^1_{\sigma(1)} \cdots (m^i_{\sigma(i)} + \mu m^j_{\sigma(j)}) \cdots m^n_{\sigma(n)} \\ &= \sum_\sigma sgn(\sigma) m^1_{\sigma(1)} \cdots m^i_{\sigma(i)} \cdots m^n_{\sigma(n)} \\ &\qquad + \sum_\sigma sgn(\sigma) m^1_{\sigma(1)} \cdots \mu m^j_{\sigma(j)} \cdots m^j_{\sigma(j)} \cdots m^n_{\sigma(n)} \\ &= \det M + \mu \det M'' \end{aligned}$$

Since M'' has two identical rows, its determinant is 0 so

$$\det M' = \det M, \tag{3.5.2.14}$$

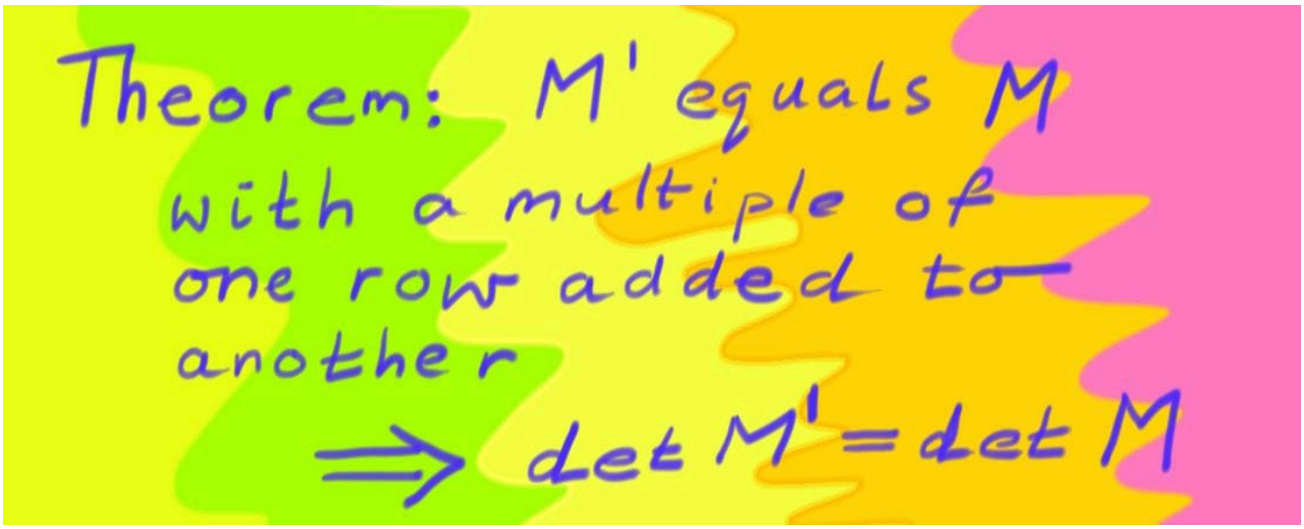
when M' is obtained from M by adding μ times row j to row i.

We also have learnt that

$$\det S^i_j(\mu) M = \det M\,. \tag{3.5.2.15}$$

Notice that if M is the identity matrix, then we have

$$\det S^i_j(\mu) = \det(S^i_j(\mu)I) = \det I = 1\,. \tag{3.5.2.16}$$



Determinant of Products

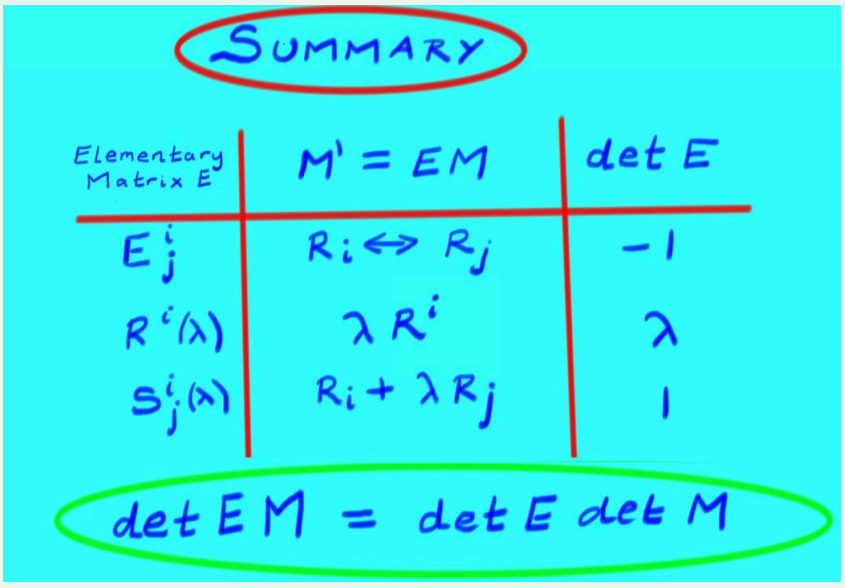
In summary, the elementary matrices for each of the row operations obey

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Moreover we found a useful formula for determinants of products:

Theorem

If E is *any* of the elementary matrices $E^i_j, R^i(\lambda), S^i_j(\mu)$, then $\det(EM) = \det E \det M$.



We have seen that any matrix M can be put into reduced row echelon form via a sequence of row operations, and we have seen that any row operation can be achieved via left matrix multiplication by an elementary matrix. Suppose that RREF(M) is the reduced row echelon form of M. Then

$$RREF(M) = E_1 E_2 \cdots E_k M\,, \tag{3.5.2.17}$$

where each E_i is an elementary matrix. We know how to compute determinants of elementary matrices and products thereof, so we ask:

$$What\ is\ the\ determinant\ of\ a\ square\ matrix\ in\ reduced\ row\ echelon\ form?\ \tag{3.5.2.18}$$

The answer has two cases:
1. If M is not invertible, then some row of $RREF(M)$ contains only zeros. Then we can multiply the zero row by any constant λ without changing M; by our previous observation, this scales the determinant of M by λ. Thus, if M is not invertible, $\det RREF(M) = \lambda \det RREF(M)$, and so $\det RREF(M) = 0$.

2. Otherwise, every row of $RREF(M)$ has a pivot on the diagonal; since M is square, this means that $RREF(M)$ is the identity matrix. So if M is invertible, $\det RREF(M) = 1$.

Notice that because $\det RREF(M) = \det(E_1 E_2 \cdots E_k M)$, by the theorem above,

$$\det RREF(M) = \det(E_1) \cdots \det(E_k) \det M\,. \tag{3.5.2.19}$$

Since each E_i has non-zero determinant, then $\det RREF(M) = 0$ if and only if $\det M = 0$. This establishes an important theorem:

Theorem

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Since we know the determinants of the elementary matrices, we can immediately obtain the following:



Corollary

Any elementary matrix $E^i_j, R^i(\lambda), S^i_j(\mu)$ is invertible, except for $R^i(0)$. In fact, the inverse of an elementary matrix is another elementary matrix.

To obtain one last important result, suppose that M and N are square $n \times n$ matrices, with reduced row echelon forms such that, for elementary matrices E_i and F_i,

$$M = E_1 E_2 \cdots E_k\, RREF(M)\,, \tag{3.5.2.20}$$

and

$$N = F_1 F_2 \cdots F_l\, RREF(N)\,. \tag{3.5.2.21}$$

If $RREF(M)$ is the identity matrix ($i.e.$, M is invertible), then:

$$\begin{aligned}\det(MN) &= \det(E_1E_2\cdots E_k\,RREF(M)F_1F_2\cdots F_l\,RREF(N))\\ &= \det(E_1E_2\cdots E_kIF_1F_2\cdots F_l\,RREF(N))\\ &= \det(E_1)\cdots\det(E_k)\det(I)\det(F_1)\cdots\det(F_l)\det RREF(N)\\ &= \det(M)\det(N)\end{aligned}$$

Otherwise, M is not invertible, and $\det M = 0 = \det RREF(M)$. Then there exists a row of zeros in $RREF(M)$, so $R^n(\lambda)RREF(M)$ $= RREF(M)$ \lambda is only supported in math mode . Then:

$$\begin{aligned}\det(MN) &= \det(E_1E_2\cdots E_k\,RREF(M)N)\\ &= \det(E_1E_2\cdots E_k\,RREF(M)N)\\ &= \det(E_1)\cdots\det(E_k)\det(RREF(M)N)\\ &= \det(E_1)\cdots\det(E_k)\det(R^n(\lambda)\,RREF(M)N)\\ &= \det(E_1)\cdots\det(E_k)\lambda\det(RREF(M)N)\\ &= \lambda\det(MN)\end{aligned}$$

Which implies that $\det(MN) = 0 = \det M\det N$.

Thus we have shown that for any matrices M and N,

$$\det(MN) = \det M\det N \tag{3.5.2.22}$$

This result is $extremely\ important$; do not forget it!



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3.E: Exercises

Exercise $3.E.1$

Find the determinants of the following matrices.

a. $\begin{bmatrix} 1 & 3 \\ 0 & 2 \end{bmatrix}$
b. $\begin{bmatrix} 0 & 3 \\ 0 & 2 \end{bmatrix}$
c. $\begin{bmatrix} 4 & 3 \\ 6 & 2 \end{bmatrix}$

Answer available at the end of this section.

Exercise $3.E.2$

Let $A = \begin{bmatrix} 1 & 2 & 4 \\ 0 & 1 & 3 \\ -2 & 5 & 1 \end{bmatrix}$. Find the following.

a. $minor(A)_{11}$
b. $minor(A)_{21}$
c. $minor(A)_{32}$
d. $cof(A)_{11}$
e. $cof(A)_{21}$
f. $cof(A)_{32}$

Answer available at the end of this section.

Exercise $3.E.3$

Find the determinants of the following matrices.

a. $\begin{bmatrix} 1 & 2 & 3 \\ 3 & 2 & 2 \\ 0 & 9 & 8 \end{bmatrix}$
b. $\begin{bmatrix} 4 & 3 & 2 \\ 1 & 7 & 8 \\ 3 & -9 & 3 \end{bmatrix}$
c. $\begin{bmatrix} 1 & 2 & 3 & 2 \\ 1 & 3 & 2 & 3 \\ 4 & 1 & 5 & 0 \\ 1 & 2 & 1 & 2 \end{bmatrix}$

Answer available at the end of this section.

Exercise $3.E.4$

Find the following determinant by expanding along the first row and second column.

$$\begin{vmatrix} 1 & 2 & 1 \\ 2 & 1 & 3 \\ 2 & 1 & 1 \end{vmatrix}$$

Answer available at the end of this section.

Exercise $3.E.5$

Find the following determinant by expanding along the first column and third row.

$$\begin{vmatrix} 1 & 2 & 1 \\ 1 & 0 & 1 \\ 2 & 1 & 1 \end{vmatrix}$$

Answer available at the end of this section.

Exercise $3.E.6$

Find the following determinant by expanding along the second row and first column.

$$\begin{vmatrix} 1 & 2 & 1 \\ 2 & 1 & 3 \\ 2 & 1 & 1 \end{vmatrix}$$

Answer available at the end of this section.

Exercise $3.E.7$

Compute the determinant by cofactor expansion. Pick the easiest row or column to use.

$$\begin{vmatrix} 1 & 0 & 0 & 1 \\ 2 & 1 & 1 & 0 \\ 0 & 0 & 0 & 2 \\ 2 & 1 & 3 & 1 \end{vmatrix}$$

Answer available at the end of this section.

Exercise $3.E.8$

Find the determinant of the following matrices.

a. $A = \begin{bmatrix} 1 & -34 \\ 0 & 2 \end{bmatrix}$

b. $A = \begin{bmatrix} 4 & 3 & 14 \\ 0 & -2 & 0 \\ 0 & 0 & 5 \end{bmatrix}$

c. $A = \begin{bmatrix} 2 & 3 & 15 & 0 \\ 0 & 4 & 1 & 7 \\ 0 & 0 & -3 & 5 \\ 0 & 0 & 0 & 1 \end{bmatrix}$

Answer available at the end of this section.

Exercise 3.E.9

An operation is done to get from the first matrix to the second. Identify what was done and tell how it will affect the value of the determinant.

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \to \cdots \to \begin{bmatrix} a & c \\ b & d \end{bmatrix}$$

Answer available at the end of this section.

Exercise 3.E.10

An operation is done to get from the first matrix to the second. Identify what was done and tell how it will affect the value of the determinant.

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \to \cdots \to \begin{bmatrix} c & d \\ a & b \end{bmatrix}$$

Answer available at the end of this section.

Exercise 3.E.11

An operation is done to get from the first matrix to the second. Identify what was done and tell how it will affect the value of the determinant.

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \to \cdots \to \begin{bmatrix} a & b \\ a+c & b+d \end{bmatrix}$$

Answer available at the end of this section.

Exercise 3.E.12

An operation is done to get from the first matrix to the second. Identify what was done and tell how it will affect the value of the determinant.

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \to \cdots \to \begin{bmatrix} a & b \\ 2c & 2d \end{bmatrix}$$

Answer available at the end of this section.

Exercise 3.E.13

An operation is done to get from the first matrix to the second. Identify what was done and tell how it will affect the value of the determinant.

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \to \cdots \to \begin{bmatrix} b & a \\ d & c \end{bmatrix}$$

Answer available at the end of this section.

Exercise $3.E.14$

Let A be an $r \times r$ matrix and suppose there are $r-1$ rows (columns) such that all rows (columns) are linear combinations of these $r-1$ rows (columns). Show $\det(A) = 0$.

Answer available at the end of this section.

Exercise $3.E.15$

Show $\det(aA) = a^n \det(A)$ for an $n \times n$ matrix A and scalar a.

Answer available at the end of this section.

Exercise $3.E.16$

Construct 2×2 matrices A and B to show that the $\det A \det B = \det(AB)$.

Answer available at the end of this section.

Exercise $3.E.17$

Is it true that $\det(A+B) = \det(A) + \det(B)$? If this is so, explain why. If it is not so, give a counter example.

Answer available at the end of this section.

Exercise $3.E.18$

An $n \times n$ matrix is called **nilpotent** if for some positive integer, k it follows $A^k = 0$. If A is a nilpotent matrix and k is the smallest possible integer such that $A^k = 0$, what are the possible values of $\det(A)$?

Answer available at the end of this section.

Exercise $3.E.19$

A matrix is said to be **orthogonal** if $A^T A = I$. Thus the inverse of an orthogonal matrix is just its transpose. What are the possible values of $\det(A)$ if A is an orthogonal matrix?

Answer available at the end of this section.

Exercise $3.E.20$

Let A and B be two $n \times n$ matrices. $A \sim B$ (A is **similar** to B) means there exists an invertible matrix P such that $A = P^{-1}BP$. Show that if $A \sim B$, then $\det(A) = \det(B)$.

Answer available at the end of this section.

Exercise $3.E.21$

Tell whether each statement is true or false. If true, provide a proof. If false, provide a counter example.

a. If A is a 3×3 matrix with a zero determinant, then one column must be a multiple of some other column.
b. If any two columns of a square matrix are equal, then the determinant of the matrix equals zero.
c. For two $n \times n$ matrices A and B, $\det(A+B) = \det(A) + \det(B)$.
d. For an $n \times n$ matrix A, $\det(3A) = 3\det(A)$
e. If A^{-1} exists then $\det(A^{-1}) = \det(A)^{-1}$.
f. If B is obtained by multiplying a single row of A by 4 then $\det(B) = 4\det(A)$.
g. For A an $n \times n$ matrix, $\det(-A) = (-1)^n \det(A)$.
h. If A is a real $n \times n$ matrix, then $\det(A^T A) \geq 0$.
i. If $A^k = 0$ for some positive integer k, then $\det(A) = 0$.
j. If $AX = 0$ for some $X \neq 0$, then $\det(A) = 0$.

Answer available at the end of this section.

Exercise $3.E.22$

Find the determinant using row operations to first simplify.

$$\begin{vmatrix} 1 & 2 & 1 \\ 2 & 3 & 2 \\ -4 & 1 & 2 \end{vmatrix}$$

Answer available at the end of this section.

Exercise $3.E.23$

Find the determinant using row operations to first simplify.

$$\begin{vmatrix} 2 & 1 & 3 \\ 2 & 4 & 2 \\ 1 & 4 & -5 \end{vmatrix}$$

Answer available at the end of this section.

Exercise $3.E.24$

Find the determinant using row operations to first simplify.

$$\begin{vmatrix} 1 & 2 & 1 & 2 \\ 3 & 1 & -2 & 3 \\ -1 & 0 & 3 & 1 \\ 2 & 3 & 2 & -2 \end{vmatrix}$$

Answer available at the end of this section.

Exercise $3.E.25$

Find the determinant using row operations to first simplify.

$$\begin{vmatrix} 1 & 4 & 1 & 2 \\ 3 & 2 & -2 & 3 \\ -1 & 0 & 3 & 3 \\ 2 & 1 & 2 & -2 \end{vmatrix}$$

Answer available at the end of this section.

Exercise 3.E.26

Let

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 2 & 1 \\ 3 & 1 & 0 \end{bmatrix}$$

Determine whether the matrix A has an inverse by finding whether the determinant is non zero. If the determinant is nonzero, find the inverse using the formula for the inverse which involves the cofactor matrix.

Answer available at the end of this section.

Exercise 3.E.27

Let

$$A = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 2 & 1 \\ 3 & 1 & 1 \end{bmatrix}$$

Determine whether the matrix A has an inverse by finding whether the determinant is non zero. If the determinant is nonzero, find the inverse using the formula for the inverse.

Answer available at the end of this section.

Exercise 3.E.28

Let

$$A = \begin{bmatrix} 1 & 3 & 3 \\ 2 & 4 & 1 \\ 0 & 1 & 1 \end{bmatrix}$$

Determine whether the matrix A has an inverse by finding whether the determinant is non zero. If the determinant is nonzero, find the inverse using the formula for the inverse.

Answer available at the end of this section.

Exercise 3.E.29

Let

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 2 & 1 \\ 2 & 6 & 7 \end{bmatrix}$$

Determine whether the matrix A has an inverse by finding whether the determinant is non zero. If the determinant is nonzero, find the inverse using the formula for the inverse.

Exercise $3.E.30$

Let

$$A = \begin{bmatrix} 1 & 0 & 3 \\ 1 & 0 & 1 \\ 3 & 1 & 0 \end{bmatrix}$$

Determine whether the matrix A has an inverse by finding whether the determinant is non zero. If the determinant is nonzero, find the inverse using the formula for the inverse.

Answer available at the end of this section.

Exercise $3.E.31$

For the following matrices, determine if they are invertible. If so, use the formula for the inverse in terms of the cofactor matrix to find each inverse. If the inverse does not exist, explain why.

a. $\begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix}$

b. $\begin{bmatrix} 1 & 2 & 3 \\ 0 & 2 & 1 \\ 4 & 1 & 1 \end{bmatrix}$

c. $\begin{bmatrix} 1 & 2 & 1 \\ 2 & 3 & 0 \\ 0 & 1 & 2 \end{bmatrix}$

Answer available at the end of this section.

Exercise $3.E.32$

Consider the matrix

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos t & -\sin t \\ 0 & \sin t & \cos t \end{bmatrix}$$

Does there exist a value of t for which this matrix fails to have an inverse? Explain.

Answer available at the end of this section.

Exercise $3.E.33$

Consider the matrix

$$A = \begin{bmatrix} 1 & t & t^2 \\ 0 & 1 & 2t \\ t & 0 & 2 \end{bmatrix}$$

Does there exist a value of t for which this matrix fails to have an inverse? Explain.

Answer available at the end of this section.

Exercise 3.E.34

Consider the matrix

$$A = \begin{bmatrix} e^t & \cosh t & \sinh t \\ e^t & \sinh t & \cosh t \\ e^t & \cosh t & \sinh t \end{bmatrix}$$

Does there exist a value of t for which this matrix fails to have an inverse? Explain.

Answer available at the end of this section.

Exercise 3.E.35

Consider the matrix

$$A = \begin{bmatrix} e^t & e^{-t}\cos t & e^{-t}\sin t \\ e^t & -e^{-t}\cos t - e^{-t}\sin t & -e^{-t}\sin t + e^{-t}\cos t \\ e^t & 2e^{-t}\sin t & -2e^{-t}\cos t \end{bmatrix}$$

Does there exist a value of t for which this matrix fails to have an inverse? Explain.

Answer available at the end of this section.

Exercise 3.E.36

Show that if $\det(A) \neq 0$ for A an $n \times n$ matrix, it follows that if $AX = 0$, then $X = 0$.

Answer available at the end of this section.

Exercise 3.E.37

Suppose A, B are $n \times n$ matrices and that $AB = I$. Show that then $BA = I$. **Hint**: First explain why $\det(A)$, $\det(B)$ are both nonzero. Then $(AB)A = A$ and then show $BA(BA - I) = 0$. From this use what is given to conclude $A(BA - I) = 0$. Then use Exercise 3.E.36.

Answer available at the end of this section.

Exercise 3.E.38

Use the formula for the inverse in terms of the cofactor matrix to find the inverse of the matrix

$$A = \begin{bmatrix} e^t & 0 & 0 \\ 0 & e^t\cos t & e^t\sin t \\ 0 & e^t\cos t - e^t\sin t & e^t\cos t + e^t\sin t \end{bmatrix}$$

Answer available at the end of this section.

Exercise 3.E.39

Find the inverse, if it exists, of the matrix

$$A = \begin{bmatrix} e^t & \cos t & \sin t \\ e^t & -\sin t & \cos t \\ e^t & -\cos t & -\sin t \end{bmatrix}$$

Answer available at the end of this section.

Exercise $3.E.40$

Suppose A is an upper triangular matrix. Show that A^{-1} exists if and only if all elements of the main diagonal are non zero. Is it true that A^{-1} will also be upper triangular? Explain. Could the same be concluded for lower triangular matrices?

Answer available at the end of this section.

Exercise $3.E.41$

If $A,\ B$, and C are each $n \times n$ matrices and ABC is invertible, show why each of $A,\ B$, and C are invertible.

Answer available at the end of this section.

Exercise $3.E.42$

Decide if this statement is true or false: Cramer's rule is useful for finding solutions to systems of linear equations in which there is an infinite set of solutions.

Answer available at the end of this section.

Exercise $3.E.43$

Use Cramer's rule to find the solution to

$$\begin{aligned} x + 2y &= 1 \\ 2x - y &= 2 \end{aligned} \tag{3.E.1}$$

Answer available at the end of this section.

Exercise $3.E.44$

Use Cramer's rule to find the solution to

$$\begin{aligned} x + 2y + z &= 1 \\ 2x - y - z &= 2 \\ x + z &= 1 \end{aligned}$$

Answer available at the end of this section.

Answers

Exercise $3.E.1$

Exercise $3.E.2$

Exercise $3.E.3$

a. The answer is 31.
b. The answer is 375.

c. The answer is -2.

Exercise $3.E.4$

$$\begin{vmatrix} 1 & 2 & 1 \\ 2 & 1 & 3 \\ 2 & 1 & 1 \end{vmatrix} = 6$$

Exercise $3.E.5$

$$\begin{vmatrix} 1 & 2 & 1 \\ 1 & 0 & 1 \\ 2 & 1 & 1 \end{vmatrix} = 2$$

Exercise $3.E.6$

$$\begin{vmatrix} 1 & 2 & 1 \\ 2 & 1 & 3 \\ 2 & 1 & 1 \end{vmatrix} = 6$$

Exercise $3.E.7$

$$\begin{vmatrix} 1 & 0 & 0 & 1 \\ 2 & 1 & 1 & 0 \\ 0 & 0 & 0 & 2 \\ 2 & 1 & 3 & 1 \end{vmatrix} = -4$$

Exercise $3.E.8$

Exercise $3.E.9$

It does not change the determinant. This was just taking the transpose.

Exercise $3.E.10$

In this case two rows were switched and so the resulting determinant is -1 times the first

Exercise $3.E.11$

The determinant is unchanged. It was just the first row added to the second.

Exercise $3.E.12$

The second row was multiplied by 2 so the determinant of the result is 2 times the original determinant.

Exercise $3.E.13$

In this case the two columns were switched so the determinant of the second is -1 times the determinant of the first.

Exercise $3.E.14$

If the determinant is nonzero, then it will remain nonzero with row operations applied to the matrix. However, by assumption, you can obtain a row of zeros by doing row operations. Thus the determinant must have been zero after all.

Exercise $3.E.15$

$\det(aA) = \det(aIA) = \det(aI)\det(A) = a^n \det(A)$. The matrix which has a down the main diagonal has determinant equal to a^n.

Exercise $3.E.16$

$$\det\left(\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}\begin{bmatrix} -1 & 2 \\ -5 & 6 \end{bmatrix}\right) = -8$$

$$\det\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}\det\begin{bmatrix} -1 & 2 \\ -5 & 6 \end{bmatrix} = -2 \times 4 = -8$$

Exercise $3.E.17$

This is not true at all. Consider $A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $B = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}$.

Exercise $3.E.18$

It must be 0 because $0 = \det(0) = \det(A^k) = (\det(A))^k$.

Exercise $3.E.19$

You would need $\det(AA^T) = \det(A)\det(A^T) = \det(A)^2 = 1$ and so $\det(A) = 1$, or -1.

Exercise $3.E.20$

$\det(A) = \det(S^{-1}BS) = \det(S^{-1})\det(B)\det(S) = \det(B)\det(S^{-1}S) = \det(B)$.

Exercise $3.E.21$

a. False. Consider $\begin{bmatrix} 1 & 1 & 2 \\ -1 & 5 & 4 \\ 0 & 3 & 3 \end{bmatrix}$

b. True.

c. False.

d. False.

e. True.

f. False.

g. True.

h. True.

i. True.

j. True.

Exercise $3.E.22$

$$\begin{vmatrix} 1 & 2 & 1 \\ 2 & 3 & 2 \\ -4 & 1 & 2 \end{vmatrix} = -6$$

Exercise $3.E.23$

$$\begin{vmatrix} 2 & 1 & 3 \\ 2 & 4 & 2 \\ 1 & 4 & -5 \end{vmatrix} = -32$$

Exercise $3.E.24$

One can row reduce this using only row operation 3 to

$$\begin{bmatrix} 1 & 2 & 1 & 2 \\ 0 & -5 & -5 & -3 \\ 0 & 0 & 2 & \frac{9}{5} \\ 0 & 0 & 0 & -\frac{63}{10} \end{bmatrix}$$

and therefore, the determinant is -63.

$$\begin{vmatrix} 1 & 2 & 1 & 2 \\ 3 & 1 & -2 & 3 \\ -1 & 0 & 3 & 1 \\ 2 & 3 & 2 & -2 \end{vmatrix} = 63$$

Exercise $3.E.25$

One can row reduce this using only row operation 3 to

$$\begin{bmatrix} 1 & 4 & 1 & 2 \\ 0 & -10 & -5 & -3 \\ 0 & 0 & 2 & \frac{19}{5} \\ 0 & 0 & 0 & -\frac{211}{20} \end{bmatrix}$$

Thus the determinant is given by

$$\begin{vmatrix} 1 & 4 & 1 & 2 \\ 3 & 2 & -2 & 3 \\ -1 & 0 & 3 & 3 \\ 2 & 1 & 2 & -2 \end{vmatrix} = 211$$

Exercise $3.E.26$

$\det \begin{bmatrix} 1 & 2 & 3 \\ 0 & 2 & 1 \\ 3 & 1 & 0 \end{bmatrix} = -13$ and so it has an inverse. This inverse is

$$\frac{1}{-13}\begin{bmatrix} \begin{vmatrix} 2 & 1 \\ 1 & 0 \end{vmatrix} & -\begin{vmatrix} 0 & 1 \\ 3 & 0 \end{vmatrix} & \begin{vmatrix} 0 & 2 \\ 3 & 1 \end{vmatrix} \\ -\begin{vmatrix} 2 & 3 \\ 1 & 0 \end{vmatrix} & \begin{vmatrix} 1 & 3 \\ 3 & 0 \end{vmatrix} & -\begin{vmatrix} 1 & 2 \\ 3 & 1 \end{vmatrix} \\ \begin{vmatrix} 2 & 3 \\ 2 & 1 \end{vmatrix} & -\begin{vmatrix} 1 & 3 \\ 0 & 1 \end{vmatrix} & \begin{vmatrix} 1 & 2 \\ 0 & 2 \end{vmatrix} \end{bmatrix}^T = \frac{1}{-13}\begin{bmatrix} -1 & 3 & -6 \\ 3 & -9 & 5 \\ -4 & -1 & 2 \end{bmatrix}^T \tag{3.E.2}$$

$$= \begin{bmatrix} \frac{1}{13} & -\frac{3}{13} & \frac{4}{13} \\ -\frac{3}{13} & \frac{9}{13} & \frac{1}{13} \\ \frac{6}{13} & -\frac{5}{13} & -\frac{2}{13} \end{bmatrix}$$

Exercise $3.E.27$

$\det \begin{bmatrix} 1 & 2 & 0 \\ 0 & 2 & 1 \\ 3 & 1 & 1 \end{bmatrix} = 7$ so it has an inverse. This inverse is $\frac{1}{7}\begin{bmatrix} 1 & 3 & -6 \\ -2 & 1 & 5 \\ 2 & -1 & 2 \end{bmatrix}^T = \begin{bmatrix} \frac{1}{7} & -\frac{2}{7} & \frac{2}{7} \\ \frac{3}{7} & \frac{1}{7} & -\frac{1}{7} \\ -\frac{6}{7} & \frac{5}{7} & \frac{2}{7} \end{bmatrix}$

Exercise $3.E.28$

$$\det \begin{bmatrix} 1 & 3 & 3 \\ 2 & 4 & 1 \\ 0 & 1 & 1 \end{bmatrix} = 3$$

so it has an inverse which is

$$\begin{bmatrix} 1 & 0 & -3 \\ -\frac{2}{3} & \frac{1}{3} & \frac{5}{3} \\ \frac{2}{3} & -\frac{1}{3} & -\frac{2}{3} \end{bmatrix}$$

Exercise $3.E.30$

$$\det\begin{bmatrix}1&0&3\\1&0&1\\3&1&0\end{bmatrix}=2$$

and so it has an inverse. The inverse turns out to equal

$$\begin{bmatrix}-\frac{1}{2}&\frac{3}{2}&0\\\frac{3}{2}&-\frac{9}{2}&1\\\frac{1}{2}&-\frac{1}{2}&0\end{bmatrix}$$

Exercise $3.E.31$

a. $\begin{vmatrix}1&1\\1&2\end{vmatrix}=1$

b. $\begin{vmatrix}1&2&3\\0&2&1\\4&1&1\end{vmatrix}=-15$

c. $\begin{vmatrix}1&2&1\\2&3&0\\0&1&2\end{vmatrix}=0$

Exercise $3.E.32$

No. It has a nonzero determinant for all t

Exercise $3.E.33$

$$\det\begin{bmatrix}1&t&t^2\\0&1&2t\\t&0&2\end{bmatrix}=t^3+2$$

and so it has no inverse when $t=-\sqrt[3]{2}$

Exercise $3.E.34$

$$\det\begin{bmatrix}e^t&\cosh t&\sinh t\\e^t&\sinh t&\cosh t\\e^t&\cosh t&\sinh t\end{bmatrix}=0$$

and so this matrix fails to have a nonzero determinant at any value of t.

Exercise $3.E.35$

$$\det\begin{bmatrix}e^t&e^{-t}\cos t&e^{-t}\sin t\\e^t&-e^{-t}\cos t-e^{-t}\sin t&-e^{-t}\sin t+e^{-t}\cos t\\e^t&2e^{-t}\sin t&-2e^{-t}\cos t\end{bmatrix}=5e^{-t}\neq 0$$

and so this matrix is always invertible.

Exercise $3.E.36$

If $\det(A)\neq 0$, then A^{-1} exists and so you could multiply on both sides on the left by A^{-1} and obtain that $X=0$.

Exercise $3.E.37$

You have $1=\det(A)\det(B)$. Hence both A and B have inverses. Letting X be given,

$$A(BA-I)X=(AB)AX-AX=AX-AX=0$$

and so it follows from the above problem that $(BA-I)X=0$. Since X is arbitrary, it follows that $BA=I$.

Exercise $3.E.38$

$$\det\begin{bmatrix}e^t&0&0\\0&e^t\cos t&e^t\sin t\\0&e^t\cos t-e^t\sin t&e^t\cos t+e^t\sin t\end{bmatrix}=e^{3t}.$$

Hence the inverse is

$$e^{-3t}\begin{bmatrix}e^{2t}&0&0\\0&e^{2t}\cos t+e^{2t}\sin t&-(e^{2t}\cos t-e^{2t}\sin)t\\0&-e^{2t}\sin t&e^{2t}\cos(t)\end{bmatrix}^T$$
$$=\begin{bmatrix}e^{-t}&0&0\\0&e^{-t}(\cos t+\sin t)&-(\sin t)e^{-t}\\0&-e^{-t}(\cos t-\sin t)&(\cos t)e^{-t}\end{bmatrix}$$

Exercise $3.E.39$

$$\begin{bmatrix}e^t&\cos t&\sin t\\e^t&-\sin t&\cos t\\e^t&-\cos t&-\sin t\end{bmatrix}^{-1}$$
$$=\begin{bmatrix}\frac{1}{2}e^{-t}&0&\frac{1}{2}e^{-t}\\\frac{1}{2}\cos t+\frac{1}{2}\sin t&-\sin t&\frac{1}{2}\sin t-\frac{1}{2}\cos t\\\frac{1}{2}\sin t-\frac{1}{2}\cos t&\cos t&-\frac{1}{2}\cos t-\frac{1}{2}\sin t\end{bmatrix}$$

Exercise $3.E.40$

The given condition is what it takes for the determinant to be non zero. Recall that the determinant of an upper triangular matrix is just the product of the entries on the main diagonal

Exercise $3.E.41$

This follows because $\det(ABC) = \det(A)\det(B)\det(C)$ and if this product is nonzero, then each determinant in the product is nonzero and so each of these matrices is invertible.

Exercise $3.E.42$

False.

Exercise $3.E.43$

Solution is: $[x = 1, y = 0]$

Exercise $3.E.44$

Solution is: $[x = 1, y = 0, z = 0]$. For example,

$$y = \frac{\begin{vmatrix} 1 & 1 & 1 \\ 2 & 2 & -1 \\ 1 & 1 & 1 \end{vmatrix}}{\begin{vmatrix} 1 & 2 & 1 \\ 2 & -1 & -1 \\ 1 & 0 & 1 \end{vmatrix}} = 0$$

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4: R^n

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4.1: Vectors in Rⁿ

Outcomes

A. Find the position vector of a point in $\mathbb{R}^n$.

The notation $\mathbb{R}^n$ refers to the collection of ordered lists of n real numbers, that is

$$\mathbb{R}^n = \{(x_1 \cdots x_n) : x_j \in \mathbb{R} \text{ for } j = 1, \cdots, n\}$$

In this chapter, we take a closer look at vectors in $\mathbb{R}^n$. First, we will consider what $\mathbb{R}^n$ looks like in more detail. Recall that the point given by $0 = (0, \cdots, 0)$ is called the **origin**.

Now, consider the case of $\mathbb{R}^n$ for $n = 1$. Then from the definition we can identify $\mathbb{R}$ with points in $\mathbb{R}^1$ as follows:

$$\mathbb{R} = \mathbb{R}^1 = \{(x_1) : x_1 \in \mathbb{R}\}$$

Hence, $\mathbb{R}$ is defined as the set of all real numbers and geometrically, we can describe this as all the points on a line.

Now suppose $n = 2$. Then, from the definition,

$$\mathbb{R}^2 = \{(x_1, x_2) : x_j \in \mathbb{R} \text{ for } j = 1, 2\}$$

Consider the familiar coordinate plane, with an x axis and a y axis. Any point within this coordinate plane is identified by where it is located along the x axis, and also where it is located along the y axis. Consider as an example the following diagram.

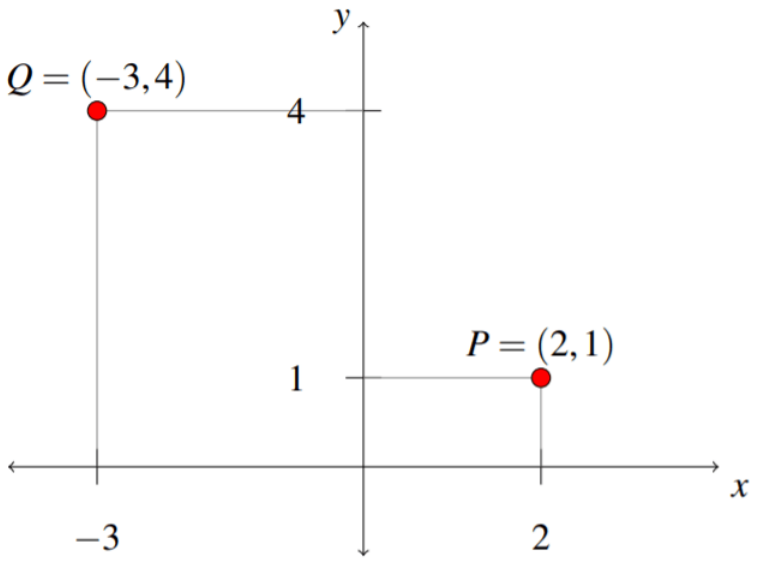


Figure 4.1.1

Hence, every element in $\mathbb{R}^2$ is identified by two components, x and y, in the usual manner. The coordinates x, y (or x_1,x_2) uniquely determine a point in the plan. Note that while the definition uses x_1 and x_2 to label the coordinates and you may be used to x and y, these notations are equivalent.

Now suppose $n = 3$. You may have previously encountered the 3-dimensional coordinate system, given by

$$\mathbb{R}^3 = \{(x_1, x_2, x_3) : x_j \in \mathbb{R} \text{ for } j = 1, 2, 3\}$$

Points in $\mathbb{R}^3$ will be determined by three coordinates, often written (x, y, z) which correspond to the x, y, and z axes. We can think as above that the first two coordinates determine a point in a plane. The third component determines the height above or below the plane, depending on whether this number is positive or negative, and all together this determines a point in space. You see that the ordered triples correspond to points in space just as the ordered pairs correspond to points in a plane and single real

numbers correspond to points on a line.

The idea behind the more general $\mathbb{R}^n$ is that we can extend these ideas beyond $n = 3$. This discussion regarding points in $\mathbb{R}^n$ leads into a study of vectors in $\mathbb{R}^n$. While we consider $\mathbb{R}^n$ for all n, we will largely focus on $n = 2, 3$ in this section.

Consider the following definition.

Definition 4.1.1 THe Position Vector

Let $P = (p_1, \cdots, p_n)$ be the coordinates of a point in $\mathbb{R}^n$. Then the vector $\overrightarrow{0P}$ with its tail at $0 = (0, \cdots, 0)$ and its tip at P is called the **position vector** of the point P. We write

$$\overrightarrow{0P} = \begin{bmatrix} p_1 \\ \vdots \\ p_n \end{bmatrix}$$

For this reason we may write both $P = (p_1, \cdots, p_n) \in \mathbb{R}^n$ and $\overrightarrow{0P} = [p_1 \cdots p_n]^T \in \mathbb{R}^n$.

This definition is illustrated in the following picture for the special case of $\mathbb{R}^3$.

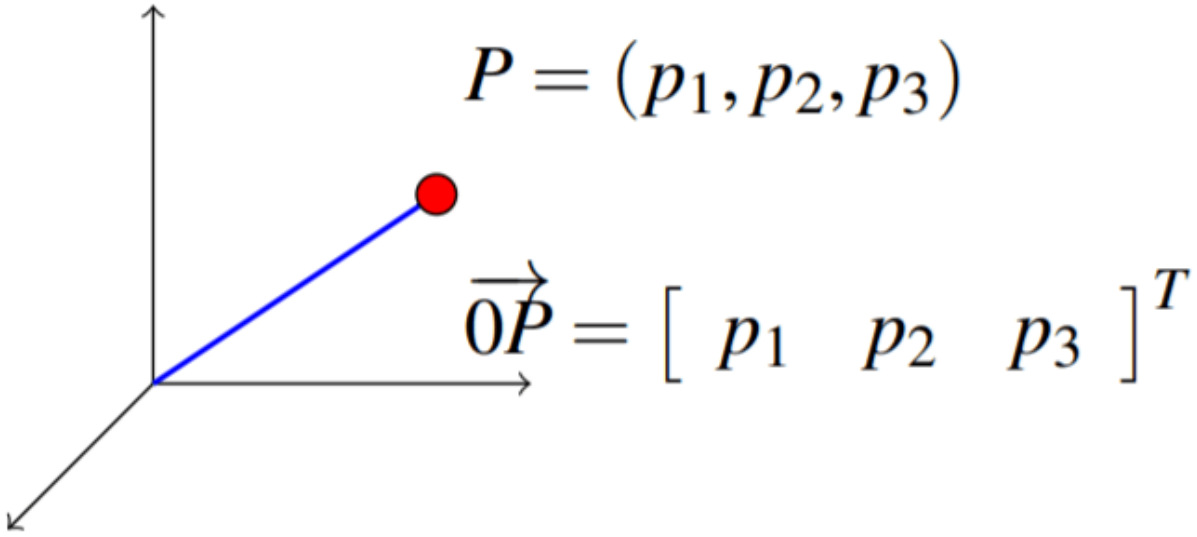


Figure 4.1.2

Thus every point P in $\mathbb{R}^n$ determines its position vector $\overrightarrow{0P}$. Conversely, every such position vector $\overrightarrow{0P}$ which has its tail at 0 and point at P determines the point P of $\mathbb{R}^n$.

Now suppose we are given two points, P, Q whose coordinates are $(p_1, \cdots, p_n)$ and $(q_1, \cdots, q_n)$ respectively. We can also determine the **position vector from** P **to** Q (also called the **vector from** P **to** Q) defined as follows.

$$\overrightarrow{PQ} = \begin{bmatrix} q_1 - p_1 \\ \vdots \\ q_n - p_n \end{bmatrix} = \overrightarrow{0Q} - \overrightarrow{0P}$$

Now, imagine taking a vector in $\mathbb{R}^n$ and moving it around, always keeping it pointing in the same direction as shown in the following picture.

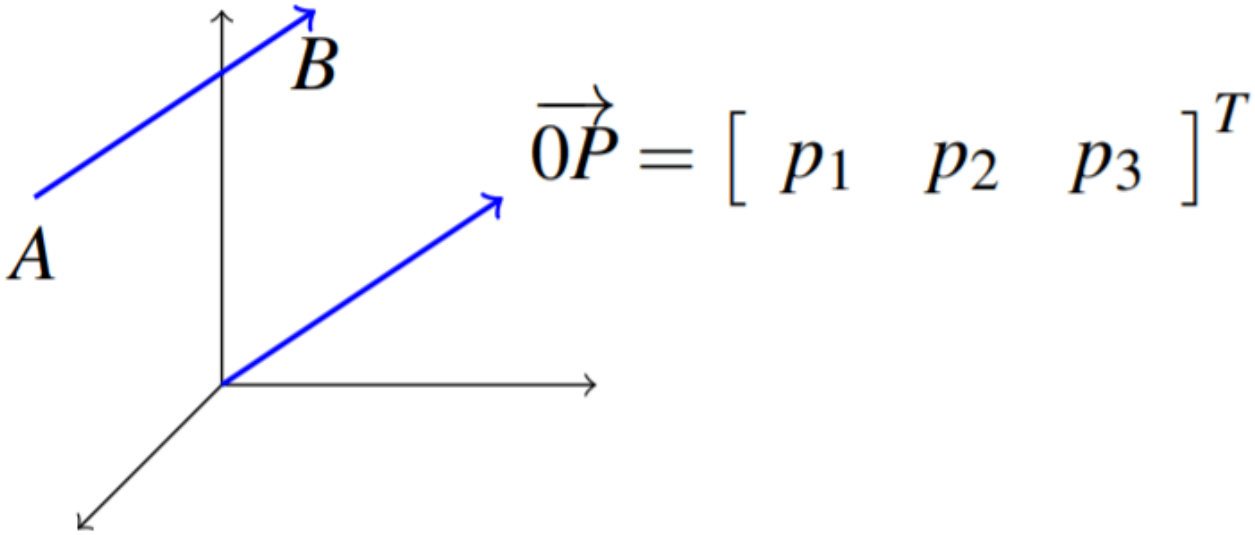


Figure 4.1.3

After moving it around, it is regarded as the same vector. Each vector, $\overrightarrow{0P}$ and $\overrightarrow{AB}$ has the same length (or magnitude) and direction. Therefore, they are equal.

Consider now the general definition for a vector in $\mathbb{R}^n$.

Definition 4.1.2 Vectors in $\mathbb{R}^n$

Let $\mathbb{R}^n = \{(x_1, \cdots, x_n) : x_j \in \mathbb{R} \text{ for } j = 1, \cdots, n\}$. Then,

$$\vec{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

is called a **vector**. Vectors have both size (magnitude) and direction. The numbers x_j are called the **components** of $\vec{x}$.

Using this notation, we may use $\vec{p}$ to denote the position vector of point P. Notice that in this context, $\vec{p} = \overrightarrow{0P}$. These notations may be used interchangeably.

You can think of the components of a vector as directions for obtaining the vector. Consider $n = 3$. Draw a vector with its tail at the point $(0, 0, 0)$ and its tip at the point (a, b, c). This vector it is obtained by starting at $(0, 0, 0)$, moving parallel to the x axis to $(a, 0, 0)$ and then from here, moving parallel to the y axis to $(a, b, 0)$ and finally parallel to the z axis to (a, b, c). Observe that the same vector would result if you began at the point (d, e, f), moved parallel to the x axis to $(d + a, e, f)$, then parallel to the y axis to $(d + a, e + b, f)$, and finally parallel to the z axis to $(d + a, e + b, f + c)$. Here, the vector would have its tail sitting at the point determined by $A = (d, e, f)$ and its point at $B = (d + a, e + b, f + c)$. It is the **same vector** because it will point in the same direction and have the same length. It is like you took an actual arrow, and moved it from one location to another keeping it pointing the same direction.

We conclude this section with a brief discussion regarding notation. In previous sections, we have written vectors as columns, or $n \times 1$ matrices. For convenience in this chapter we may write vectors as the transpose of row vectors, or $1 \times n$ matrices. These are of course equivalent and we may move between both notations. Therefore, recognize that

$$\begin{bmatrix} 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 2 & 3 \end{bmatrix}^T$$

Notice that two vectors $\vec{u} = [u_1 \cdots u_n]^T$ and $\vec{v} = [v_1 \cdots v_n]^T$ are equal if and only if all corresponding components are equal. Precisely,

$$\vec{u} = \vec{v} \text{ if and only if}$$
$$u_j = v_j \text{ for all } j = 1, \cdots, n$$

Thus $\begin{bmatrix} 1 & 2 & 4 \end{bmatrix}^T \in \mathbb{R}^3$ and $\begin{bmatrix} 2 & 1 & 4 \end{bmatrix}^T \in \mathbb{R}^3$ but $\begin{bmatrix} 1 & 2 & 4 \end{bmatrix}^T \neq \begin{bmatrix} 2 & 1 & 4 \end{bmatrix}^T$ because, even though the same numbers are involved, the order of the numbers is different.

For the specific case of $\mathbb{R}^3$, there are three special vectors which we often use. They are given by

$$\vec{i} = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}^T$$
$$\vec{j} = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix}^T$$
$$\vec{k} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}^T$$

We can write any vector $\vec{u} = \begin{bmatrix} u_1 & u_2 & u_3 \end{bmatrix}^T$ as a linear combination of these vectors, written as $\vec{u} = u_1\vec{i} + u_2\vec{j} + u_3\vec{k}$. This notation will be used throughout this chapter.

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4.2: Vector Algebra

Outcomes

A. Understand vector addition and scalar multiplication, algebraically.
B. Introduce the notion of linear combination of vectors.

Addition and scalar multiplication are two important algebraic operations done with vectors. Notice that these operations apply to vectors in $\mathbb{R}^n$, for any value of n. We will explore these operations in more detail in the following sections.

Addition of Vectors in $\mathbb{R}^n$

Addition of vectors in $\mathbb{R}^n$ is defined as follows.

Definition 4.2.1: Addition of Vectors in $\mathbb{R}^n$

If $\vec{u} = \begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix}$, $\vec{v} = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix} \in \mathbb{R}^n$ then $\vec{u} + \vec{v} \in \mathbb{R}^n$ and is defined by

$$\begin{aligned} \vec{u} + \vec{v} &= \begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix} + \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix} \\ &= \begin{bmatrix} u_1 + v_1 \\ \vdots \\ u_n + v_n \end{bmatrix} \end{aligned} \tag{4.2.1}$$

To add vectors, we simply add corresponding components. Therefore, in order to add vectors, they must be the same size.

Addition of vectors satisfies some important properties which are outlined in the following theorem.

Theorem 4.2.1: Properties of Vector Addition

The following properties hold for vectors $\vec{u}, \vec{v}, \vec{w} \in \mathbb{R}^n$.

- The Commutative Law of Addition
$$\vec{u} + \vec{v} = \vec{v} + \vec{u}$$
- The Associative Law of Addition
$$(\vec{u} + \vec{v}) + \vec{w} = \vec{u} + (\vec{v} + \vec{w})$$
- The Existence of an Additive Identity
$$\vec{u} + \vec{0} = \vec{u} \tag{4.2.2}$$
- The Existence of an Additive Inverse
$$\vec{u} + (-\vec{u}) = \vec{0}$$

The additive identity shown in Equation (4.2.2) is also called the **zero vector**, the $n \times 1$ vector in which all components are equal to 0. Further, $-\vec{u}$ is simply the vector with all components having same value as those of $\vec{u}$ but opposite sign; this is just $(-1)\vec{u}$. This will be made more explicit in the next section when we explore scalar multiplication of vectors. Note that subtraction is

defined as $\vec{u} - \vec{v} = \vec{u} + (-\vec{v})$.

Scalar Multiplication of Vectors in $\mathbb{R}^n$

Scalar multiplication of vectors in $\mathbb{R}^n$ is defined as follows.

Definition 4.2.2: Scalar Multiplication of Vectors in $\mathbb{R}^n$

If $\vec{u} \in \mathbb{R}^n$ and $k \in \mathbb{R}$ is a scalar, then $k\vec{u} \in \mathbb{R}^n$ is defined by

$$k\vec{u} = k \begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix} = \begin{bmatrix} ku_1 \\ \vdots \\ ku_n \end{bmatrix}$$

Just as with addition, scalar multiplication of vectors satisfies several important properties. These are outlined in the following theorem.

Theorem 4.2.2: Properties of Scalar Multiplication

The following properties hold for vectors $\vec{u}, \vec{v} \in \mathbb{R}^n$ and k, p scalars.

- The Distributive Law over Vector Addition
$$k\left(\vec{u} + \vec{v}\right) = k\vec{u} + k\vec{v}$$
- The Distributive Law over Scalar Addition
$$\left(k + p\right)\vec{u} = k\vec{u} + p\vec{u}$$
- The Associative Law for Scalar Multiplication
$$k\left(p\vec{u}\right) = \left(kp\right)\vec{u}$$
- Rule for Multiplication by 1
$$1\vec{u} = \vec{u}$$

Proof available at the end of this section.

We now present a useful notion you may have seen earlier combining vector addition and scalar multiplication

Definition 4.2.3: Linear Combination

A vector $\vec{v}$ is said to be a **linear combination** of the vectors $\vec{u}_1, \cdots, \vec{u}_n$ if there exist scalars, $a_1, \cdots, a_n$ such that

$$\vec{v} = a_1\vec{u}_1 + \cdots + a_n\vec{u}_n$$

For example,

$$3\begin{bmatrix} -4 \\ 1 \\ 0 \end{bmatrix} + 2\begin{bmatrix} -3 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} -18 \\ 3 \\ 2 \end{bmatrix}.$$

Thus we can say that

$$\vec{v} = \begin{bmatrix} -18 \\ 3 \\ 2 \end{bmatrix}$$

is a linear combination of the vectors

$$\vec{u}_1 = \begin{bmatrix} -4 \\ 1 \\ 0 \end{bmatrix} \text{ and } \vec{u}_2 = \begin{bmatrix} -3 \\ 0 \\ 1 \end{bmatrix}$$

Answers

Theorem 4.2.2**: Properties of Scalar Multiplication**

We will show the proof of:

$$k(\vec{u} + \vec{v}) = k\vec{u} + k\vec{v}$$

Note that:

$$\begin{aligned} k(\vec{u} + \vec{v}) &= k[u_1 + v_1 \cdots u_n + v_n]^T \\ &= [k(u_1 + v_1) \cdots k(u_n + v_n)]^T \\ &= [ku_1 + kv_1 \cdots ku_n + kv_n]^T \\ &= [ku_1 \cdots ku_n]^T + [kv_1 \cdots kv_n]^T \\ &= k\vec{u} + k\vec{v} \end{aligned}$$

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4.3: Geometric Meaning of Vector Addition

Learning Objectives

A. Understand vector addition, geometrically.

Recall that an element of $\mathbb{R}^n$ is an ordered list of numbers. For the specific case of $n = 2, 3$ this can be used to determine a point in two or three dimensional space. This point is specified relative to some coordinate axes.

Consider the case $n = 3$. Recall that taking a vector and moving it around without changing its length or direction does not change the vector. This is important in the geometric representation of vector addition.

Suppose we have two vectors, $\vec{u}$ and $\vec{v}$ in $\mathbb{R}^3$. Each of these can be drawn geometrically by placing the tail of each vector at 0 and its point at (u_1, u_2, u_3) and (v_1, v_2, v_3) respectively. Suppose we slide the vector $\vec{v}$ so that its tail sits at the point of $\vec{u}$. We know that this does not change the vector $\vec{v}$. Now, draw a new vector from the tail of $\vec{u}$ to the point of $\vec{v}$. This vector is $\vec{u} + \vec{v}$.

The geometric significance of vector addition in $\mathbb{R}^n$ for any n is given in the following definition.

Definition 4.3.1: Geometry of Vector Addition

Let $\vec{u}$ and $\vec{v}$ be two vectors. Slide $\vec{v}$ so that the tail of $\vec{v}$ is on the point of $\vec{u}$. Then draw the arrow which goes from the tail of $\vec{u}$ to the point of $\vec{v}$. This arrow represents the vector $\vec{u} + \vec{v}$.

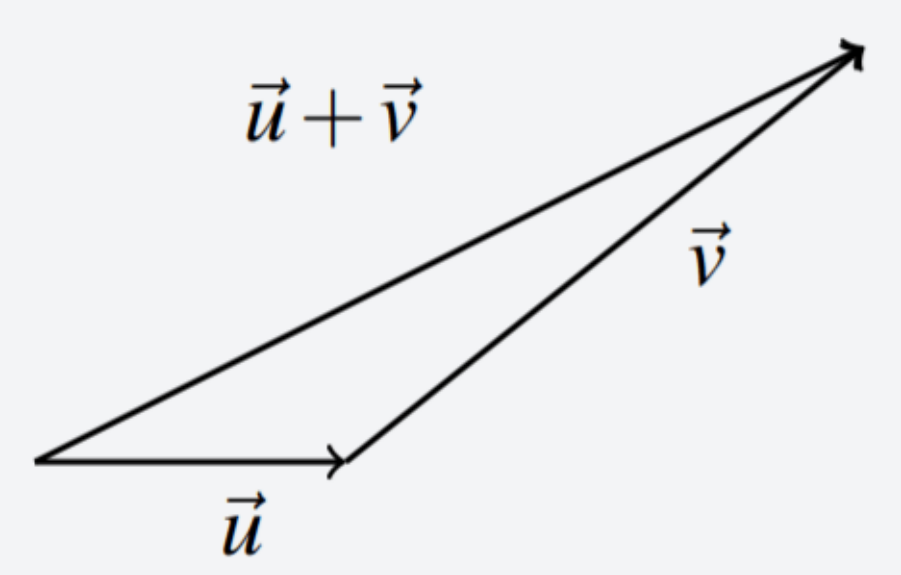


Figure 4.3.1

This definition is illustrated in the following picture in which $\vec{u} + \vec{v}$ is shown for the special case $n = 3$.

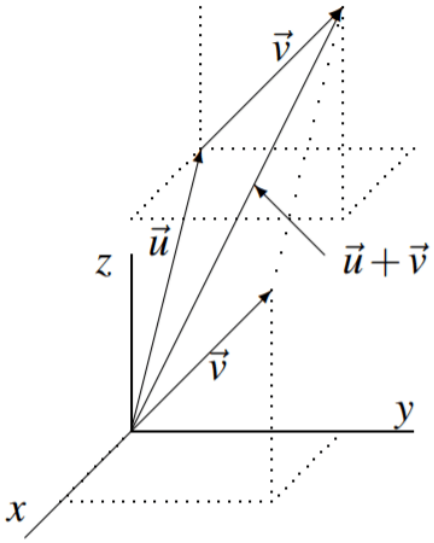


Figure 4.3.2

Notice the parallelogram created by $\vec{u}$ and $\vec{v}$ in the above diagram. Then $\vec{u}+\vec{v}$ is the directed diagonal of the parallelogram determined by the two vectors $\vec{u}$ and $\vec{v}$.

When you have a vector $\vec{v}$, its additive inverse $-\vec{v}$ will be the vector which has the same magnitude as $\vec{v}$ but the opposite direction. When one writes $\vec{u}-\vec{v}$, the meaning is $\vec{u}+(-\vec{v})$ as with real numbers. The following example illustrates these definitions and conventions.

Example 4.3.1: Graphing Vector Addition

Consider the following picture of vectors $\vec{u}$ and $\vec{v}$.



Figure 4.3.3

Sketch a picture of $\vec{u}+\vec{v}, \vec{u}-\vec{v}$.

Solution

We will first sketch $\vec{u}+\vec{v}$. Begin by drawing $\vec{u}$ and then at the point of $\vec{u}$, place the tail of $\vec{v}$ as shown. Then $\vec{u}+\vec{v}$ is the vector which results from drawing a vector from the tail of $\vec{u}$ to the tip of $\vec{v}$.

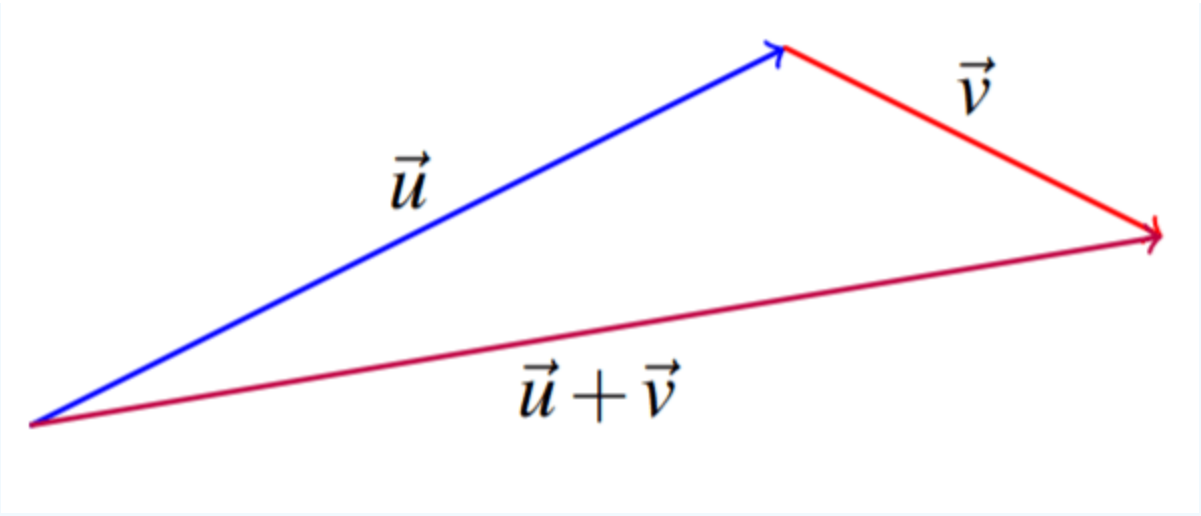


Figure 4.3.4

Next consider $\vec{u}-\vec{v}$. This means $\vec{u}+(-\vec{v})$. From the above geometric description of vector addition, $-\vec{v}$ is the vector which has the same length but which points in the opposite direction to $\vec{v}$. Here is a picture.

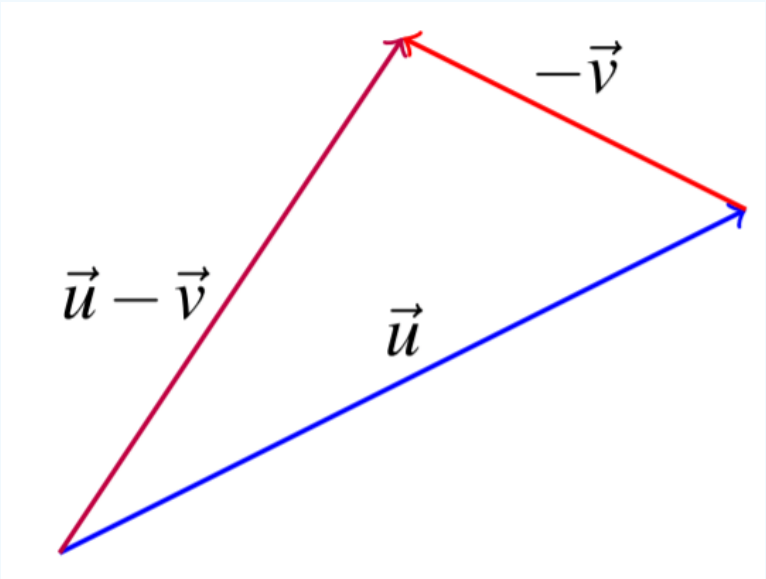


Figure 4.3.5

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4.4: Length of a Vector

Learning Objectives

- Find the length of a vector and the distance between two points in $\mathbb{R}^n$.
- Find the corresponding unit vector to a vector in $\mathbb{R}^n$.

In this section, we explore what is meant by the length of a vector in $\mathbb{R}^n$. We develop this concept by first looking at the distance between two points in $\mathbb{R}^n$.

First, we will consider the concept of distance for $\mathbb{R}$, that is, for points in $\mathbb{R}^1$. Here, the distance between two points P and Q is given by the absolute value of their difference. We denote the distance between P and Q by $d(P,Q)$ which is defined as

$$d(P,Q) = \sqrt{(P-Q)^2} \tag{4.4.1}$$

Consider now the case for $n = 2$, demonstrated by the following picture.

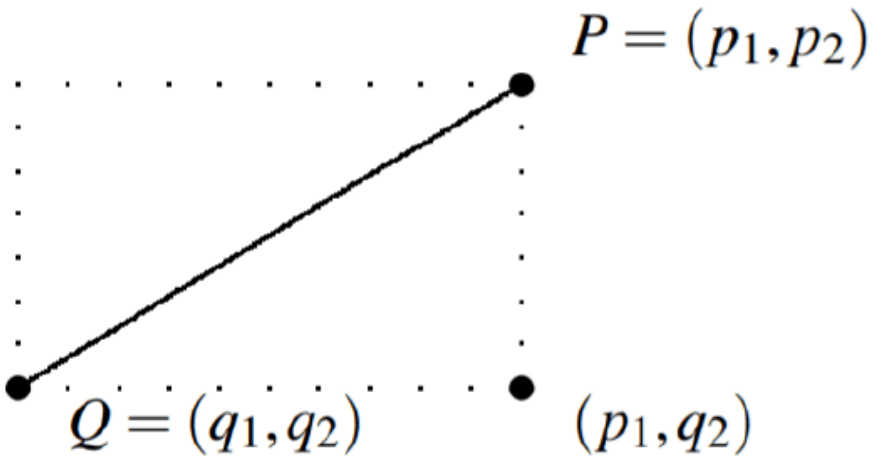


Figure 4.4.1

There are two points $P = (p_1, p_2)$ and $Q = (q_1, q_2)$ in the plane. The distance between these points is shown in the picture as a solid line. Notice that this line is the hypotenuse of a right triangle which is half of the rectangle shown in dotted lines. We want to find the length of this hypotenuse which will give the distance between the two points. Note the lengths of the sides of this triangle are $|p_1 - q_1|$ and $|p_2 - q_2|$, the absolute value of the difference in these values. Therefore, the Pythagorean Theorem implies the length of the hypotenuse (and thus the distance between P and Q) equals

$$\left(|p_1 - q_1|^2 + |p_2 - q_2|^2\right)^{1/2} = \left((p_1 - q_1)^2 + (p_2 - q_2)^2\right)^{1/2} \tag{4.4.2}$$

Now suppose $n = 3$ and let $P = (p_1, p_2, p_3)$ and $Q = (q_1, q_2, q_3)$ be two points in $\mathbb{R}^3$. Consider the following picture in which the solid line joins the two points and a dotted line joins the points (q_1, q_2, q_3) and (p_1, p_2, q_3).

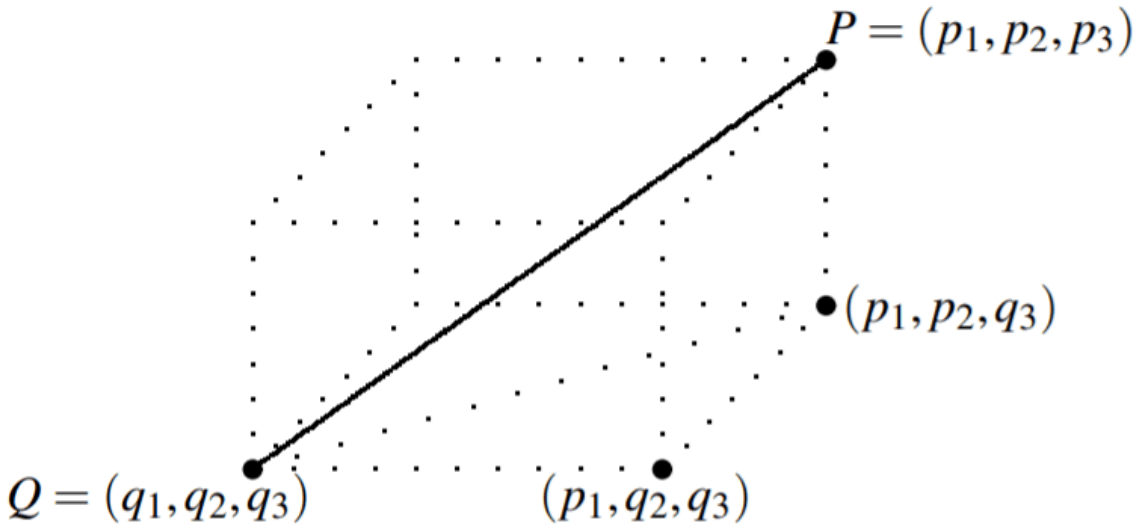


Figure 4.4.2

Here, we need to use Pythagorean Theorem twice in order to find the length of the solid line. First, by the Pythagorean Theorem, the length of the dotted line joining (q_1, q_2, q_3) and (p_1, p_2, q_3) equals

$$\left((p_1 - q_1)^2 + (p_2 - q_2)^2\right)^{1/2}$$

while the length of the line joining (p_1, p_2, q_3) to (p_1, p_2, p_3) is just $|p_3 - q_3|$. Therefore, by the Pythagorean Theorem again, the length of the line joining the points $P = (p_1, p_2, p_3)$ and $Q = (q_1, q_2, q_3)$ equals

$$\begin{aligned} &\left(\left(\left((p_1 - q_1)^2 + (p_2 - q_2)^2\right)^{1/2}\right)^2 + (p_3 - q_3)^2\right)^{1/2} \\ &= \left((p_1 - q_1)^2 + (p_2 - q_2)^2 + (p_3 - q_3)^2\right)^{1/2} \end{aligned} \tag{4.4.3}$$

This discussion motivates the following definition for the distance between points in $\mathbb{R}^n$.

Definition 4.4.1: Distance Between Points

Let $P = (p_1, \cdots, p_n)$ and $Q = (q_1, \cdots, q_n)$ be two points in $\mathbb{R}^n$. Then the distance between these points is defined as

$$\text{distance between } P \text{ and } Q \ = d(P, Q) = \left(\sum_{k=1}^{n} |p_k - q_k|^2\right)^{1/2}$$

This is called the **distance formula**. We may also write $|P - Q|$ as the distance between P and Q.

From the above discussion, you can see that Definition 4.4.1 holds for the special cases $n = 1, 2, 3$, as in Equations (4.4.1), (4.4.2), (4.4.3). In the following example, we use Definition 4.4.1 to find the distance between two points in $\mathbb{R}^4$.

Example 4.4.1: Distance Between Points

Find the distance between the points P and Q in $\mathbb{R}^4$, where P and Q are given by

$$P = (1, 2, -4, 6)$$

and

$$Q = (2, 3, -1, 0)$$

Solution

We will use the formula given in Definition 4.4.1 to find the distance between P and Q. Use the distance formula and write

$$d(P,Q) = \left((1-2)^2 + (2-3)^2 + (-4-(-1))^2 + (6-0)^2\right)^{\frac{1}{2}} = 47$$

Therefore, $d(P,Q) = \sqrt{47}$.

There are certain properties of the distance between points which are important in our study. These are outlined in the following theorem.

Theorem 4.4.1: Properties of Distance

Let P and Q be points in $\mathbb{R}^n$, and let the distance between them, $d(P,Q)$, be given as in Definition 4.4.1. Then, the following properties hold.

- $d(P,Q) = d(Q,P)$
- $d(P,Q) \geq 0$, and equals 0 exactly when $P = Q$.

There are many applications of the concept of distance. For instance, given two points, we can ask what collection of points are all the same distance between the given points. This is explored in the following example.

Example 4.4.2: The Plane Between Two Points

Describe the points in $\mathbb{R}^3$ which are at the same distance between $(1,2,3)$ and $(0,1,2)$.

Solution

Let $P = (p_1, p_2, p_3)$ be such a point. Therefore, P is the same distance from $(1,2,3)$ and $(0,1,2)$. Then byDefinition 4.4.1,

$$\sqrt{(p_1-1)^2 + (p_2-2)^2 + (p_3-3)^2} = \sqrt{(p_1-0)^2 + (p_2-1)^2 + (p_3-2)^2}$$

Squaring both sides we obtain

$$(p_1-1)^2 + (p_2-2)^2 + (p_3-3)^2 = p_1^2 + (p_2-1)^2 + (p_3-2)^2$$

and so

$$p_1^2 - 2p_1 + 14 + p_2^2 - 4p_2 + p_3^2 - 6p_3 = p_1^2 + p_2^2 - 2p_2 + 5 + p_3^2 - 4p_3$$

Simplifying, this becomes

$$-2p_1 + 14 - 4p_2 - 6p_3 = -2p_2 + 5 - 4p_3$$

which can be written as

$$2p_1 + 2p_2 + 2p_3 = -9 \tag{4.4.4}$$

Therefore, the points $P = (p_1, p_2, p_3)$ which are the same distance from each of the given points form a plane whose equation is given by (4.4.4).

We can now use our understanding of the distance between two points to define what is meant by the length of a vector. Consider the following definition.

Definition 4.4.2: Length of a Vector

Let $\vec{u} = [u_1 \cdots u_n]^T$ be a vector in $\mathbb{R}^n$. Then, the length of $\vec{u}$, written $\|\vec{u}\|$ is given by

$$\|\vec{u}\| = \sqrt{u_1^2 + \cdots + u_n^2}$$

This definition corresponds to Definition 4.4.1, if you consider the vector $\vec{u}$ to have its tail at the point $0 = (0, \cdots, 0)$ and its tip at

the point $U = (u_1, \cdots, u_n)$. Then the length of $\vec{u}$ is equal to the distance between 0 and U, $d(0, U)$. In general, $d(P, Q) = ||\vec{PQ}||$.

ConsiderExample 4.4.1. ByDefinition 4.4.2, we could also find the distance between P and Q as the length of the vector connecting them. Hence, if we were to draw a vector $\overrightarrow{PQ}$ with its tail at P and its point at Q, this vector would have length equal to $\sqrt{47}$.

We conclude this section with a new definition for the special case of vectors of length 1.

Definition 4.4.3: Unit Vector

Let $\vec{u}$ be a vector in $\mathbb{R}^n$. Then, we call $\vec{u}$ a **unit vector** if it has length 1, that is if

$$\|\vec{u}\| = 1$$

Let $\vec{v}$ be a vector in $\mathbb{R}^n$. Then, the vector $\vec{u}$ which has the same direction as $\vec{v}$ but length equal to 1 is the corresponding unit vector of $\vec{v}$. This vector is given by

$$\vec{u} = \frac{1}{\|\vec{v}\|}\vec{v}$$

We often use the term **normalize** to refer to this process. When we **normalize** a vector, we find the corresponding unit vector of length 1. Consider the following example.

Example 4.4.3: Finding a Unit Vector

Let $\vec{v}$ be given by

$$\vec{v} = \begin{bmatrix} 1 & -3 & 4 \end{bmatrix}^T$$

Find the unit vector $\vec{u}$ which has the same direction as $\vec{v}$.

Solution

We will use Definition 4.4.3 to solve this. Therefore, we need to find the length of $\vec{v}$ which, by Definition 4.4.2 is given by

$$\|\vec{v}\| = \sqrt{v_1^2 + v_2^2 + v_3^2}$$

Using the corresponding values we find that

$$\begin{aligned} \|\vec{v}\| &= \sqrt{1^2 + (-3)^2 + 4^2} \\ &= \sqrt{1 + 9 + 16} \\ &= \sqrt{26} \end{aligned} \tag{4.4.5}$$

In order to find $\vec{u}$, we divide $\vec{v}$ by $\sqrt{26}$. The result is

$$\begin{aligned} \vec{u} &= \frac{1}{\|\vec{v}\|}\vec{v} \\ &= \frac{1}{\sqrt{26}}\begin{bmatrix} 1 & -3 & 4 \end{bmatrix}^T \\ &= \begin{bmatrix} \frac{1}{\sqrt{26}} & -\frac{3}{\sqrt{26}} & \frac{4}{\sqrt{26}} \end{bmatrix}^T \end{aligned} \tag{4.4.6}$$

You can verify using the Definition 4.4.1 that $\|\vec{u}\| = 1$.

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4.5: Geometric Meaning of Scalar Multiplication

Outcomes

A. Understand scalar multiplication, geometrically.

Recall that the point $P = (p_1, p_2, p_3)$ determines a vector $\vec{p}$ from 0 to P. The length of $\vec{p}$, denoted $\|\vec{p}\|$, is equal to $\sqrt{p_1^2 + p_2^2 + p_3^2}$ by Definition 4.4.1.

Now suppose we have a vector $\vec{u} = \begin{bmatrix} u_1 & u_2 & u_3 \end{bmatrix}^T$ and we multiply $\vec{u}$ by a scalar k. By Definition 4.2.2, $k\vec{u} = \begin{bmatrix} ku_1 & ku_2 & ku_3 \end{bmatrix}^T$. Then, by using Definition 4.4.1, the length of this vector is given by

$$\sqrt{\left((ku_1)^2 + (ku_2)^2 + (ku_3)^2\right)} = |k| \sqrt{u_1^2 + u_2^2 + u_3^2}$$

Thus the following holds.

$$\|k\vec{u}\| = |k| \, \|\vec{u}\|$$

In other words, multiplication by a scalar magnifies or shrinks the length of the vector by a factor of $|k|$. If $|k| > 1$, the length of the resulting vector will be magnified. If $|k| < 1$, the length of the resulting vector will shrink. Remember that by the definition of the absolute value, $|k| > 0$.

What about the direction? Draw a picture of $\vec{u}$ and $k\vec{u}$ where k is negative. Notice that this causes the resulting vector to point in the opposite direction while if $k > 0$ it preserves the direction the vector points. Therefore the direction can either reverse, if $k < 0$, or remain preserved, if $k > 0$.

Consider the following example.

Example 4.5.1: Graphing Scalar Multiplication

Consider the vectors $\vec{u}$ and $\vec{v}$ drawn below.



Figure 4.5.1

Draw $-\vec{u}$, $2\vec{v}$, and $-\frac{1}{2}\vec{v}$.

Solution

In order to find $-\vec{u}$, we preserve the length of $\vec{u}$ and simply reverse the direction. For $2\vec{v}$, we double the length of $\vec{v}$, while preserving the direction. Finally $-\frac{1}{2}\vec{v}$ is found by taking half the length of $\vec{v}$ and reversing the direction. These vectors are shown in the following diagram.

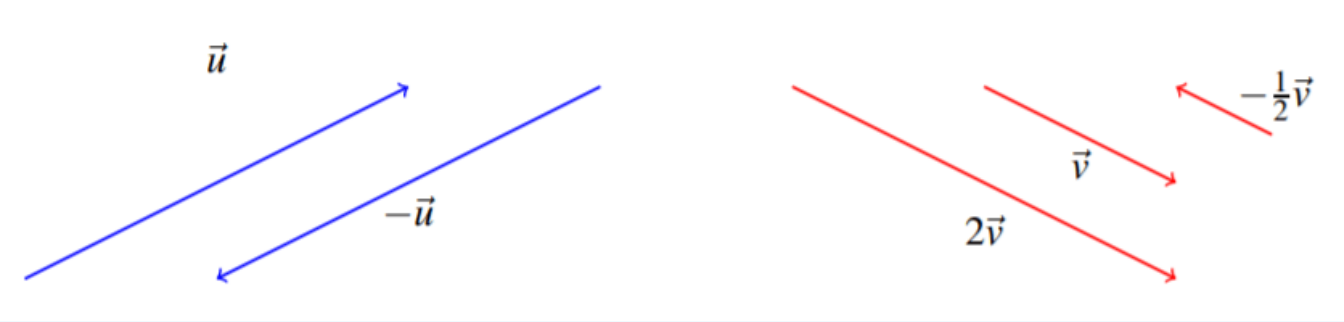


Figure 4.5.2

Now that we have studied both vector addition and scalar multiplication, we can combine the two actions. Recall Definition 9.2.2 of linear combinations of column matrices. We can apply this definition to vectors in $\mathbb{R}^n$. A linear combination of vectors in $\mathbb{R}^n$ is a sum of vectors multiplied by scalars.

In the following example, we examine the geometric meaning of this concept.

Example 4.5.2: Graphing a Linear Combination of Vectors

Consider the following picture of the vectors $\vec{u}$ and $\vec{v}$



Figure 4.5.3

Sketch a picture of $\vec{u}+2\vec{v}, \vec{u}-\frac{1}{2}\vec{v}$.

Solution

The two vectors are shown below.

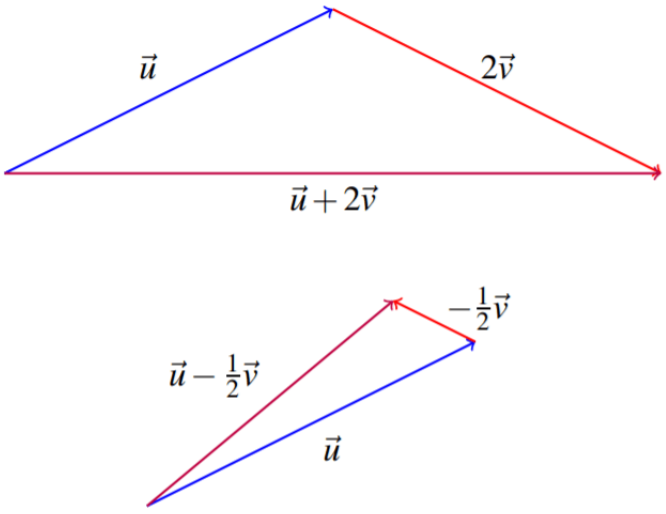


Figure 4.5.4

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4.6: Parametric Lines

Outcomes

A. Find the vector and parametric equations of a line.

We can use the concept of vectors and points to find equations for arbitrary lines in $\mathbb{R}^n$, although in this section the focus will be on lines in $\mathbb{R}^3$.

To begin, consider the case $n = 1$ so we have $\mathbb{R}^1 = \mathbb{R}$. There is only one line here which is the familiar number line, that is $\mathbb{R}$ itself. Therefore it is not necessary to explore the case of $n = 1$ further.

Now consider the case where $n = 2$, in other words $\mathbb{R}^2$. Let P and P_0 be two different points in $\mathbb{R}^2$ which are contained in a line L. Let $\vec{p}$ and $\vec{p_0}$ be the position vectors for the points P and P_0 respectively. Suppose that Q is an arbitrary point on L. Consider the following diagram.

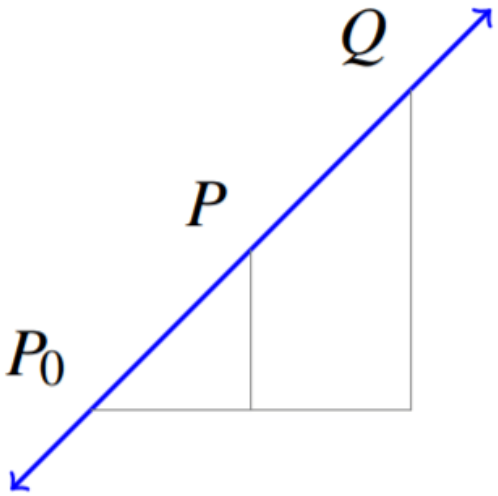


Figure 4.6.1

Our goal is to be able to define Q in terms of P and P_0. Consider the vector $\overrightarrow{P_0P} = \vec{p} - \vec{p_0}$ which has its tail at P_0 and point at P. If we add $\vec{p} - \vec{p_0}$ to the position vector $\vec{p_0}$ for P_0, the sum would be a vector with its point at P. In other words,

$$\vec{p} = \vec{p_0} + (\vec{p} - \vec{p_0})$$

Now suppose we were to add $t(\vec{p} - \vec{p_0})$ to $\vec{p}$ where t is some scalar. You can see that by doing so, we could find a vector with its point at Q. In other words, we can find t such that

$$\vec{q} = \vec{p_0} + t\,(\vec{p} - \vec{p_0})$$

This equation determines the line L in $\mathbb{R}^2$. In fact, it determines a line L in $\mathbb{R}^n$. Consider the following definition.

Definition 4.6.1: Vector Equation of a Line

Suppose a line L in $\mathbb{R}^n$ contains the two different points P and P_0. Let $\vec{p}$ and $\vec{p_0}$ be the position vectors of these two points, respectively. Then, L is the collection of points Q which have the position vector $\vec{q}$ given by

$$\vec{q} = \vec{p_0} + t\,(\vec{p} - \vec{p_0})$$

where $t \in \mathbb{R}$.

Let $\vec{d} = \vec{p} - \vec{p_0}$. Then $\vec{d}$ is the **direction vector for** L and the **vector equation** for L is given by

$$\vec{p} = \vec{p_0} + t\vec{d}, t \in \mathbb{R}$$

Note that this definition agrees with the usual notion of a line in two dimensions and so this is consistent with earlier concepts. Consider now points in $\mathbb{R}^3$. If a point $P \in \mathbb{R}^3$ is given by $P = (x, y, z)$, $P_0 \in \mathbb{R}^3$ by $P_0 = (x_0, y_0, z_0)$, then we can write

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x_0 \\ y_0 \\ z_0 \end{bmatrix} + t \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

where $\vec{d} = \begin{bmatrix} a \\ b \\ c \end{bmatrix}$. This is the vector equation of L written in **component form** .

The following theorem claims that such an equation is in fact a line.

Proposition 4.6.1: Algebraic Description of a Straight Line

Let $\vec{a}, \vec{b} \in \mathbb{R}^n$ with $\vec{b} \neq \vec{0}$. Then $\vec{x} = \vec{a} + t\vec{b}, \ \ t \in \mathbb{R}$, is a line.

Proof available at the end of this section.

We can use the above discussion to find the equation of a line when given two distinct points. Consider the following example.

Example 4.6.1: A Line From Two Points

Find a vector equation for the line through the points $P_0 = (1, 2, 0)$ and $P = (2, -4, 6)$.

Solution

We will use the definition of a line given above in Definition 4.6.1 to write this line in the form

$$\vec{q} = \vec{p_0} + t\left(\vec{p} - \vec{p_0}\right)$$

Let $\vec{q} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} B$. Then, we can find $\vec{p}$ and $\vec{p_0}$ by taking the position vectors of points P and P_0 respectively. Then,

$$\vec{q} = \vec{p_0} + t\left(\vec{p} - \vec{p_0}\right)$$

can be written as

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} B = \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix} B + t \begin{bmatrix} 1 \\ -6 \\ 6 \end{bmatrix} B, \ t \in \mathbb{R}$$

Here, the direction vector $\begin{bmatrix} 1 \\ -6 \\ 6 \end{bmatrix} B$ is obtained by $\vec{p} - \vec{p_0} = \begin{bmatrix} 2 \\ -4 \\ 6 \end{bmatrix} B - \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix} B$ as indicated above in Definition 4.6.1.

Notice that in the above example we said that we found “a” vector equation for the line, not “the” equation. The reason for this terminology is that there are infinitely many different vector equations for the same line. To see this, replace t with another parameter, say $3s$. Then you obtain a different vector equation for the same line because the same set of points is obtained.

In Example 4.6.1, the vector given by $\begin{bmatrix} 1 \\ -6 \\ 6 \end{bmatrix} B$ is the direction vector defined in Definition 4.6.1. If we know the direction vector of a line, as well as a point on the line, we can find the vector equation.

Consider the following example.

Example 4.6.2: A Line From a Point and a Direction Vector

Find a vector equation for the line which contains the point $P_0 = (1, 2, 0)$ and has direction vector $\vec{d} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} B$

Solution

We will use Definition 4.6.1 to write this line in the form $\vec{p} = \vec{p_0} + t\vec{d}, \quad t \in \mathbb{R}$. We are given the direction vector $\vec{d}$. In order to find $\vec{p_0}$, we can use the position vector of the point P_0. This is given by $\begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix} B$. Letting $\vec{p} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} B$, the equation for the line is given by

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} B = \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix} B + t \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} B, \; t \in \mathbb{R} \tag{4.6.1}$$

We sometimes elect to write a line such as the one given in (4.6.1) in the form

$$\left.\begin{array}{l} x = 1 + t \\ y = 2 + 2t \\ z = t \end{array}\right\} \quad \text{where } t \in \mathbb{R} \tag{4.6.2}$$

This set of equations give the same information as (4.6.1), and is called the **parametric equation of the line**.

Consider the following definition.

Definition 4.6.2: Parametric Equation of a Line

Let L be a line in $\mathbb{R}^3$ which has direction vector $\vec{d} = \begin{bmatrix} a \\ b \\ c \end{bmatrix} B$ and goes through the point $P_0 = (x_0, y_0, z_0)$. Then, letting t be a parameter, we can write L as

$$\left.\begin{array}{l} x = x_0 + ta \\ y = y_0 + tb \\ z = z_0 + tc \end{array}\right\} \quad \text{where } t \in \mathbb{R}$$

This is called a **parametric equation** of the line L.

You can verify that the form discussed following Example 4.6.2 in equation (4.6.2) is of the form given in Definition 4.6.2.

There is one other form for a line which is useful, which is the **symmetric form**. Consider the line given by (4.6.2). You can solve for the parameter t to write

$$\begin{array}{l} t = x - 1 \\ t = \frac{y-2}{2} \\ t = z \end{array}$$

Therefore,

$$x-1=\frac{y-2}{2}=z$$

This is the **symmetric form** of the line.

In the following example, we look at how to take the equation of a line from symmetric form to parametric form.

Example 4.6.3: Change Symmetric Form to Parametric Form

Suppose the **symmetric form of a line** is

$$\frac{x-2}{3}=\frac{y-1}{2}=z+3$$

Write the line in parametric form as well as vector form.

Solution

We want to write this line in the form given by Definition 4.6.2. This is of the form

$$\left.\begin{array}{l} x=x_0+ta \\ y=y_0+tb \\ z=z_0+tc \end{array}\right\} \text{ where } t\in\mathbb{R}$$

Let $t=\frac{x-2}{3}, t=\frac{y-1}{2}$ and $t=z+3$, as given in the symmetric form of the line. Then solving for x,y,z, yields

$$\left.\begin{array}{l} x=2+3t \\ y=1+2t \\ z=-3+t \end{array}\right\} \text{ with } t\in\mathbb{R}$$

This is the parametric equation for this line.

Now, we want to write this line in the form given by Definition 4.6.1. This is the form

$$\vec{p}=\vec{p_0}+t\vec{d}$$

where $t\in\mathbb{R}$. This equation becomes

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} B=\begin{bmatrix} 2 \\ 1 \\ -3 \end{bmatrix} B+t\begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} B,\ t\in\mathbb{R}$$

Answers

Proposition 4.6.1: Algebraic Description of a Straight Line

Let $\vec{x}_1,\vec{x}_2\in\mathbb{R}^n$. Define $\vec{x}_1=\vec{a}$ and let $\vec{x}_2-\vec{x}_1=\vec{b}$. Since $\vec{b}\neq\vec{0}$, it follows that $\vec{x}_2\neq\vec{x}_1$. Then $\vec{a}+t\vec{b}=\vec{x}_1+t\left(\vec{x}_2-\vec{x}_1\right)$. It follows that $\vec{x}=\vec{a}+t\vec{b}$ is a line containing the two different points X_1 and X_2 whose position vectors are given by $\vec{x}_1$ and $\vec{x}_2$ respectively.

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4.7: The Dot Product

Outcomes

A. Compute the dot product of vectors, and use this to compute vector projections.

The Dot Product

There are two ways of multiplying vectors which are of great importance in applications. The first of these is called the **dot product**. When we take the dot product of vectors, the result is a scalar. For this reason, the dot product is also called the **scalar product** and sometimes the **inner product**. The definition is as follows.

Definition 4.7.1: Dot Product

Let $\vec{u}, \vec{v}$ be two vectors in $\mathbb{R}^n$. Then we define the **dot product** $\vec{u} \bullet \vec{v}$ as

$$\vec{u} \bullet \vec{v} = \sum_{k=1}^{n} u_k v_k$$

The dot product $\vec{u} \bullet \vec{v}$ is sometimes denoted as $(\vec{u}, \vec{v})$ where a comma replaces $\bullet$. It can also be written as $\langle \vec{u}, \vec{v} \rangle$. If we write the vectors as column or row matrices, it is equal to the matrix product $\vec{v}\vec{w}^T$.

Consider the following example.

Example 4.7.1: Compute a Dot Product

Find $\vec{u} \bullet \vec{v}$ for

$$\vec{u} = \begin{bmatrix} 1 \\ 2 \\ 0 \\ -1 \end{bmatrix}, \vec{v} = \begin{bmatrix} 0 \\ 1 \\ 2 \\ 3 \end{bmatrix}$$

Solution

By Definition 4.7.1, we must compute

$$\vec{u} \bullet \vec{v} = \sum_{k=1}^{4} u_k v_k$$

This is given by

$$\begin{aligned} \vec{u} \bullet \vec{v} &= (1)(0) + (2)(1) + (0)(2) + (-1)(3) \\ &= 0 + 2 + 0 + -3 \\ &= -1 \end{aligned} \tag{4.7.1}$$

With this definition, there are several important properties satisfied by the dot product.

Proposition 4.7.1: Properties of the Dot Product

Let k and p denote scalars and $\vec{u}, \vec{v}, \vec{w}$ denote vectors. Then the dot product $\vec{u} \bullet \vec{v}$ satisfies the following properties.

- $\vec{u} \bullet \vec{v} = \vec{v} \bullet \vec{u}$
- $\vec{u} \bullet \vec{u} \geq 0$ and equals zero if and only if $\vec{u} = \vec{0}$
- $(k\vec{u} + p\vec{v}) \bullet \vec{w} = k(\vec{u} \bullet \vec{w}) + p(\vec{v} \bullet \vec{w})$
- $\vec{u} \bullet (k\vec{v} + p\vec{w}) = k(\vec{u} \bullet \vec{v}) + p(\vec{u} \bullet \vec{w})$
- $\|\vec{u}\|^2 = \vec{u} \bullet \vec{u}$

Proof available at the end of this section.

This proposition tells us that we can also use the dot product to find the length of a vector.

Example 4.7.2: Length of a Vector

Find the length of

$$\vec{u} = \begin{bmatrix} 2 \\ 1 \\ 4 \\ 2 \end{bmatrix}$$

That is, find $\|\vec{u}\|$.

Solution

By Proposition 4.7.1, $\|\vec{u}\|^2 = \vec{u} \bullet \vec{u}$. Therefore, $\|\vec{u}\| = \sqrt{\vec{u} \bullet \vec{u}}$. First, compute $\vec{u} \bullet \vec{u}$.

This is given by

$$\begin{aligned} \vec{u} \bullet \vec{u} &= (2)(2) + (1)(1) + (4)(4) + (2)(2) \\ &= 4 + 1 + 16 + 4 \\ &= 25 \end{aligned} \tag{4.7.2}$$

Then,

$$\begin{aligned} \|\vec{u}\| &= \sqrt{\vec{u} \bullet \vec{u}} \\ &= \sqrt{25} \\ &= 5 \end{aligned} \tag{4.7.3}$$

You may wish to compare this to our previous definition of length, given in Definition 4.4.2.

The **Cauchy Schwarz inequality** is a fundamental inequality satisfied by the dot product. It is given in the following theorem.

Theorem 4.7.1: Cauchy Schwarz Inequality

The dot product satisfies the inequality

$$\left|\vec{u} \bullet \vec{v}\right| \leq \|\vec{u}\|\|\vec{v}\| \tag{4.7.4}$$

Furthermore equality is obtained if and only if one of $\vec{u}$ or $\vec{v}$ is a scalar multiple of the other.

Proof available at the end of this section.

Notice that this proof was based only on the properties of the dot product listed in Proposition 4.7.1. This means that whenever an operation satisfies these properties, the Cauchy Schwarz inequality holds. There are many other instances of these properties besides vectors in $\mathbb{R}^n$.

The Cauchy Schwarz inequality provides another proof of the **triangle inequality** for distances in $\mathbb{R}^n$.

Theorem 4.7.2: Triangle Inequality

For $\vec{u}, \vec{v} \in \mathbb{R}^n$

$$\|\vec{u} + \vec{v}\| \leq \|\vec{u}\| + \|\vec{v}\| \tag{4.7.5}$$

and equality holds if and only if one of the vectors is a non-negative scalar multiple of the other.

Also

$$\|\|\vec{u}\| - \|\vec{v}\|\| \leq \|\vec{u} - \vec{v}\| \tag{4.7.6}$$

Proof available at the end of this section.

The Geometric Significance of the Dot Product

Given two vectors, $\vec{u}$ and $\vec{v}$, the **included angle** is the angle between these two vectors which is given by θ such that $0 \leq \theta \leq \pi$. The dot product can be used to determine the included angle between two vectors. Consider the following picture where θ gives the included angle.

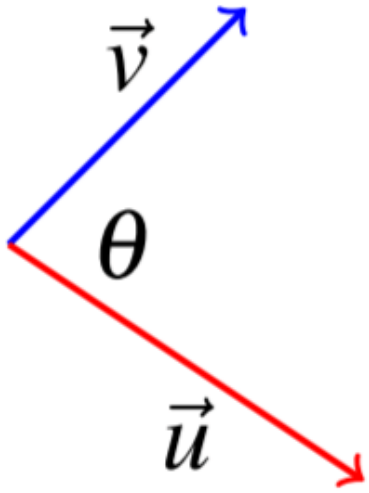


Figure 4.7.1

Proposition 4.7.2: The Dot Product and the Included Angle

Let $\vec{u}$ and $\vec{v}$ be two vectors in $\mathbb{R}^n$, and let θ be the included angle. Then the following equation holds.

$$\vec{u} \bullet \vec{v} = \|\vec{u}\|\|\vec{v}\| \cos\theta$$

In words, the dot product of two vectors equals the product of the magnitude (or length) of the two vectors multiplied by the cosine of the included angle. Note this gives a geometric description of the dot product which does not depend explicitly on the coordinates of the vectors.

Consider the following example.

Example 4.7.3: Find the Angle Between Two Vectors

Find the angle between the vectors given by

$$\vec{u} = \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix}, \vec{v} = \begin{bmatrix} 3 \\ 4 \\ 1 \end{bmatrix}$$

Solution

By Proposition 4.7.2,

$$\vec{u} \bullet \vec{v} = \|\vec{u}\|\|\vec{v}\| \cos\theta$$

Hence,

$$\cos\theta = \frac{\vec{u} \bullet \vec{v}}{\|\vec{u}\|\|\vec{v}\|}$$

First, we can compute $\vec{u} \bullet \vec{v}$. By Definition 4.7.1, this equals

$$\vec{u} \bullet \vec{v} = (2)(3) + (1)(4) + (-1)(1) = 9$$

Then,

$$\|\vec{u}\| = \sqrt{(2)(2) + (1)(1) + (1)(1)} = \sqrt{6}$$
$$\|\vec{v}\| = \sqrt{(3)(3) + (4)(4) + (1)(1)} = \sqrt{26}$$

Therefore, the cosine of the included angle equals

$$\cos\theta = \frac{9}{\sqrt{26}\sqrt{6}} = 0.7205766...$$

With the cosine known, the angle can be determined by computing the inverse cosine of that angle, giving approximately $\theta = 0.76616$ radians.

Another application of the geometric description of the dot product is in finding the angle between two lines. Typically one would assume that the lines intersect. In some situations, however, it may make sense to ask this question when the lines do not intersect, such as the angle between two object trajectories. In any case we understand it to mean the smallest angle between (any of) their direction vectors. The only subtlety here is that if $\vec{u}$ is a direction vector for a line, then so is any multiple $k\vec{u}$, and thus we will find complementary angles among all angles between direction vectors for two lines, and we simply take the smaller of the two.

Example 4.7.4: Find the Angle Between Two Lines

Find the angle between the two lines

$$L_1 : \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix} + t \begin{bmatrix} -1 \\ 1 \\ 2 \end{bmatrix}$$

and

$$L_2 : \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 4 \\ -3 \end{bmatrix} + s \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix}$$

Solution

You can verify that these lines do not intersect, but as discussed above this does not matter and we simply find the smallest angle between any directions vectors for these lines.

To do so we first find the angle between the direction vectors given above:

$$\vec{u} = \begin{bmatrix} -1 \\ 1 \\ 2 \end{bmatrix}, \vec{v} = \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix}$$

In order to find the angle, we solve the following equation for θ

$$\vec{u} \bullet \vec{v} = \|\vec{u}\|\|\vec{v}\| \cos\theta$$

to obtain $\cos\theta = -\frac{1}{2}$ and since we choose included angles between 0 and π we obtain $\theta = \frac{2\pi}{3}$.

Now the angles between any two direction vectors for these lines will either be $\frac{2\pi}{3}$ or its complement $\phi = \pi - \frac{2\pi}{3} = \frac{\pi}{3}$. We choose the smaller angle, and therefore conclude that the angle between the two lines is $\frac{\pi}{3}$.

We can also use Proposition 4.7.2 to compute the dot product of two vectors.

Example 4.7.5: Using Geometric Description to Find a Dot Product

Let $\vec{u}, \vec{v}$ be vectors with $\|\vec{u}\| = 3$ and $\|\vec{v}\| = 4$. Suppose the angle between $\vec{u}$ and $\vec{v}$ is $\pi/3$. Find $\vec{u} \bullet \vec{v}$.

Solution

From the geometric description of the dot product in Proposition 4.7.2

$$\vec{u} \bullet \vec{v} = (3)(4)\cos(\pi/3) = 3 \times 4 \times 1/2 = 6$$

Two nonzero vectors are said to be **perpendicular**, sometimes also called **orthogonal**, if the included angle is $\pi/2$ radians (90°).

Consider the following proposition.

Proposition 4.7.3: Perpendicular Vectors

Let $\vec{u}$ and $\vec{v}$ be nonzero vectors in $\mathbb{R}^n$. Then, $\vec{u}$ and $\vec{v}$ are said to be **perpendicular** exactly when

$$\vec{u} \bullet \vec{v} = 0$$

Proof available at the end of this section.

Consider the following example.

Example 4.7.6: Determine if Two Vectors are Perpendicular

Determine whether the two vectors,

$$\vec{u} = \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix}, \vec{v} = \begin{bmatrix} 1 \\ 3 \\ 5 \end{bmatrix}$$

are perpendicular.

Solution

In order to determine if these two vectors are perpendicular, we compute the dot product. This is given by

$$\vec{u} \bullet \vec{v} = (2)(1) + (1)(3) + (-1)(5) = 0$$

Therefore, by Proposition 4.7.3 these two vectors are perpendicular.

Projections

In some applications, we wish to write a vector as a sum of two related vectors. Through the concept of projections, we can find these two vectors. First, we explore an important theorem. The result of this theorem will provide our definition of a vector projection.

Theorem 4.7.3: Vector Projections

Let $\vec{v}$ and $\vec{u}$ be nonzero vectors. Then there exist unique vectors $\vec{v}_{||}$ and $\vec{v}_{\perp}$ such that

$$\vec{v} = \vec{v}_{||} + \vec{v}_{\perp} \tag{4.7.7}$$

where $\vec{v}_{||}$ is a scalar multiple of $\vec{u}$, and $\vec{v}_{\perp}$ is perpendicular to $\vec{u}$.

Proof available at the end of this section.

The vector $\vec{v}_{||}$ in Theorem 4.7.3 is called the **projection** of $\vec{v}$ onto $\vec{u}$ and is denoted by

$$\vec{v}_{||} = \text{proj}_{\vec{u}}\left(\vec{v}\right)$$

We now make a formal definition of the vector projection.

Definition 4.7.2: Vector Projection

Let $\vec{u}$ and $\vec{v}$ be vectors. Then, the **projection of $\vec{v}$ onto $\vec{u}$** is given by

$$\text{proj}_{\vec{u}}\left(\vec{v}\right) = \left(\frac{\vec{v} \bullet \vec{u}}{\vec{u} \bullet \vec{u}}\right)\vec{u} = \frac{\vec{v} \bullet \vec{u}}{\|\vec{u}\|^2}\vec{u}$$

Consider the following example of a projection.

Example 4.7.7: Find the Projection of One Vector Onto Another

Find $\text{proj}_{\vec{u}}\left(\vec{v}\right)$ if

$$\vec{u} = \begin{bmatrix} 2 \\ 3 \\ -4 \end{bmatrix}, \vec{v} = \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}$$

Solution

We can use the formula provided in Definition 4.7.2 to find $\text{proj}_{\vec{u}}\left(\vec{v}\right)$. First, compute $\vec{v} \bullet \vec{u}$. This is given by

$$\begin{aligned} \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix} \bullet \begin{bmatrix} 2 \\ 3 \\ -4 \end{bmatrix} &= (2)(1) + (3)(-2) + (-4)(1) \\ &= 2 - 6 - 4 \\ &= -8 \end{aligned} \tag{4.7.8}$$

Similarly, $\vec{u} \bullet \vec{u}$ is given by

$$\begin{aligned} \begin{bmatrix} 2 \\ 3 \\ -4 \end{bmatrix} \bullet \begin{bmatrix} 2 \\ 3 \\ -4 \end{bmatrix} &= (2)(2) + (3)(3) + (-4)(-4) \\ &= 4 + 9 + 16 \\ &= 29 \end{aligned} \tag{4.7.9}$$

Therefore, the projection is equal to

$$\begin{aligned} \text{proj}_{\vec{u}}\left(\vec{v}\right) &= -\frac{8}{29}\begin{bmatrix} 2 \\ 3 \\ -4 \end{bmatrix} \\ &= \begin{bmatrix} -\frac{16}{29} \\ -\frac{24}{29} \\ \frac{32}{29} \end{bmatrix} \end{aligned} \tag{4.7.10}$$

We will conclude this section with an important application of projections. Suppose a line L and a point P are given such that P is not contained in L. Through the use of projections, we can determine the shortest distance from P to L.

Example 4.7.8: Shortest Distance from a Point to a Line

Let $P = (1, 3, 5)$ be a point in $\mathbb{R}^3$, and let L be the line which goes through point $P_0 = (0, 4, -2)$ with direction vector $\vec{d} = \begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix}$. Find the shortest distance from P to the line L, and find the point Q on L that is closest to P.

Solution

In order to determine the shortest distance from P to L, we will first find the vector $\overrightarrow{P_0P}$ and then find the projection of this vector onto L. The vector $\overrightarrow{P_0P}$ is given by

$$\begin{bmatrix} 1 \\ 3 \\ 5 \end{bmatrix} - \begin{bmatrix} 0 \\ 4 \\ -2 \end{bmatrix} = \begin{bmatrix} 1 \\ -1 \\ 7 \end{bmatrix}$$

Then, if Q is the point on L closest to P, it follows that

$$\begin{aligned} \overrightarrow{P_0Q} &= \text{proj}_{\vec{d}}\overrightarrow{P_0P} \\ &= \left(\frac{\overrightarrow{P_0P} \bullet \vec{d}}{\|\vec{d}\,\|^2}\right)\vec{d} \\ &= \frac{15}{9}\begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix} \\ &= \frac{5}{3}\begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix} \end{aligned} \tag{4.7.11}$$

Now, the distance from P to L is given by

$$\|\overrightarrow{QP}\| = \|\overrightarrow{P_0P} - \overrightarrow{P_0Q}\| = \sqrt{26}$$

The point Q is found by adding the vector $\overrightarrow{P_0Q}$ to the position vector $\overrightarrow{0P_0}$ for P_0 as follows

$$\begin{bmatrix} 0 \\ 4 \\ -2 \end{bmatrix} + \frac{5}{3}\begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix} = \begin{bmatrix} \frac{10}{3} \\ \frac{17}{3} \\ \frac{4}{3} \end{bmatrix} \tag{4.7.12}$$

Therefore, $Q = (\frac{10}{3}, \frac{17}{3}, \frac{4}{3})$.

Answers

Proposition 4.7.1: Properties of the Dot Product

The proof is left as an exercise.

Theorem 4.7.1: Cauchy Schwarz Inequality

First note that if $\vec{v}=\vec{0}$ both sides of (4.7.4) equal zero and so the inequality holds in this case. Therefore, it will be assumed in what follows that $\vec{v}\neq\vec{0}$.

Define a function of $t\in\mathbb{R}$ by

$$f(t)=(\vec{u}+t\vec{v})\bullet(\vec{u}+t\vec{v})$$

Then by Proposition 4.7.1, $f(t)\geq 0$ for all $t\in\mathbb{R}$. Also from Proposition 4.7.1

$$\begin{aligned} f(t) &= \vec{u}\bullet(\vec{u}+t\vec{v})+t\vec{v}\bullet(\vec{u}+t\vec{v}) \\ &= \vec{u}\bullet\vec{u}+t(\vec{u}\bullet\vec{v})+t\vec{v}\bullet\vec{u}+t^2\vec{v}\bullet\vec{v} \\ &= \|\vec{u}\|^2+2t(\vec{u}\bullet\vec{v})+\|\vec{v}\|^2t^2 \end{aligned} \tag{4.7.13}$$

Now this means the graph of $y=f(t)$ is a parabola which opens up and either its vertex touches the t axis or else the entire graph is above the t axis. In the first case, there exists some t where $f(t)=0$ and this requires $\vec{u}+t\vec{v}=\vec{0}$ so one vector is a multiple of the other. Then clearly equality holds in (4.7.4). In the case where $\vec{v}$ is not a multiple of $\vec{u}$, it follows $f(t)>0$ for all t which says $f(t)$ has no real zeros and so from the quadratic formula,

$$(2(\vec{u}\bullet\vec{v}))^2-4\|\vec{u}\|^2\|\vec{v}\|^2<0$$

which is equivalent to $|\vec{u}\bullet\vec{v}|<\|\vec{u}\|\|\vec{v}\|$.

Theorem 4.7.2: Triangle Inequality

By properties of the dot product and the Cauchy Schwarz inequality,

$$\begin{aligned} \|\vec{u}+\vec{v}\|^2 &= (\vec{u}+\vec{v})\bullet(\vec{u}+\vec{v}) \\ &= (\vec{u}\bullet\vec{u})+(\vec{u}\bullet\vec{v})+(\vec{v}\bullet\vec{u})+(\vec{v}\bullet\vec{v}) \\ &= \|\vec{u}\|^2+2(\vec{u}\bullet\vec{v})+\|\vec{v}\|^2 \\ &\leq \|\vec{u}\|^2+2|\vec{u}\bullet\vec{v}|+\|\vec{v}\|^2 \\ &\leq \|\vec{u}\|^2+2\|\vec{u}\|\|\vec{v}\|+\|\vec{v}\|^2=(\|\vec{u}\|+\|\vec{v}\|)^2 \end{aligned} \tag{4.7.14}$$

Hence,

$$\|\vec{u}+\vec{v}\|^2\leq(\|\vec{u}\|+\|\vec{v}\|)^2$$

Taking square roots of both sides you obtain (4.7.5).

It remains to consider when equality occurs. Suppose $\vec{u}=\vec{0}$. Then, $\vec{u}=0\vec{v}$ and the claim about when equality occurs is verified. The same argument holds if $\vec{v}=\vec{0}$. Therefore, it can be assumed both vectors are nonzero. To get equality in (4.7.5) above, Theorem 4.7.1 implies one of the vectors must be a multiple of the other. Say $\vec{v}=k\vec{u}$. If $k<0$ then equality cannot occur in (4.7.5) because in this case

$$\vec{u}\bullet\vec{v}=k\|\vec{u}\|^2<0<|k|\|\vec{u}\|^2=|\vec{u}\bullet\vec{v}|$$

Therefore, $k\geq 0$.

To get the other form of the triangle inequality write

$$\vec{u}=\vec{u}-\vec{v}+\vec{v}$$

so

$$\begin{aligned} \|\vec{u}\| &= \|\vec{u}-\vec{v}+\vec{v}\| \\ &\leq \|\vec{u}-\vec{v}\|+\|\vec{v}\| \end{aligned} \tag{4.7.15}$$

Therefore,

$$\|\vec{u}\|-\|\vec{v}\|\leq\|\vec{u}-\vec{v}\| \tag{4.7.16}$$

Similarly,

$$\|\vec{v}\|-\|\vec{u}\|\leq\|\vec{v}-\vec{u}\|=\|\vec{u}-\vec{v}\| \tag{4.7.17}$$

It follows from (4.7.16) and (4.7.17) that (4.7.6) holds. This is because $|\|\vec{u}\|-\|\vec{v}\||$ equals the left side of either (4.7.16) or (4.7.17) and either way, $|\|\vec{u}\|-\|\vec{v}\||\leq\|\vec{u}-\vec{v}\|$.

Proposition 4.7.3: Perpendicular Vectors

This follows directly from Proposition 4.7.2. First if the dot product of two nonzero vectors is equal to 0, this tells us that $\cos\theta=0$ (this is where we need nonzero vectors). Thus $\theta=\pi/2$ and the vectors are perpendicular.

If on the other hand $\vec{v}$ is perpendicular to $\vec{u}$, then the included angle is $\pi/2$ radians. Hence $\cos\theta=0$ and $\vec{u}\bullet\vec{v}=0$.

Theorem 4.7.3: Vector Projections

Suppose (4.7.7) holds and $\vec{v}_{||}=k\vec{u}$. Taking the dot product of both sides of (4.7.7) with $\vec{u}$ and using $\vec{v}_{\perp}\bullet\vec{u}=0$, this yields

$$\begin{aligned} \vec{v}\bullet\vec{u} &= (\vec{v}_{||}+\vec{v}_{\perp})\bullet\vec{u} \\ &= k\vec{u}\bullet\vec{u}+\vec{v}_{\perp}\bullet\vec{u} \\ &= k\|\vec{u}\|^2 \end{aligned}$$

which requires $k=\vec{v}\bullet\vec{u}/\|\vec{u}\|^2$. Thus there can be no more than one vector $\vec{v}_{||}$. It follows $\vec{v}_{\perp}$ must equal $\vec{v}-\vec{v}_{||}$. This verifies there can be no more than one choice for both $\vec{v}_{||}$ and $\vec{v}_{\perp}$ and proves their uniqueness.

Now let

$$\vec{v}_{||}=\frac{\vec{v}\bullet\vec{u}}{\|\vec{u}\|^2}\vec{u}$$

and let

$$\vec{v}_{\perp} = \vec{v} - \vec{v}_{||} = \vec{v} - \frac{\vec{v} \bullet \vec{u}}{\|\vec{u}\|^2}\vec{u}$$

Then $\vec{v}_{||} = k\vec{u}$ where $k = \frac{\vec{v} \bullet \vec{u}}{\|\vec{u}\|^2}$. It only remains to verify $\vec{v}_{\perp} \bullet \vec{u} = 0$. But

$$\begin{aligned} \vec{v}_{\perp} \bullet \vec{u} &= \vec{v} \bullet \vec{u} - \frac{\vec{v} \bullet \vec{u}}{\|\vec{u}\|^2}\vec{u} \bullet \vec{u} \\ &= \vec{v} \bullet \vec{u} - \vec{v} \bullet \vec{u} \\ &= 0 \end{aligned} \tag{4.7.18}$$

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4.8: Planes in $\mathbb{R}^n$

Outcomes

A. Find the vector and scalar equations of a plane.

Much like the above discussion with lines, vectors can be used to determine planes in $\mathbb{R}^n$. Given a vector $\vec{n}$ in $\mathbb{R}^n$ and a point P_0, it is possible to find a **unique** plane which contains P_0 and is perpendicular to the given vector.

Definition 4.8.1: Normal Vector

Let $\vec{n}$ be a nonzero vector in $\mathbb{R}^n$. Then $\vec{n}$ is called a **normal vector** to a plane if and only if

$$\vec{n} \bullet \vec{v} = 0$$

for every vector $\vec{v}$ in the plane.

In other words, we say that $\vec{n}$ is orthogonal (perpendicular) to every vector in the plane.

Consider now a plane with normal vector given by $\vec{n}$, and containing a point P_0. Notice that this plane is unique. If P is an arbitrary point on this plane, then by definition the normal vector is orthogonal to the vector between P_0 and P. Letting $\overrightarrow{0P}$ and $\overrightarrow{0P_0}$ be the position vectors of points P and P_0 respectively, it follows that

$$\vec{n} \bullet (\overrightarrow{0P} - \overrightarrow{0P_0}) = 0$$

or

$$\vec{n} \bullet \overrightarrow{P_0P} = 0$$

The first of these equations gives the **vector equation** of the plane.

Definition 4.8.2: Vector Equation of a Plane

Let $\vec{n}$ be the normal vector for a plane which contains a point P_0. If P is an arbitrary point on this plane, then the **vector equation** of the plane is given by

$$\vec{n} \bullet (\overrightarrow{0P} - \overrightarrow{0P_0}) = 0$$

Notice that this equation can be used to determine if a point P is contained in a certain plane.

Example 4.8.1: A Point in a Plane

Let $\vec{n} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$ be the normal vector for a plane which contains the point $P_0 = (2, 1, 4)$. Determine if the point $P = (5, 4, 1)$ is contained in this plane.

Solution

By Definition 4.8.2, P is a point in the plane if it satisfies the equation

$$\vec{n} \bullet (\overrightarrow{0P} - \overrightarrow{0P_0}) = 0$$

Given the above $\vec{n}$, P_0, and P, this equation becomes

$$\begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \bullet \left(\begin{bmatrix} 5 \\ 4 \\ 1 \end{bmatrix} - \begin{bmatrix} 2 \\ 1 \\ 4 \end{bmatrix} \right) = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \bullet \left(\begin{bmatrix} 3 \\ 3 \\ -3 \end{bmatrix} \right) \\ = 3 + 6 - 9 = 0 \tag{4.8.1}$$

Therefore $P = (5, 4, 1)$ is contained in the plane.

Suppose $\vec{n} = \begin{bmatrix} a \\ b \\ c \end{bmatrix}$, $P = (x, y, z)$ and $P_0 = (x_0, y_0, z_0)$.

Then

$$\begin{aligned} \vec{n} \bullet (\overrightarrow{0P} - \overrightarrow{0P_0}) &= 0 \\ \begin{bmatrix} a \\ b \\ c \end{bmatrix} \bullet \left(\begin{bmatrix} x \\ y \\ z \end{bmatrix} - \begin{bmatrix} x_0 \\ y_0 \\ z_0 \end{bmatrix} \right) &= 0 \\ \begin{bmatrix} a \\ b \\ c \end{bmatrix} \bullet \begin{bmatrix} x - x_0 \\ y - y_0 \\ z - z_0 \end{bmatrix} &= 0 \\ a(x - x_0) + b(y - y_0) + c(z - z_0) &= 0 \end{aligned} \tag{4.8.2}$$

We can also write this equation as

$$ax + by + cz = ax_0 + by_0 + cz_0$$

Notice that since P_0 is given, $ax_0 + by_0 + cz_0$ is a known scalar, which we can call d. This equation becomes

$$ax + by + cz = d$$

Definition 4.8.3: Scalar Equation of a Plane

Let $\vec{n} = \begin{bmatrix} a \\ b \\ c \end{bmatrix}$ be the normal vector for a plane which contains the point $P_0 = (x_0, y_0, z_0)$.Then if $P = (x, y, z)$ is an arbitrary point on the plane, the **scalar equation** of the plane is given by

$$ax + by + cz = d$$

where $a, b, c, d \in \mathbb{R}$ and $d = ax_0 + by_0 + cz_0$.

Consider the following equation.

Example 4.8.2: Finding the Equation of a Plane

Find an equation of the plane containing $P_0 = (3, -2, 5)$ and orthogonal to $\vec{n} = \begin{bmatrix} -2 \\ 4 \\ 1 \end{bmatrix}$.

Solution

The above vector $\vec{n}$ is the normal vector for this plane. Using Definition 4.8.2, we can determine the vector equation for this plane.

$$\begin{aligned} \vec{n} \bullet (\overrightarrow{0P} - \overrightarrow{0P_0}) &= 0 \\ \begin{bmatrix} -2 \\ 4 \\ 1 \end{bmatrix} \bullet \left(\begin{bmatrix} x \\ y \\ z \end{bmatrix} - \begin{bmatrix} 3 \\ -2 \\ 5 \end{bmatrix} \right) &= 0 \\ \begin{bmatrix} -2 \\ 4 \\ 1 \end{bmatrix} \bullet \begin{bmatrix} x-3 \\ y+2 \\ z-5 \end{bmatrix} &= 0 \end{aligned} \tag{4.8.3}$$

Using Definition 4.8.3, we can determine the scalar equation of the plane.

$$-2x + 4y + 1z = -2(3) + 4(-2) + 1(5) = -9$$

Hence, the vector equation of the plane is

$$\begin{bmatrix} -2 \\ 4 \\ 1 \end{bmatrix} \bullet \begin{bmatrix} x-3 \\ y+2 \\ z-5 \end{bmatrix} = 0$$

and the scalar equation is

$$-2x + 4y + 1z = -9$$

Suppose a point P is not contained in a given plane. We are then interested in the shortest distance from that point P to the given plane. Consider the following example.

Example 4.8.3: Shortest Distance From a Point to a Plane

Find the shortest distance from the point $P = (3, 2, 3)$ to the plane given by $2x + y + 2z = 2$, and find the point Q on the plane that is closest to P.

Solution

Pick an arbitrary point P_0 on the plane. Then, it follows that

$$\overrightarrow{QP} = proj_{\vec{n}} \overrightarrow{P_0P}$$

and $\|\overrightarrow{QP}\|$ is the shortest distance from P to the plane. Further, the vector $\overrightarrow{0Q} = \overrightarrow{0P} - \overrightarrow{QP}$ gives the necessary point Q.

From the above scalar equation, we have that $\vec{n} = \begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix}$. Now, choose $P_0 = (1, 0, 0)$ so that $\vec{n} \bullet \overrightarrow{0P} = 2 = d$. Then, $\overrightarrow{P_0P} = \begin{bmatrix} 3 \\ 2 \\ 3 \end{bmatrix} - \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \\ 3 \end{bmatrix}$.

Next, compute $\overrightarrow{QP} = proj_{\vec{n}} \overrightarrow{P_0P}$.

$$\begin{aligned} \overrightarrow{QP} &= proj_{\vec{n}} \overrightarrow{P_0P} \\ &= \left(\frac{\overrightarrow{P_0P} \bullet \vec{n}}{\|\vec{n}\|^2} \right) \vec{n} \\ &= \frac{12}{9} \begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix} \\ &= \frac{4}{3} \begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix} \end{aligned} \tag{4.8.4}$$

Then, $\|\overrightarrow{QP}\| = 4$ so the shortest distance from P to the plane is 4.

Next, to find the point Q on the plane which is closest to P we have

$$\begin{aligned} \overrightarrow{0Q} &= \overrightarrow{0P} - \overrightarrow{QP} \\ &= \begin{bmatrix} 3 \\ 2 \\ 3 \end{bmatrix} - \frac{4}{3} \begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix} \\ &= \frac{1}{3} \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \end{aligned} \tag{4.8.5}$$

Therefore, $Q = (\frac{1}{3}, \frac{2}{3}, \frac{1}{3})$.

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4.9: The Cross Product

Outcomes

A. Compute the cross product and box product of vectors in $\mathbb{R}^3$.

Recall that the dot product is one of two important products for vectors. The second type of product for vectors is called the cross product. It is important to note that the cross product is only defined in $\mathbb{R}^3$. First we discuss the geometric meaning and then a description in terms of coordinates is given, both of which are important. The geometric description is essential in order to understand the applications to physics and geometry while the coordinate description is necessary to compute the cross product.

Consider the following definition.

Definition 4.9.1: Right Hand System of Vectors

Three vectors, $\vec{u}, \vec{v}, \vec{w}$ form a right hand system if when you extend the fingers of your right hand along the direction of vector $\vec{u}$ and close them in the direction of $\vec{v}$, the thumb points roughly in the direction of $\vec{w}$.

For an example of a right handed system of vectors, see the following picture.

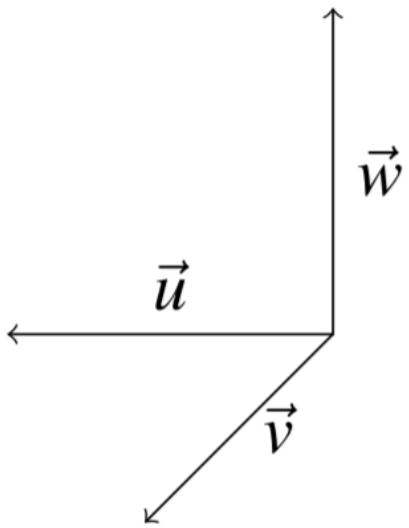


Figure 4.9.1

In this picture the vector $\vec{w}$ points upwards from the plane determined by the other two vectors. Point the fingers of your right hand along $\vec{u}$, and close them in the direction of $\vec{v}$. Notice that if you extend the thumb on your right hand, it points in the direction of $\vec{w}$.

You should consider how a right hand system would differ from a left hand system. Try using your left hand and you will see that the vector $\vec{w}$ would need to point in the opposite direction.

Notice that the special vectors, $\vec{i}, \vec{j}, \vec{k}$ will always form a right handed system. If you extend the fingers of your right hand along $\vec{i}$ and close them in the direction $\vec{j}$, the thumb points in the direction of $\vec{k}$.

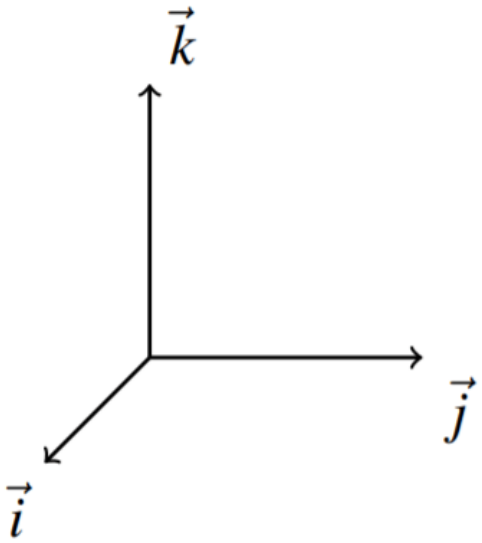


Figure 4.9.2

The following is the geometric description of the cross product. Recall that the dot product of two vectors results in a scalar. In contrast, the cross product results in a vector, as the product gives a direction as well as magnitude.

Definition 4.9.2: Geometric Definition of Cross Product

Let $\vec{u}$ and $\vec{v}$ be two vectors in $\mathbb{R}^3$. Then the **cross product**, written $\vec{u} \times \vec{v}$, is defined by the following two rules.

1. Its length is
$$\|\vec{u} \times \vec{v}\| = \|\vec{u}\|\|\vec{v}\| \sin\theta,$$
where θ is the included angle between $\vec{u}$ and $\vec{v}$.
2. It is perpendicular to both $\vec{u}$ and $\vec{v}$, that is
$$\begin{aligned} (\vec{u} \times \vec{v}) \cdot \vec{u} &= 0, \\ (\vec{u} \times \vec{v}) \cdot \vec{v} &= 0, \end{aligned} \tag{4.9.1}$$
and
$$\vec{u}, \vec{v}, \vec{u} \times \vec{v}$$
form a right hand system.

The cross product of the special vectors $\vec{i}, \vec{j}, \vec{k}$ is as follows.

$$\begin{aligned} \vec{i} \times \vec{j} &= \vec{k} \quad \vec{j} \times \vec{i} = -\vec{k} \\ \vec{k} \times \vec{i} &= \vec{j} \quad \vec{i} \times \vec{k} = -\vec{j} \\ \vec{j} \times \vec{k} &= \vec{i} \quad \vec{k} \times \vec{j} = -\vec{i} \end{aligned}$$

With this information, the following gives the coordinate description of the cross product.

Recall that the vector $\vec{u} = \begin{bmatrix} u_1 & u_2 & u_3 \end{bmatrix}^T$ can be written in terms of $\vec{i}, \vec{j}, \vec{k}$ as $\vec{u} = u_1\vec{i} + u_2\vec{j} + u_3\vec{k}$.

Theorem 4.9.1: Coordinate Description of Cross Product

Let $\vec{u} = u_1\vec{i} + u_2\vec{j} + u_3\vec{k}$ and $\vec{v} = v_1\vec{i} + v_2\vec{j} + v_3\vec{k}$ be two vectors. Then

$$\vec{u} \times \vec{v} = (u_2v_3 - u_3v_2)\,\vec{i} - (u_1v_3 - u_3v_1)\,\vec{j} + (u_1v_2 - u_2v_1)\,\vec{k} \tag{4.9.2}$$

Writing $\vec{u} \times \vec{v}$ in the usual way, it is given by

$$\vec{u} \times \vec{v} = \begin{bmatrix} u_2v_3 - u_3v_2 \\ -(u_1v_3 - u_3v_1) \\ u_1v_2 - u_2v_1 \end{bmatrix}$$

We now prove this proposition.

Proof available at the end of this section.

There is another version of (4.9.2) which may be easier to remember. We can express the cross product as the determinant of a matrix, as follows.

$$\vec{u} \times \vec{v} = \begin{vmatrix} \vec{i} & \vec{j} & \vec{k} \\ u_1 & u_2 & u_3 \\ v_1 & v_2 & v_3 \end{vmatrix} \tag{4.9.3}$$

Expanding the determinant along the top row yields

$$\vec{i}\,(-1)^{1+1}\begin{vmatrix} u_2 & u_3 \\ v_2 & v_3 \end{vmatrix} + \vec{j}\,(-1)^{2+1}\begin{vmatrix} u_1 & u_3 \\ v_1 & v_3 \end{vmatrix} + \vec{k}\,(-1)^{3+1}\begin{vmatrix} u_1 & u_2 \\ v_1 & v_2 \end{vmatrix}$$

\

$$= \vec{i}\begin{vmatrix} u_2 & u_3 \\ v_2 & v_3 \end{vmatrix} - \vec{j}\begin{vmatrix} u_1 & u_3 \\ v_1 & v_3 \end{vmatrix} + \vec{k}\begin{vmatrix} u_1 & u_2 \\ v_1 & v_2 \end{vmatrix}$$

Expanding these determinants leads to

$$(u_2v_3 - u_3v_2)\,\vec{i} - (u_1v_3 - u_3v_1)\,\vec{j} + (u_1v_2 - u_2v_1)\,\vec{k}$$

which is the same as (4.9.7).

The cross product satisfies the following properties.

Proposition 4.9.1: Properties of the Cross Product

Let $\vec{u}, \vec{v}, \vec{w}$ be vectors in $\mathbb{R}^3$, and k a scalar. Then, the following properties of the cross product hold.

1. $\vec{u} \times \vec{v} = -(\vec{v} \times \vec{u})$, and $\vec{u} \times \vec{u} = \vec{0}$
2. $(k\vec{u}) \times \vec{v} = k(\vec{u} \times \vec{v}) = \vec{u} \times (k\vec{v})$
3. $\vec{u} \times (\vec{v} + \vec{w}) = \vec{u} \times \vec{v} + \vec{u} \times \vec{w}$
4. $(\vec{v} + \vec{w}) \times \vec{u} = \vec{v} \times \vec{u} + \vec{w} \times \vec{u}$

Proof available at the end of this section.

We will now look at an example of how to compute a cross product.

Example 4.9.1: Find a Cross Product

Find $\vec{u} \times \vec{v}$ for the following vectors

$$\vec{u} = \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix}, \vec{v} = \begin{bmatrix} 3 \\ -2 \\ 1 \end{bmatrix}$$

Solution

Note that we can write $\vec{u}, \vec{v}$ in terms of the special vectors $\vec{i}, \vec{j}, \vec{k}$ as

$$\vec{u} = \vec{i} - \vec{j} + 2\vec{k}$$
$$\vec{v} = 3\vec{i} - 2\vec{j} + \vec{k}$$

We will use the equation given by $(4.9.3)$ to compute the cross product.

$$\vec{u} \times \vec{v} = \begin{vmatrix} \vec{i} & \vec{j} & \vec{k} \\ 1 & -1 & 2 \\ 3 & -2 & 1 \end{vmatrix} = \begin{vmatrix} -1 & 2 \\ -2 & 1 \end{vmatrix} \vec{i} - \begin{vmatrix} 1 & 2 \\ 3 & 1 \end{vmatrix} \vec{j} + \begin{vmatrix} 1 & -1 \\ 3 & -2 \end{vmatrix} \vec{k} = 3\vec{i} + 5\vec{j} + \vec{k}$$

We can write this result in the usual way, as

$$\vec{u} \times \vec{v} = \begin{bmatrix} 3 \\ 5 \\ 1 \end{bmatrix}$$

An important geometrical application of the cross product is as follows. The size of the cross product, $\|\vec{u} \times \vec{v}\|$, is the area of the parallelogram determined by $\vec{u}$ and $\vec{v}$, as shown in the following picture.

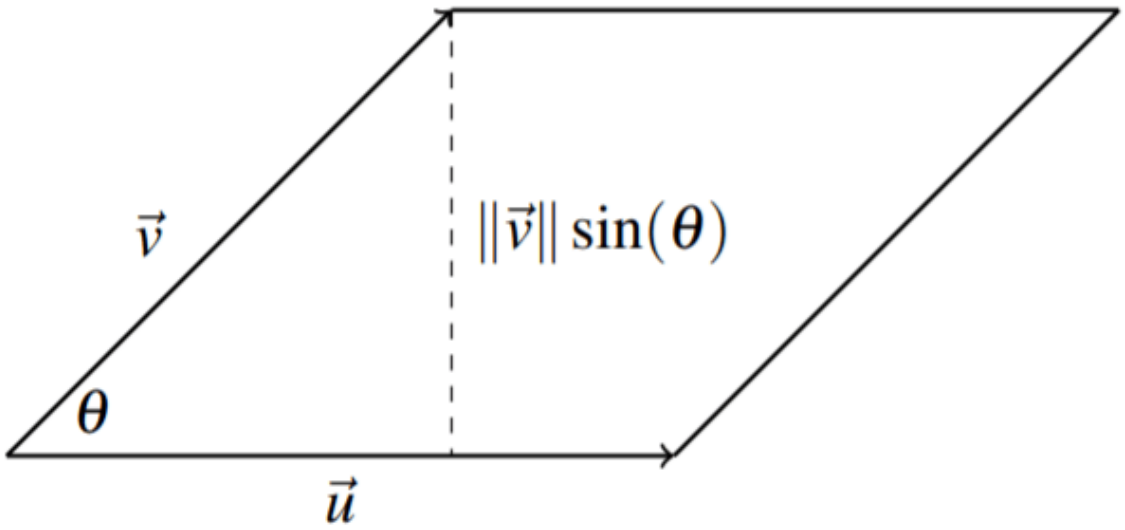


Figure $4.9.3$

We examine this concept in the following example.

Example $4.9.2$: Area of a Parallelogram

Find the area of the parallelogram determined by the vectors $\vec{u}$ and $\vec{v}$ given by

$$\vec{u} = \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix}, \vec{v} = \begin{bmatrix} 3 \\ -2 \\ 1 \end{bmatrix}$$

Solution

Notice that these vectors are the same as the ones given in Example 4.9.1. Recall from the geometric description of the cross product, that the area of the parallelogram is simply the magnitude of $\vec{u} \times \vec{v}$. From Example 4.9.1, $\vec{u} \times \vec{v} = 3\vec{i} + 5\vec{j} + \vec{k}$. We can also write this as

$$\vec{u} \times \vec{v} = \begin{bmatrix} 3 \\ 5 \\ 1 \end{bmatrix}$$

Thus the area of the parallelogram is

$$\|\vec{u} \times \vec{v}\| = \sqrt{(3)(3) + (5)(5) + (1)(1)} = \sqrt{9 + 25 + 1} = \sqrt{35}$$

We can also use this concept to find the area of a triangle. Consider the following example.

Example 4.9.3: Area of Triangle

Find the area of the triangle determined by the points $(1, 2, 3), (0, 2, 5), (5, 1, 2)$

Solution

This triangle is obtained by connecting the three points with lines. Picking $(1, 2, 3)$ as a starting point, there are two displacement vectors, $\begin{bmatrix} -1 & 0 & 2 \end{bmatrix}^T$ and $\begin{bmatrix} 4 & -1 & -1 \end{bmatrix}^T$. Notice that if we add either of these vectors to the position vector of the starting point, the result is the position vectors of the other two points. Now, the area of the triangle is half the area of the parallelogram determined by $\begin{bmatrix} -1 & 0 & 2 \end{bmatrix}^T$ and $\begin{bmatrix} 4 & -1 & -1 \end{bmatrix}^T$. The required cross product is given by

$$\begin{bmatrix} -1 \\ 0 \\ 2 \end{bmatrix} \times \begin{bmatrix} 4 \\ -1 \\ -1 \end{bmatrix} = \begin{bmatrix} 2 & 7 & 1 \end{bmatrix}$$

Taking the size of this vector gives the area of the parallelogram, given by

$$\sqrt{(2)(2) + (7)(7) + (1)(1)} = \sqrt{4 + 49 + 1} = \sqrt{54}$$

Hence the area of the triangle is $\frac{1}{2}\sqrt{54} = \frac{3}{2}\sqrt{6}$.

In general, if you have three points in $\mathbb{R}^3$, P, Q, R, the area of the triangle is given by

$$\frac{1}{2}\|\vec{PQ} \times \vec{PR}\|$$

Recall that $\vec{PQ}$ is the vector running from point P to point Q.

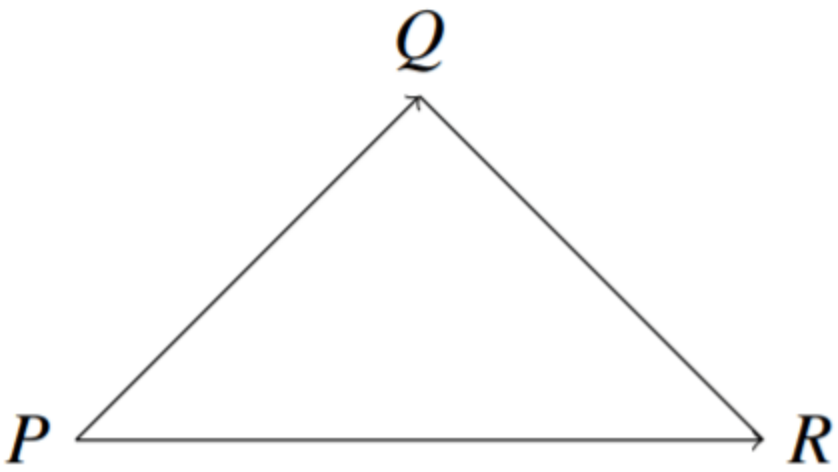


Figure 4.9.4

In the next section, we explore another application of the cross product.

The Box Product

Recall that we can use the cross product to find the the area of a parallelogram. It follows that we can use the cross product together with the dot product to find the volume of a parallelepiped. We begin with a definition.

Definition 4.9.3: Parallelepiped

A **parallelepiped** determined by the three vectors, $\vec{u}, \vec{v}$, and $\vec{w}$ consists of

$$\{r\vec{u} + s\vec{v} + t\vec{w} : r, s, t \in [0, 1]\}$$

That is, if you pick three numbers, r, s, and t each in $[0, 1]$ and form $r\vec{u} + s\vec{v} + t\vec{w}$ then the collection of all such points makes up the parallelepiped determined by these three vectors.

The following is an example of a parallelepiped.

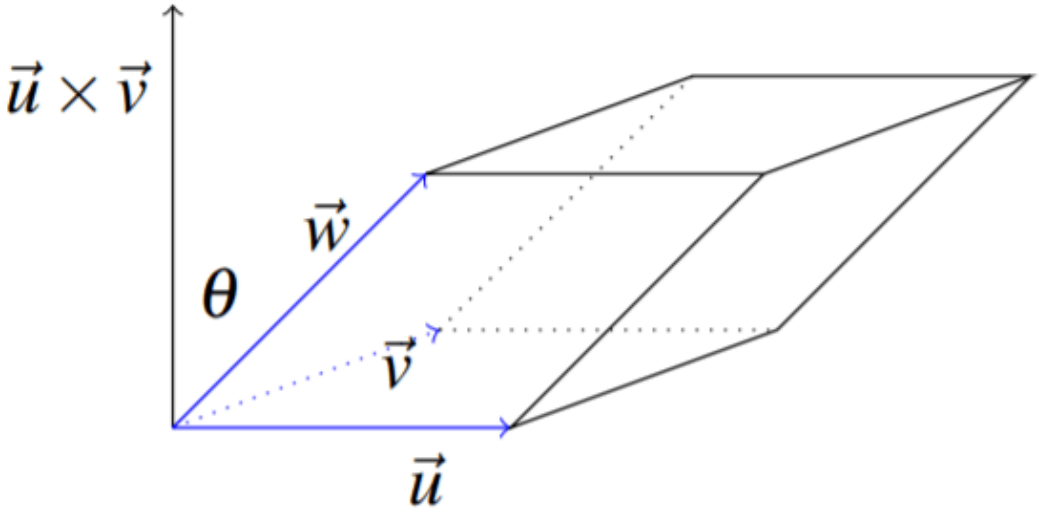


Figure 4.9.5

Notice that the base of the parallelepiped is the parallelogram determined by the vectors $\vec{u}$ and $\vec{v}$. Therefore, its area is equal to $\|\vec{u}\times\vec{v}\|$. The height of the parallelepiped is $\|\vec{w}\|\cos\theta$ where θ is the angle shown in the picture between $\vec{w}$ and $\vec{u}\times\vec{v}$. The volume of this parallelepiped is the area of the base times the height which is just

$$\|\vec{u}\times\vec{v}\|\|\vec{w}\|\cos\theta = (\vec{u}\times\vec{v})\cdot\vec{w}$$

This expression is known as the box product and is sometimes written as $[\vec{u},\vec{v},\vec{w}]$. You should consider what happens if you interchange the $\vec{v}$ with the $\vec{w}$ or the $\vec{u}$ with the $\vec{w}$. You can see geometrically from drawing pictures that this merely introduces a minus sign. In any case the box product of three vectors always equals either the volume of the parallelepiped determined by the three vectors or else -1 times this volume.

Proposition 4.9.2: The Box Product

Let $\vec{u},\vec{v},\vec{w}$ be three vectors in $\mathbb{R}^n$ that define a parallelepiped. Then the volume of the parallelepiped is the absolute value of the box product, given by

$$\left|(\vec{u}\times\vec{v})\cdot\vec{w}\right|$$

Consider an example of this concept.

Example 4.9.4: Volume of a Parallelepiped

Find the volume of the parallelepiped determined by the vectors

$$\vec{u}=\begin{bmatrix}1\\2\\-5\end{bmatrix},\vec{v}=\begin{bmatrix}1\\3\\-6\end{bmatrix},\vec{w}=\begin{bmatrix}3\\2\\3\end{bmatrix}$$

Solution

According to the above discussion, pick any two of these vectors, take the cross product and then take the dot product of this with the third of these vectors. The result will be either the desired volume or -1 times the desired volume. Therefore by taking the absolute value of the result, we obtain the volume.

We will take the cross product of $\vec{u}$ and $\vec{v}$. This is given by

$$\begin{aligned}\vec{u}\times\vec{v} &= \begin{bmatrix}1\\2\\-5\end{bmatrix}\times\begin{bmatrix}1\\3\\-6\end{bmatrix}\\ &= \begin{vmatrix}\vec{i}&\vec{j}&\vec{k}\\1&2&-5\\1&3&-6\end{vmatrix} = 3\vec{i}+\vec{j}+\vec{k} = \begin{bmatrix}3\\1\\1\end{bmatrix}\end{aligned}$$

Now take the dot product of this vector with $\vec{w}$ which yields

$$\begin{aligned}(\vec{u}\times\vec{v})\cdot\vec{w} &= \begin{bmatrix}3\\1\\1\end{bmatrix}\cdot\begin{bmatrix}3\\2\\3\end{bmatrix}\\ &= \left(3\vec{i}+\vec{j}+\vec{k}\right)\cdot\left(3\vec{i}+2\vec{j}+3\vec{k}\right)\\ &= 9+2+3\\ &= 14\end{aligned} \tag{4.9.4}$$

This shows the volume of this parallelepiped is 14 cubic units.

There is a fundamental observation which comes directly from the geometric definitions of the cross product and the dot product.

Proposition 4.9.3: Order of the Product

Let $\vec{u}, \vec{v}$, and $\vec{w}$ be vectors. Then $(\vec{u} \times \vec{v}) \cdot \vec{w} = \vec{u} \cdot (\vec{v} \times \vec{w})$.

Proof available at the end of this section.

Recall that we can express the cross product as the determinant of a particular matrix. It turns out that the same can be done for the box product. Suppose you have three vectors, $\vec{u} = \begin{bmatrix} a & b & c \end{bmatrix}^T, \vec{v} = \begin{bmatrix} d & e & f \end{bmatrix}^T$, and $\vec{w} = \begin{bmatrix} g & h & i \end{bmatrix}^T$. Then the box product $\vec{u} \cdot (\vec{v} \times \vec{w})$ is given by the following.

$$\begin{aligned} \vec{u} \cdot (\vec{v} \times \vec{w}) &= \begin{bmatrix} a \\ b \\ c \end{bmatrix} \cdot \begin{vmatrix} \vec{i} & \vec{j} & \vec{k} \\ d & e & f \\ g & h & i \end{vmatrix} \\ &= a \begin{vmatrix} e & f \\ h & i \end{vmatrix} - b \begin{vmatrix} d & f \\ g & i \end{vmatrix} + c \begin{vmatrix} d & e \\ g & h \end{vmatrix} \\ &= \det \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \end{aligned} \tag{4.9.5}$$

To take the box product, you can simply take the determinant of the matrix which results by letting the rows be the components of the given vectors in the order in which they occur in the box product.

This follows directly from the definition of the cross product given above and the way we expand determinants. Thus the volume of a parallelepiped determined by the vectors $\vec{u}, \vec{v}, \vec{w}$ is just the absolute value of the above determinant.

Answers

Theorem 4.9.1: Coordinate Description of Cross Product

From the above table and the properties of the cross product listed,

$$\begin{aligned} \vec{u} \times \vec{v} &= \left(u_1\vec{i} + u_2\vec{j} + u_3\vec{k}\right) \times \left(v_1\vec{i} + v_2\vec{j} + v_3\vec{k}\right) \\ &= u_1v_2\vec{i} \times \vec{j} + u_1v_3\vec{i} \times \vec{k} + u_2v_1\vec{j} \times \vec{i} + u_2v_3\vec{j} \times \vec{k} + + u_3v_1\vec{k} \times \vec{i} + u_3v_2\vec{k} \times \vec{j} \\ &= u_1v_2\vec{k} - u_1v_3\vec{j} - u_2v_1\vec{k} + u_2v_3\vec{i} + u_3v_1\vec{j} - u_3v_2\vec{i} \\ &= (u_2v_3 - u_3v_2)\vec{i} + (u_3v_1 - u_1v_3)\vec{j} + (u_1v_2 - u_2v_1)\vec{k} \end{aligned} \tag{4.9.6}$$

(4.9.7)

Proposition 4.9.1: Properties of the Cross Product

Formula 1. follows immediately from the definition. The vectors $\vec{u} \times \vec{v}$ and $\vec{v} \times \vec{u}$ have the same magnitude, $|\vec{u}|\,|\vec{v}| \sin\theta$, and an application of the right hand rule shows they have opposite direction.

Formula 2. is proven as follows. If k is a non-negative scalar, the direction of $(k\vec{u}) \times \vec{v}$ is the same as the direction of $\vec{u} \times \vec{v}, k(\vec{u} \times \vec{v})$ and $\vec{u} \times (k\vec{v})$. The magnitude is k times the magnitude of $\vec{u} \times \vec{v}$ which is the same as the magnitude of $k(\vec{u} \times \vec{v})$ and $\vec{u} \times (k\vec{v})$. Using this yields equality in 2. In the case where $k < 0$, everything works the same way except the vectors are all pointing in the opposite direction and you must multiply by $|k|$ when comparing their magnitudes.

The distributive laws, 3. and 4., are much harder to establish. For now, it suffices to notice that if we know that 3. is true, 4. follows. Thus, assuming 3., and using 1.,

$$\begin{aligned} (\vec{v} + \vec{w}) \times \vec{u} &= -\vec{u} \times (\vec{v} + \vec{w}) \\ &= -(\vec{u} \times \vec{v} + \vec{u} \times \vec{w}) \\ &= \vec{v} \times \vec{u} + \vec{w} \times \vec{u} \end{aligned} \tag{4.9.8}$$

Proposition 4.9.3: Order of the Product

This follows from observing that either $(\vec{u} \times \vec{v}) \cdot \vec{w}$ and $\vec{u} \cdot (\vec{v} \times \vec{w})$ both give the volume of the parallelepiped or they both give -1 times the volume.

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4.10: Spanning, Linear Independence and Basis in $\mathbb{R}^n$

Outcomes

A. Determine the span of a set of vectors, and determine if a vector is contained in a specified span.
B. Determine if a set of vectors is linearly independent.
C. Understand the concepts of subspace, basis, and dimension.
D. Find the row space, column space, and null space of a matrix.

By generating all linear combinations of a set of vectors one can obtain various subsets of $\mathbb{R}^n$ which we call subspaces. For example what set of vectors in $\mathbb{R}^3$ generate the XY-plane? What is the smallest such set of vectors can you find? The tools of spanning, linear independence and basis are exactly what is needed to answer these and similar questions and are the focus of this section. The following definition is essential.

Definition 4.10.1: Subset

Let U and W be sets of vectors in $\mathbb{R}^n$. If all vectors in U are also in W, we say that U is a **subset** of W, denoted

$$U \subseteq W$$

Spanning Set of Vectors

We begin this section with a definition.

Definition 4.10.2: Span of a Set of Vectors

The collection of all linear combinations of a set of vectors $\{\vec{u}_1, \cdots, \vec{u}_k\}$ in $\mathbb{R}^n$ is known as the span of these vectors and is written as $\text{span}\{\vec{u}_1, \cdots, \vec{u}_k\}$.

Consider the following example.

Example 4.10.1: Span of Vectors

Describe the span of the vectors $\vec{u} = \begin{bmatrix} 1 & 1 & 0 \end{bmatrix}^T$ and $\vec{v} = \begin{bmatrix} 3 & 2 & 0 \end{bmatrix}^T \in \mathbb{R}^3$.

Solution

You can see that any linear combination of the vectors $\vec{u}$ and $\vec{v}$ yields a vector of the form $\begin{bmatrix} x & y & 0 \end{bmatrix}^T$ in the XY-plane.

Moreover every vector in the XY-plane is in fact such a linear combination of the vectors $\vec{u}$ and $\vec{v}$. That's because

$$\begin{bmatrix} x \\ y \\ 0 \end{bmatrix} = (-2x + 3y) \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} + (x - y) \begin{bmatrix} 3 \\ 2 \\ 0 \end{bmatrix}$$

Thus $\text{span}\{\vec{u}, \vec{v}\}$ is precisely the XY-plane.

You can convince yourself that no single vector can span the XY-plane. In fact, take a moment to consider what is meant by the span of a single vector.

However you can make the set larger if you wish. For example consider the larger set of vectors $\{\vec{u},\vec{v},\vec{w}\}$ where $\vec{w}=\begin{bmatrix}4&5&0\end{bmatrix}^T$. Since the first two vectors already span the entire XY-plane, the span is once again precisely the XY-plane and nothing has been gained. Of course if you add a new vector such as $\vec{w}=\begin{bmatrix}0&0&1\end{bmatrix}^T$ then it does span a different space. What is the span of $\vec{u},\vec{v},\vec{w}$ in this case?

The distinction between the sets $\{\vec{u},\vec{v}\}$ and $\{\vec{u},\vec{v},\vec{w}\}$ will be made using the concept of linear independence.

Consider the vectors $\vec{u},\vec{v}$, and $\vec{w}$ discussed above. In the next example, we will show how to formally demonstrate that $\vec{w}$ is in the span of $\vec{u}$ and $\vec{v}$.

Example 4.10.2: Vector in a Span

Let $\vec{u}=\begin{bmatrix}1&1&0\end{bmatrix}^T$ and $\vec{v}=\begin{bmatrix}3&2&0\end{bmatrix}^T\in\mathbb{R}^3$. Show that $\vec{w}=\begin{bmatrix}4&5&0\end{bmatrix}^T$ is in $\operatorname{span}\{\vec{u},\vec{v}\}$.

Solution

For a vector to be in $\operatorname{span}\{\vec{u},\vec{v}\}$, it must be a linear combination of these vectors. If $\vec{w}\in\operatorname{span}\{\vec{u},\vec{v}\}$, we must be able to find scalars a,b such that

$$\vec{w}=a\vec{u}+b\vec{v}$$

We proceed as follows.

$$\begin{bmatrix}4\\5\\0\end{bmatrix}=a\begin{bmatrix}1\\1\\0\end{bmatrix}+b\begin{bmatrix}3\\2\\0\end{bmatrix}$$

This is equivalent to the following system of equations

$$\begin{aligned}a+3b&=4\\a+2b&=5\end{aligned}\tag{4.10.1}$$

We solving this system the usual way, constructing the augmented matrix and row reducing to find the reduced row-echelon form.

$$\begin{bmatrix}1&3&4\\1&2&5\end{bmatrix}\to\cdots\to\begin{bmatrix}1&0&7\\0&1&-1\end{bmatrix}$$

The solution is $a=7,b=-1$. This means that

$$\vec{w}=7\vec{u}-\vec{v}$$

Therefore we can say that $\vec{w}$ is in $\operatorname{span}\{\vec{u},\vec{v}\}$.

Linearly Independent Set of Vectors

We now turn our attention to the following question: what linear combinations of a given set of vectors $\{\vec{u}_1,\cdots,\vec{u}_k\}$ in $\mathbb{R}^n$ yields the zero vector? Clearly $0\vec{u}_1+0\vec{u}_2+\cdots+0\vec{u}_k=\vec{0}$, but is it possible to have $\sum_{i=1}^k a_i\vec{u}_i=\vec{0}$ without all coefficients being zero?

You can create examples where this easily happens. For example if $\vec{u}_1=\vec{u}_2$, then $1\vec{u}_1-\vec{u}_2+0\vec{u}_3+\cdots+0\vec{u}_k=\vec{0}$, no matter the vectors $\{\vec{u}_3,\cdots,\vec{u}_k\}$. ØBut sometimes it can be more subtle.

Example 4.10.3: Linearly Dependent Set of Vectors

Consider the vectors

$$\vec{u}_1=\begin{bmatrix}0&1&-2\end{bmatrix}^T,\vec{u}_2=\begin{bmatrix}1&1&0\end{bmatrix}^T,\vec{u}_3=\begin{bmatrix}-2&3&2\end{bmatrix}^T,\text{ and }\vec{u}_4=\begin{bmatrix}1&-2&0\end{bmatrix}^T$$

in $\mathbb{R}^3$.

Then verify that

$$1\vec{u}_1 + 0\vec{u}_2 + -\vec{u}_3 - 2\vec{u}_4 = \vec{0}$$

You can see that the linear combination does yield the zero vector but has some non-zero coefficients. Thus we define a set of vectors to be *linearly dependent* if this happens.

Definition 4.10.3: Linearly Dependent Set of Vectors

A set of non-zero vectors $\{\vec{u}_1, \cdots, \vec{u}_k\}$ in $\mathbb{R}^n$ is said to be **linearly dependent** if a linear combination of these vectors without all coefficients being zero does yield the zero vector.

Note that if $\sum_{i=1}^{k} a_i\vec{u}_i = \vec{0}$ and some coefficient is non-zero, say $a_1 \neq 0$, then

$$\vec{u}_1 = \frac{-1}{a_1}\sum_{i=2}^{k} a_i\vec{u}_i$$

and thus $\vec{u}_1$ is in the span of the other vectors. And the converse clearly works as well, so we get that a set of vectors is linearly dependent precisely when one of its vector is in the span of the other vectors of that set.

In particular, you can show that the vector $\vec{u}_1$ in the above example is in the span of the vectors $\{\vec{u}_2, \vec{u}_3, \vec{u}_4\}$.

If a set of vectors is NOT linearly dependent, then it must be that any linear combination of these vectors which yields the zero vector must use all zero coefficients. This is a very important notion, and we give it its own name of *linear independence*.

Definition 4.10.4: Linearly Independent Set of Vectors

A set of non-zero vectors $\{\vec{u}_1, \cdots, \vec{u}_k\}$ in $\mathbb{R}^n$ is said to be **linearly independent** if whenever

$$\sum_{i=1}^{k} a_i\vec{u}_i = \vec{0}$$

it follows that each $a_i = 0$.

Note also that we require all vectors to be non-zero to form a linearly independent set.

To view this in a more familiar setting, form the $n \times k$ matrix A having these vectors as columns. Then all we are saying is that the set $\{\vec{u}_1, \cdots, \vec{u}_k\}$ is linearly independent precisely when $AX = 0$ has only the trivial solution.

Here is an example.

Example 4.10.4: Linearly Independent Vectors

Consider the vectors $\vec{u} = \begin{bmatrix} 1 & 1 & 0 \end{bmatrix}^T$, $\vec{v} = \begin{bmatrix} 1 & 0 & 1 \end{bmatrix}^T$, and $\vec{w} = \begin{bmatrix} 0 & 1 & 1 \end{bmatrix}^T$ in $\mathbb{R}^3$. Verify whether the set $\{\vec{u}, \vec{v}, \vec{w}\}$ is linearly independent.

Solution

So suppose that we have a linear combinations $a\vec{u} + b\vec{v} + c\vec{w} = \vec{0}$. Then you can see that this can only happen with $a = b = c = 0$.

As mentioned above, you can equivalently form the 3×3 matrix $A = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}$, and show that $AX = 0$ has only the trivial solution.

Thus this means the set $\{\vec{u}, \vec{v}, \vec{w}\}$ is linearly independent.

In terms of spanning, a set of vectors is linearly independent if it does not contain unnecessary vectors, that is not vector is in the span of the others.

Thus we put all this together in the following important theorem.

Theorem 4.10.1: Linear Independence as a Linear Combination

Let $\{\vec{u}_1, \cdots, \vec{u}_k\}$ be a collection of vectors in $\mathbb{R}^n$. Then the following are equivalent:

1. It is linearly independent, that is whenever
$$\sum_{i=1}^{k} a_i \vec{u}_i = \vec{0}$$
it follows that each coefficient $a_i = 0$.
2. No vector is in the span of the others.
3. The system of linear equations $AX = 0$ has only the trivial solution, where A is the $n \times k$ matrix having these vectors as columns.

The last sentence of this theorem is useful as it allows us to use the reduced row-echelon form of a matrix to determine if a set of vectors is linearly independent. Let the vectors be columns of a matrix A. Find the reduced row-echelon form of A. If each column has a leading one, then it follows that the vectors are linearly independent.

Sometimes we refer to the condition regarding sums as follows: The set of vectors, $\{\vec{u}_1, \cdots, \vec{u}_k\}$ is linearly independent if and only if there is no nontrivial linear combination which equals the zero vector. A nontrivial linear combination is one in which not all the scalars equal zero. Similarly, a trivial linear combination is one in which all scalars equal zero.

Here is a detailed example in $\mathbb{R}^4$.

Example 4.10.5: Linear Independence

Determine whether the set of vectors given by
$$\left\{ \begin{bmatrix} 1 \\ 2 \\ 3 \\ 0 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 3 \\ 2 \\ 2 \\ 0 \end{bmatrix} \right\}$$
is linearly independent. If it is linearly dependent, express one of the vectors as a linear combination of the others.

Solution

In this case the matrix of the corresponding homogeneous system of linear equations is
$$\begin{bmatrix} 1 & 2 & 0 & 3 & 0 \\ 2 & 1 & 1 & 2 & 0 \\ 3 & 0 & 1 & 2 & 0 \\ 0 & 1 & 2 & 0 & 0 \end{bmatrix}$$

The reduced row-echelon form is
$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

and so every column is a pivot column and the corresponding system $AX = 0$ only has the trivial solution. Therefore, these vectors are linearly independent and there is no way to obtain one of the vectors as a linear combination of the others.

Consider another example.

Example 4.10.6: Linear Independence

Determine whether the set of vectors given by

$$\left\{ \begin{bmatrix} 1 \\ 2 \\ 3 \\ 0 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 3 \\ 2 \\ 2 \\ -1 \end{bmatrix} \right\}$$

is linearly independent. If it is linearly dependent, express one of the vectors as a linear combination of the others.

Solution

Form the 4×4 matrix A having these vectors as columns:

$$A = \begin{bmatrix} 1 & 2 & 0 & 3 \\ 2 & 1 & 1 & 2 \\ 3 & 0 & 1 & 2 \\ 0 & 1 & 2 & -1 \end{bmatrix}$$

Then by Theorem 4.10.1, the given set of vectors is linearly independent exactly if the system $AX = 0$ has only the trivial solution.

The augmented matrix for this system and corresponding reduced row-echelon form are given by

$$\begin{bmatrix} 1 & 2 & 0 & 3 & 0 \\ 2 & 1 & 1 & 2 & 0 \\ 3 & 0 & 1 & 2 & 0 \\ 0 & 1 & 2 & -1 & 0 \end{bmatrix} \rightarrow \cdots \rightarrow \begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Not all the columns of the coefficient matrix are pivot columns and so the vectors are not linearly independent. In this case, we say the vectors are linearly dependent.

It follows that there are infinitely many solutions to $AX = 0$, one of which is

$$\begin{bmatrix} 1 \\ 1 \\ -1 \\ -1 \end{bmatrix}$$

Therefore we can write

$$1 \begin{bmatrix} 1 \\ 2 \\ 3 \\ 0 \end{bmatrix} + 1 \begin{bmatrix} 2 \\ 1 \\ 0 \\ 1 \end{bmatrix} - 1 \begin{bmatrix} 0 \\ 1 \\ 1 \\ 2 \end{bmatrix} - 1 \begin{bmatrix} 3 \\ 2 \\ 2 \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

This can be rearranged as follows

$$1 \begin{bmatrix} 1 \\ 2 \\ 3 \\ 0 \end{bmatrix} + 1 \begin{bmatrix} 2 \\ 1 \\ 0 \\ 1 \end{bmatrix} - 1 \begin{bmatrix} 0 \\ 1 \\ 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 3 \\ 2 \\ 2 \\ -1 \end{bmatrix}$$

This gives the last vector as a linear combination of the first three vectors.

Notice that we could rearrange this equation to write any of the four vectors as a linear combination of the other three.

When given a linearly independent set of vectors, we can determine if related sets are linearly independent.

Example 4.10.7: Related Sets of Vectors

Let $\{\vec{u},\vec{v},\vec{w}\}$ be an independent set of $\mathbb{R}^n$. Is $\{\vec{u}+\vec{v},2\vec{u}+\vec{w},\vec{v}-5\vec{w}\}$ linearly independent?

Solution

Suppose $a(\vec{u}+\vec{v})+b(2\vec{u}+\vec{w})+c(\vec{v}-5\vec{w})=\vec{0}_n$ for some $a,b,c\in\mathbb{R}$. Then

$$(a+2b)\vec{u}+(a+c)\vec{v}+(b-5c)\vec{w}=\vec{0}_n.$$

Since $\{\vec{u},\vec{v},\vec{w}\}$ is independent,

$$\begin{aligned} a+2b&=0\\ a+c&=0\\ b-5c&=0 \end{aligned} \tag{4.10.2}$$

This system of three equations in three variables has the unique solution $a=b=c=0$. Therefore, $\{\vec{u}+\vec{v},2\vec{u}+\vec{w},\vec{v}-5\vec{w}\}$ is independent.

The following corollary follows from the fact that if the augmented matrix of a homogeneous system of linear equations has more columns than rows, the system has infinitely many solutions.

Corollary 4.10.1: Linear Dependence in $\mathbb{R}''$

Let $\{\vec{u}_1,\cdots,\vec{u}_k\}$ be a set of vectors in $\mathbb{R}^n$. If $k>n$, then the set is linearly dependent (i.e. NOT linearly independent).

Proof available at the end of this section.

Example 4.10.8: Linear Dependence

Consider the vectors

$$\left\{\begin{bmatrix}1\\4\end{bmatrix},\begin{bmatrix}2\\3\end{bmatrix},\begin{bmatrix}3\\2\end{bmatrix}\right\}$$

Are these vectors linearly independent?

Solution

This set contains three vectors in $\mathbb{R}^2$. By Corollary 4.10.1 these vectors are linearly dependent. In fact, we can write

$$(-1)\begin{bmatrix}1\\4\end{bmatrix}+(2)\begin{bmatrix}2\\3\end{bmatrix}=\begin{bmatrix}3\\2\end{bmatrix}$$

showing that this set is linearly dependent.

The third vector in the previous example is in the span of the first two vectors. We could find a way to write this vector as a linear combination of the other two vectors. It turns out that the linear combination which we found is the **only** one, provided that the set is linearly independent.

Theorem 4.10.2: Unique Linear Combination

Let $U \subseteq \mathbb{R}^n$ be an independent set. Then any vector $\vec{x} \in \text{span}(U)$ can be written uniquely as a linear combination of vectors of U.

Proof available at the end of this section.

Suppose that $\vec{u}, \vec{v}$ and $\vec{w}$ are nonzero vectors in $\mathbb{R}^3$, and that $\{\vec{v}, \vec{w}\}$ is independent. Consider the set $\{\vec{u}, \vec{v}, \vec{w}\}$. When can we know that this set is independent? It turns out that this follows exactly when $\vec{u} \notin \text{span}\{\vec{v}, \vec{w}\}$.

Example 4.10.9

Suppose that $\vec{u}, \vec{v}$ and $\vec{w}$ are nonzero vectors in $\mathbb{R}^3$, and that $\{\vec{v}, \vec{w}\}$ is independent. Prove that $\{\vec{u}, \vec{v}, \vec{w}\}$ is independent if and only if $\vec{u} \notin \text{span}\{\vec{v}, \vec{w}\}$.

Solution

If $\vec{u} \in \text{span}\{\vec{v}, \vec{w}\}$, then there exist $a, b \in \mathbb{R}$ so that $\vec{u} = a\vec{v} + b\vec{w}$. This implies that $\vec{u} - a\vec{v} - b\vec{w} = \vec{0}_3$, so $\vec{u} - a\vec{v} - b\vec{w}$ is a nontrivial linear combination of $\{\vec{u}, \vec{v}, \vec{w}\}$ that vanishes, and thus $\{\vec{u}, \vec{v}, \vec{w}\}$ is dependent.

Now suppose that $\vec{u} \notin \text{span}\{\vec{v}, \vec{w}\}$, and suppose that there exist $a, b, c \in \mathbb{R}$ such that $a\vec{u} + b\vec{v} + c\vec{w} = \vec{0}_3$. If $a \neq 0$, then $\vec{u} = -\frac{b}{a}\vec{v} - \frac{c}{a}\vec{w}$, and $\vec{u} \in \text{span}\{\vec{v}, \vec{w}\}$, a contradiction. Therefore, $a = 0$, implying that $b\vec{v} + c\vec{w} = \vec{0}_3$. Since $\{\vec{v}, \vec{w}\}$ is independent, $b = c = 0$, and thus $a = b = c = 0$, i.e., the only linear combination of $\vec{u}, \vec{v}$ and $\vec{w}$ that vanishes is the trivial one.

Therefore, $\{\vec{u}, \vec{v}, \vec{w}\}$ is independent.

Consider the following useful theorem.

Theorem 4.10.3: Invertible Matrices

Let A be an invertible $n \times n$ matrix. Then the columns of A are independent and span $\mathbb{R}^n$. Similarly, the rows of A are independent and span the set of all $1 \times n$ vectors.

This theorem also allows us to determine if a matrix is invertible. If an $n \times n$ matrix A has columns which are independent, or span $\mathbb{R}^n$, then it follows that A is invertible. If it has rows that are independent, or span the set of all $1 \times n$ vectors, then A is invertible.

A Short Application to Chemistry

The following section applies the concepts of spanning and linear independence to the subject of chemistry.

When working with chemical reactions, there are sometimes a large number of reactions and some are in a sense redundant. Suppose you have the following chemical reactions.

$$CO + \tfrac{1}{2}O_2 \to CO_2$$
$$H_2 + \tfrac{1}{2}O_2 \to H_2O$$
$$CH_4 + \tfrac{3}{2}O_2 \to CO + 2H_2O$$
$$CH_4 + 2O_2 \to CO_2 + 2H_2O$$

There are four chemical reactions here but they are not independent reactions. There is some redundancy. What are the independent reactions? Is there a way to consider a shorter list of reactions? To analyze this situation, we can write the reactions in a matrix as follows

$$\begin{bmatrix} CO & O_2 & CO_2 & H_2 & H_2O & CH_4 \\ 1 & 1/2 & -1 & 0 & 0 & 0 \\ 0 & 1/2 & 0 & 1 & -1 & 0 \\ -1 & 3/2 & 0 & 0 & -2 & 1 \\ 0 & 2 & -1 & 0 & -2 & 1 \end{bmatrix}$$

Each row contains the coefficients of the respective elements in each reaction. For example, the top row of numbers comes from $CO + \frac{1}{2}O_2 - CO_2 = 0$ which represents the first of the chemical reactions.

We can write these coefficients in the following matrix

$$\begin{bmatrix} 1 & 1/2 & -1 & 0 & 0 & 0 \\ 0 & 1/2 & 0 & 1 & -1 & 0 \\ -1 & 3/2 & 0 & 0 & -2 & 1 \\ 0 & 2 & -1 & 0 & -2 & 1 \end{bmatrix}$$

Rather than listing all of the reactions as above, it would be more efficient to only list those which are independent by throwing out that which is redundant. We can use the concepts of the previous section to accomplish this.

First, take the reduced row-echelon form of the above matrix.

$$\begin{bmatrix} 1 & 0 & 0 & 3 & -1 & -1 \\ 0 & 1 & 0 & 2 & -2 & 0 \\ 0 & 0 & 1 & 4 & -2 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The top three rows represent “independent" reactions which come from the original four reactions. One can obtain each of the original four rows of the matrix given above by taking a suitable linear combination of rows of this reduced row-echelon matrix.

With the redundant reaction removed, we can consider the simplified reactions as the following equations

$$\begin{gathered} CO + 3H_2 - 1H_2O - 1CH_4 = 0 \\ O_2 + 2H_2 - 2H_2O = 0 \\ CO_2 + 4H_2 - 2H_2O - 1CH_4 = 0 \end{gathered}$$

In terms of the original notation, these are the reactions

$$\begin{gathered} CO + 3H_2 \to H_2O + CH_4 \\ O_2 + 2H_2 \to 2H_2O \\ CO_2 + 4H_2 \to 2H_2O + CH_4 \end{gathered}$$

These three reactions provide an equivalent system to the original four equations. The idea is that, in terms of what happens chemically, you obtain the same information with the shorter list of reactions. Such a simplification is especially useful when dealing with very large lists of reactions which may result from experimental evidence.

Subspaces and Basis

The goal of this section is to develop an understanding of a subspace of $\mathbb{R}^n$. Before a precise definition is considered, we first examine the subspace test given below.

Theorem 4.10.4: Subspace Test

A subset V of $\mathbb{R}^n$ is a subspace of $\mathbb{R}^n$ if

1. the zero vector of $\mathbb{R}^n$, $\vec{0}_n$, is in V;
2. V is closed under addition, i.e., for all $\vec{u}, \vec{w} \in V$, $\vec{u} + \vec{w} \in V$;
3. V is closed under scalar multiplication, i.e., for all $\vec{u} \in V$ and $k \in \mathbb{R}$, $k\vec{u} \in V$.

This test allows us to determine if a given set is a subspace of $\mathbb{R}^n$. Notice that the subset $V = \left\{\vec{0}\right\}$ is a subspace of $\mathbb{R}^n$ (called the

zero subspace), as is $\mathbb{R}^n$ itself. A subspace which is not the zero subspace of $\mathbb{R}^n$ is referred to as a proper subspace.

A subspace is simply a set of vectors with the property that linear combinations of these vectors remain in the set. Geometrically in $\mathbb{R}^3$, it turns out that a subspace can be represented by either the origin as a single point, lines and planes which contain the origin, or the entire space $\mathbb{R}^3$.

Consider the following example of a line in $\mathbb{R}^3$.

Example 4.10.10: Subspace of $\mathbb{R}^3$

In $\mathbb{R}^3$, the line L through the origin that is parallel to the vector $\vec{d} = \begin{bmatrix} -5 \\ 1 \\ -4 \end{bmatrix}$ has (vector) equation $\begin{bmatrix} x \\ y \\ z \end{bmatrix} = t \begin{bmatrix} -5 \\ 1 \\ -4 \end{bmatrix}, t \in \mathbb{R}$,

so

$$L = \left\{ t\vec{d} \mid t \in \mathbb{R} \right\}.$$

Then L is a subspace of $\mathbb{R}^3$.

Solution

Using the subspace test given above we can verify that L is a subspace of $\mathbb{R}^3$.

- First: $\vec{0}_3 \in L$ since $0\vec{d} = \vec{0}_3$.
- Suppose $\vec{u}, \vec{v} \in L$. Then by definition, $\vec{u} = s\vec{d}$ and $\vec{v} = t\vec{d}$, for some $s, t \in \mathbb{R}$. Thus

  $$\vec{u} + \vec{v} = s\vec{d} + t\vec{d} = (s+t)\vec{d}.$$

  Since $s + t \in \mathbb{R}$, $\vec{u} + \vec{v} \in L$; i.e., L is closed under addition.
- Suppose $\vec{u} \in L$ and $k \in \mathbb{R}$ (k is a scalar). Then $\vec{u} = t\vec{d}$, for some $t \in \mathbb{R}$, so

  $$k\vec{u} = k(t\vec{d}) = (kt)\vec{d}.$$

  Since $kt \in \mathbb{R}$, $k\vec{u} \in L$; i.e., L is closed under scalar multiplication.

Since L satisfies all conditions of the subspace test, it follows that L is a subspace.

Note that there is nothing special about the vector $\vec{d}$ used in this example; the same proof works for any nonzero vector $\vec{d} \in \mathbb{R}^3$, so any line through the origin is a subspace of $\mathbb{R}^3$.

We are now prepared to examine the precise definition of a subspace as follows.

Definition 4.10.5: Subspace

Let V be a nonempty collection of vectors in $\mathbb{R}^n$. Then V is called a subspace if whenever a and b are scalars and $\vec{u}$ and $\vec{v}$ are vectors in V, the linear combination $a\vec{u} + b\vec{v}$ is also in V.

More generally this means that a subspace contains the span of any finite collection vectors in that subspace. It turns out that in $\mathbb{R}^n$, a subspace is exactly the span of finitely many of its vectors.

Theorem 4.10.5: Subspaces are Spans

Let V be a nonempty collection of vectors in $\mathbb{R}^n$. Then V is a subspace of $\mathbb{R}^n$ if and only if there exist vectors $\{\vec{u}_1, \cdots, \vec{u}_k\}$ in V such that

$$V = \text{span}\{\vec{u}_1, \cdots, \vec{u}_k\}$$

Furthermore, let W be another subspace of $\mathbb{R}^n$ and suppose $\{\vec{u}_1, \cdots, \vec{u}_k\} \in W$. Then it follows that V is a subset of W.

Note that since W is arbitrary, the statement that $V \subseteq W$ means that any other subspace of $\mathbb{R}^n$ that contains these vectors will also contain V.

Proof available at the end of this section.

Since the vectors $\vec{u}_i$ we constructed in the proof above are not in the span of the previous vectors (by definition), they must be linearly independent and thus we obtain the following corollary.

Corollary 4.10.2: Subspaces are Spans of Independent Vectors

If V is a subspace of $\mathbb{R}^n$, then there exist linearly independent vectors $\{\vec{u}_1, \cdots, \vec{u}_k\}$ in V such that $V = \text{span}\{\vec{u}_1, \cdots, \vec{u}_k\}$.

In summary, subspaces of $\mathbb{R}^n$ consist of spans of finite, linearly independent collections of vectors of $\mathbb{R}^n$. Such a collection of vectors is called a basis.

Definition 4.10.6: Basis of a Subspace

Let V be a subspace of $\mathbb{R}^n$. Then $\{\vec{u}_1, \cdots, \vec{u}_k\}$ is a **basis** for V if the following two conditions hold.

1. $\text{span}\{\vec{u}_1, \cdots, \vec{u}_k\} = V$
2. $\{\vec{u}_1, \cdots, \vec{u}_k\}$ is linearly independent

Note the plural of basis is **bases**.

The following is a simple but very useful example of a basis, called the standard basis.

Definition 4.10.7: Standard Basis of $\mathbb{R}^n$

Let $\vec{e}_i$ be the vector in $\mathbb{R}^n$ which has a 1 in the i^{th} entry and zeros elsewhere, that is the i^{th} column of the identity matrix. Then the collection $\{\vec{e}_1, \vec{e}_2, \cdots, \vec{e}_n\}$ is a basis for $\mathbb{R}^n$ and is called the standard basis of $\mathbb{R}^n$.

The main theorem about bases is not only they exist, but that they must be of the same size. To show this, we will need the the following fundamental result, called the Exchange Theorem.

Theorem 4.10.6: Exchange Theorem

Suppose $\{\vec{u}_1, \cdots, \vec{u}_r\}$ is a linearly independent set of vectors in $\mathbb{R}^n$, and each $\vec{u}_k$ is contained in $\text{span}\{\vec{v}_1, \cdots, \vec{v}_s\}$ Then $s \geq r$. In words, spanning sets have at least as many vectors as linearly independent sets.

Proof available at the end of this section.

We are now ready to show that any two bases are of the same size.

Theorem 4.10.7: Bases of $\mathbb{R}^n$ are of the Same Size

Let V be a subspace of $\mathbb{R}^n$ with two bases B_1 and B_2. Suppose B_1 contains s vectors and B_2 contains r vectors. Then $s = r$.

Proof available at the end of this section.

The following definition can now be stated.

Definition 4.10.8: Dimension of a Subspace

Let V be a subspace of $\mathbb{R}^n$. Then the **dimension** of V, written $\dim(V)$ is defined to be the number of vectors in a basis.

The next result follows.

Corollary 4.10.3: Dimension of $\mathbb{R}^n$

The dimension of $\mathbb{R}^n$ is n.

Proof available at the end of this section.

Consider the following example.

Example 4.10.11: Basis of Subspace

Let

$$V = \left\{ \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \in \mathbb{R}^4 \ : \ a - b = d - c \right\}.$$

Show that V is a subspace of $\mathbb{R}^4$, find a basis of V, and find $\dim(V)$.

Solution

The condition $a - b = d - c$ is equivalent to the condition $a = b - c + d$, so we may write

$$V = \left\{ \begin{bmatrix} b - c + d \\ b \\ c \\ d \end{bmatrix} \ : \ b, c, d \in \mathbb{R} \right\} = \left\{ b \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} + c \begin{bmatrix} -1 \\ 0 \\ 1 \\ 0 \end{bmatrix} + d \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} \ : \ b, c, d \in \mathbb{R} \right\}$$

This shows that V is a subspace of $\mathbb{R}^4$, since $V = \text{span}\{\vec{u}_1, \vec{u}_2, \vec{u}_3\}$ where

$$\vec{u}_1 = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \vec{u}_2 = \begin{bmatrix} -1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \vec{u}_3 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

Furthermore,

$$\left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right\}$$

is linearly independent, as can be seen by taking the reduced row-echelon form of the matrix whose columns are $\vec{u}_1, \vec{u}_2$ and $\vec{u}_3$.

$$\begin{bmatrix} 1 & -1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

Since every column of the reduced row-echelon form matrix has a leading one, the columns are linearly independent.

Therefore $\{\vec{u}_1, \vec{u}_2, \vec{u}_3\}$ is linearly independent and spans V, so is a basis of V. Hence V has dimension three.

We continue by stating further properties of a set of vectors in $\mathbb{R}^n$.

Corollary 4.10.4: Linearly Independent and Spanning Sets in $\mathbb{R}^n$

The following properties hold in $\mathbb{R}^n$:

- Suppose $\{\vec{u}_1, \cdots, \vec{u}_n\}$ is linearly independent. Then $\{\vec{u}_1, \cdots, \vec{u}_n\}$ is a basis for $\mathbb{R}^n$.
- Suppose $\{\vec{u}_1, \cdots, \vec{u}_m\}$ spans $\mathbb{R}^n$. Then $m \geq n$.
- If $\{\vec{u}_1, \cdots, \vec{u}_n\}$ spans $\mathbb{R}^n$, then $\{\vec{u}_1, \cdots, \vec{u}_n\}$ is linearly independent.

Proof available at the end of this section.

The next theorem follows from the above claim.

Theorem 4.10.8: Existence of Basis

Let V be a subspace of $\mathbb{R}^n$. Then there exists a basis of V with $\dim(V) \leq n$.

Consider Corollary 4.10.4 together with Theorem 4.10.8. Let $\dim(V) = r$. Suppose there exists an independent set of vectors in V. If this set contains r vectors, then it is a basis for V. If it contains less than r vectors, then vectors can be added to the set to create a basis of V. Similarly, any spanning set of V which contains more than r vectors can have vectors removed to create a basis of V.

We illustrate this concept in the next example.

Example 4.10.12: Extending an Independent Set

Consider the set U given by

$$U = \left\{ \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \in \mathbb{R}^4 \;\middle|\; a - b = d - c \right\}$$

Then U is a subspace of $\mathbb{R}^4$ and $\dim(U) = 3$.

Then

$$S = \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 3 \\ 3 \\ 2 \end{bmatrix} \right\},$$

is an independent subset of U. Therefore S can be extended to a basis of U.

Solution

To extend S to a basis of U, find a vector in U that is **not** in $\text{span}(S)$.

$$\begin{bmatrix} 1 & 2 & ? \\ 1 & 3 & ? \\ 1 & 3 & ? \\ 1 & 2 & ? \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 & 1 \\ 1 & 3 & 0 \\ 1 & 3 & -1 \\ 1 & 2 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

Therefore, S can be extended to the following basis of U:

$$\left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 3 \\ 3 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ -1 \\ 0 \end{bmatrix} \right\},$$

Next we consider the case of removing vectors from a spanning set to result in a basis.

Theorem 4.10.9: Finding a Basis from a Span

Let W be a subspace. Also suppose that $W = span\left\{\vec{w}_1, \cdots, \vec{w}_m\right\}$. Then there exists a subset of $\left\{\vec{w}_1, \cdots, \vec{w}_m\right\}$ which is a basis for W.

Proof available at the end of this section.

The following example illustrates how to carry out this shrinking process which will obtain a subset of a span of vectors which is linearly independent.

Example 4.10.13: Subset of a Span

Let W be the subspace

$$span\left\{ \begin{bmatrix} 1 \\ 2 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 3 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 8 \\ 19 \\ -8 \\ 8 \end{bmatrix}, \begin{bmatrix} -6 \\ -15 \\ 6 \\ -6 \end{bmatrix}, \begin{bmatrix} 1 \\ 3 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 5 \\ 0 \\ 1 \end{bmatrix} \right\}$$

Find a basis for W which consists of a subset of the given vectors.

Solution

You can use the reduced row-echelon form to accomplish this reduction. Form the matrix which has the given vectors as columns.

$$\begin{bmatrix} 1 & 1 & 8 & -6 & 1 & 1 \\ 2 & 3 & 19 & -15 & 3 & 5 \\ -1 & -1 & -8 & 6 & 0 & 0 \\ 1 & 1 & 8 & -6 & 1 & 1 \end{bmatrix}$$

Then take the reduced row-echelon form

$$\begin{bmatrix} 1 & 0 & 5 & -3 & 0 & -2 \\ 0 & 1 & 3 & -3 & 0 & 2 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

It follows that a basis for W is

$$\left\{\begin{bmatrix}1\\2\\-1\\1\end{bmatrix},\begin{bmatrix}1\\3\\-1\\1\end{bmatrix},\begin{bmatrix}1\\3\\0\\1\end{bmatrix}\right\}$$

Since the first, second, and fifth columns are obviously a basis for the column space of the , the same is true for the matrix having the given vectors as columns.

Consider the following theorems regarding a subspace contained in another subspace.

Theorem 4.10.10: Subset of a Subspace

Let V and W be subspaces of $\mathbb{R}^n$, and suppose that $W \subseteq V$. Then $\dim(W) \leq \dim(V)$ with equality when $W = V$.

Theorem 4.10.11: Extending a Basis

Let W be any non-zero subspace $\mathbb{R}^n$ and let $W \subseteq V$ where V is also a subspace of $\mathbb{R}^n$. Then every basis of W can be extended to a basis for V.

The proof is left as an exercise but proceeds as follows. Begin with a basis for $W, \{\vec{w}_1, \cdots, \vec{w}_s\}$ and add in vectors from V until you obtain a basis for V. Not that the process will stop because the dimension of V is no more than n.

Consider the following example.

Example 4.10.14: Extending a Basis

Let $V = \mathbb{R}^4$ and let

$$W = \text{span}\left\{\begin{bmatrix}1\\0\\1\\1\end{bmatrix},\begin{bmatrix}0\\1\\0\\1\end{bmatrix}\right\}$$

Extend this basis of W to a basis of $\mathbb{R}^n$.

Solution

An easy way to do this is to take the reduced row-echelon form of the matrix

$$\begin{bmatrix}1&0&1&0&0&0\\0&1&0&1&0&0\\1&0&0&0&1&0\\1&1&0&0&0&1\end{bmatrix} \tag{4.10.3}$$

Note how the given vectors were placed as the first two columns and then the matrix was extended in such a way that it is clear that the span of the columns of this matrix yield all of $\mathbb{R}^4$. Now determine the pivot columns. The reduced row-echelon form is

$$\begin{bmatrix}1&0&0&0&1&0\\0&1&0&0&-1&1\\0&0&1&0&-1&0\\0&0&0&1&1&-1\end{bmatrix} \tag{4.10.4}$$

Therefore the pivot columns are

$$\left[\begin{array}{c}1\\0\\1\\1\end{array}\right],\left[\begin{array}{c}0\\1\\0\\1\end{array}\right],\left[\begin{array}{c}1\\0\\0\\0\end{array}\right],\left[\begin{array}{c}0\\1\\0\\0\end{array}\right]$$

and now this is an extension of the given basis for W to a basis for $\mathbb{R}^4$.

Why does this work? The columns of (4.10.3) obviously span $\mathbb{R}^4$. In fact the span of the first four is the same as the span of all six.

Consider another example.

Example 4.10.15: Extending a Basis

Let W be the span of $\left[\begin{array}{c}1\\0\\1\\0\end{array}\right]$ in $\mathbb{R}^4$. Let V consist of the span of the vectors

$$\left[\begin{array}{c}1\\0\\1\\0\end{array}\right],\left[\begin{array}{c}0\\1\\1\\1\end{array}\right],\left[\begin{array}{r}7\\-6\\1\\-6\end{array}\right],\left[\begin{array}{r}-5\\7\\2\\7\end{array}\right],\left[\begin{array}{c}0\\0\\0\\1\end{array}\right]$$

Find a basis for V which extends the basis for W.

Solution

Note that the above vectors are not linearly independent, but their span, denoted as V is a subspace which does include the subspace W.

Using the process outlined in the previous example, form the following matrix

$$\left[\begin{array}{rrrrr}1&0&7&-5&0\\0&1&-6&7&0\\1&1&1&2&0\\0&1&-6&7&1\end{array}\right]$$

Next find its reduced row-echelon form

$$\left[\begin{array}{rrrrr}1&0&7&-5&0\\0&1&-6&7&0\\0&0&0&0&1\\0&0&0&0&0\end{array}\right]$$

It follows that a basis for V consists of the first two vectors and the last.

$$\left\{\left[\begin{array}{c}1\\0\\1\\0\end{array}\right],\left[\begin{array}{c}0\\1\\1\\1\end{array}\right],\left[\begin{array}{c}0\\0\\0\\1\end{array}\right]\right\}$$

Thus V is of dimension 3 and it has a basis which extends the basis for W.

Row Space, Column Space, and Null Space of a Matrix

We begin this section with a new definition.

Definition 4.10.9: Row and Column Space

Let A be an $m \times n$ matrix. The **column space** of A, written $\mathrm{col}(A)$, is the span of the columns. The **row space** of A, written $\mathrm{row}(A)$, is the span of the rows.

Using the reduced row-echelon form, we can obtain an efficient description of the row and column space of a matrix. Consider the following lemma.

Lemma 4.10.1: Effect of Row Operations on Row Space

Let A and B be $m \times n$ matrices such that A can be carried to B by elementary row $[\text{column}]$ operations. Then $\mathrm{row}(A) = \mathrm{row}(B)$ $[\mathrm{col}(A) = \mathrm{col}(B)]$.

Proof available at the end of this section.

Consider the following lemma.

Lemma 4.10.2: Row Space of a reduced row-echelon form Matrix

Let A be an $m \times n$ matrix and let R be its reduced row-echelon form. Then the nonzero rows of R form a basis of $\mathrm{row}(R)$, and consequently of $\mathrm{row}(A)$.

This lemma suggests that we can examine the reduced row-echelon form of a matrix in order to obtain the row space. Consider now the column space. The column space can be obtained by simply saying that it equals the span of all the columns. However, you can often get the column space as the span of fewer columns than this. A variation of the previous lemma provides a solution. Suppose A is row reduced to its reduced row-echelon form R. Identify the pivot columns of R (columns which have leading ones), and take the corresponding columns of A. It turns out that this forms a basis of $\mathrm{col}(A)$.

Before proceeding to an example of this concept, we revisit the definition of rank.

Definition 4.10.10: Rank of a Matrix

Previously, we defined $\mathrm{rank}(A)$ to be the number of leading entries in the row-echelon form of A. Using an understanding of dimension and row space, we can now define rank as follows:

$$\mathrm{rank}(A) = \dim(\mathrm{row}(A))$$

Consider the following example.

Example 4.10.16: Rank, Column and Row Space

Find the rank of the following matrix and describe the column and row spaces.

$$A = \begin{bmatrix} 1 & 2 & 1 & 3 & 2 \\ 1 & 3 & 6 & 0 & 2 \\ 3 & 7 & 8 & 6 & 6 \end{bmatrix}$$

Solution

The reduced row-echelon form of A is

$$\begin{bmatrix} 1 & 0 & -9 & 9 & 2 \\ 0 & 1 & 5 & -3 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Therefore, the rank is 2.

Notice that the first two columns of R are pivot columns. By the discussion following Lemma 4.10.2, we find the corresponding columns of A, in this case the first two columns. Therefore a basis for $\mathrm{col}(A)$ is given by

$$\left\{ \begin{bmatrix} 1 \\ 1 \\ 3 \end{bmatrix}, \begin{bmatrix} 2 \\ 3 \\ 7 \end{bmatrix} \right\}$$

For example, consider the third column of the original matrix. It can be written as a linear combination of the first two columns of the original matrix as follows.

$$\begin{bmatrix} 1 \\ 6 \\ 8 \end{bmatrix} = -9 \begin{bmatrix} 1 \\ 1 \\ 3 \end{bmatrix} + 5 \begin{bmatrix} 2 \\ 3 \\ 7 \end{bmatrix}$$

What about an efficient description of the row space? By Lemma 4.10.2 we know that the nonzero rows of R create a basis of $\mathrm{row}(A)$. For the above matrix, the row space equals

$$\mathrm{row}(A) = \mathrm{span}\left\{ \begin{bmatrix} 1 & 0 & -9 & 9 & 2 \end{bmatrix}, \begin{bmatrix} 0 & 1 & 5 & -3 & 0 \end{bmatrix} \right\}$$

Notice that the column space of A is given as the span of columns of the original matrix, while the row space of A is the span of rows of the reduced row-echelon form of A.

Consider another example.

Example 4.10.17: Rank, Column and Row Space

Find the rank of the following matrix and describe the column and row spaces.

$$\begin{bmatrix} 1 & 2 & 1 & 3 & 2 \\ 1 & 3 & 6 & 0 & 2 \\ 1 & 2 & 1 & 3 & 2 \\ 1 & 3 & 2 & 4 & 0 \end{bmatrix}$$

Solution

The reduced row-echelon form is

$$\begin{bmatrix} 1 & 0 & 0 & 0 & \frac{13}{2} \\ 0 & 1 & 0 & 2 & -\frac{5}{2} \\ 0 & 0 & 1 & -1 & \frac{1}{2} \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

and so the rank is 3. The row space is given by

$$\mathrm{row}(A) = \mathrm{span}\left\{ \begin{bmatrix} 1 & 0 & 0 & 0 & \frac{13}{2} \end{bmatrix}, \begin{bmatrix} 0 & 1 & 0 & 2 & -\frac{5}{2} \end{bmatrix}, \begin{bmatrix} 0 & 0 & 1 & -1 & \frac{1}{2} \end{bmatrix} \right\}$$

Notice that the first three columns of the reduced row-echelon form are pivot columns. The column space is the span of the first three columns in the **original matrix**,

$$\text{col}(A) = \text{span}\left\{\begin{bmatrix}1\\1\\1\\1\end{bmatrix}, \begin{bmatrix}2\\3\\2\\3\end{bmatrix}, \begin{bmatrix}1\\6\\1\\2\end{bmatrix}\right\}$$

Consider the solution given above for Example 4.10.17, where the rank of A equals 3. Notice that the row space and the column space each had dimension equal to 3. It turns out that this is not a coincidence, and this essential result is referred to as the Rank Theorem and is given now. Recall that we defined $\text{rank}(A) = \dim(\text{row}(A))$.

Theorem 4.10.12: Rank Theorem

Let A be an $m \times n$ matrix. Then $\dim(\text{col}(A))$, the dimension of the column space, is equal to the dimension of the row space, $\dim(\text{row}(A))$.

The following statements all follow from the Rank Theorem.

Corollary 4.10.5: Results of the Rank Theorem

Let A be a matrix. Then the following are true:

1. $\text{rank}(A) = \text{rank}(A^T)$.
2. For A of size $m \times n$, $\text{rank}(A) \leq m$ and $\text{rank}(A) \leq n$.
3. For A of size $n \times n$, A is invertible if and only if $\text{rank}(A) = n$.
4. For invertible matrices B and C of appropriate size, $\text{rank}(A) = \text{rank}(BA) = \text{rank}(AC)$.

Consider the following example.

Example 4.10.18: Rank of the Transpose

Let

$$A = \begin{bmatrix} 1 & 2 \\ -1 & 1 \end{bmatrix}$$

Find $\text{rank}(A)$ and $\text{rank}(A^T)$.

Solution

To find $\text{rank}(A)$ we first row reduce to find the reduced row-echelon form.

$$A = \begin{bmatrix} 1 & 2 \\ -1 & 1 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Therefore the rank of A is 2. Now consider A^T given by

$$A^T = \begin{bmatrix} 1 & -1 \\ 2 & 1 \end{bmatrix}$$

Again we row reduce to find the reduced row-echelon form.

$$\begin{bmatrix} 1 & -1 \\ 2 & 1 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

You can see that $\text{rank}(A^T) = 2$, the same as $\text{rank}(A)$.

We now define what is meant by the null space of a general $m \times n$ matrix.

Definition 4.10.11: Null Space, or Kernel, of A

The null space of a matrix A, also referred to as the kernel of A, is defined as follows.

$$\text{null}\,(A) = \left\{\vec{x} : A\vec{x} = \vec{0}\right\}$$

It can also be referred to using the notation $\ker(A)$. Similarly, we can discuss the image of A, denoted by $\text{im}\,(A)$. The image of A consists of the vectors of $\mathbb{R}^m$ which "get hit" by A. The formal definition is as follows.

Definition 4.10.12: Image of A

The image of A, written $\text{im}\,(A)$ is given by

$$\text{im}\,(A) = \left\{A\vec{x} : \vec{x} \in \mathbb{R}^n\right\}$$

Consider A as a mapping from $\mathbb{R}^n$ to $\mathbb{R}^m$ whose action is given by multiplication. The following diagram displays this scenario.

$$\begin{matrix}\text{null}(A) & & \text{im}(A) \\ \mathbb{R}^n & \overset{A}{\rightarrow} & \mathbb{R}^m\end{matrix}$$

As indicated, $\text{im}\,(A)$ is a subset of $\mathbb{R}^m$ while $\text{null}\,(A)$ is a subset of $\mathbb{R}^n$.

It turns out that the null space and image of A are both subspaces. Consider the following example.

Example 4.10.19: Null Space

Let A be an $m \times n$ matrix. Then the null space of A, $\text{null}(A)$ is a subspace of $\mathbb{R}^n$.

Solution

- Since $A\vec{0}_n = \vec{0}_m$, $\vec{0}_n \in \text{null}(A)$.
- Let $\vec{x}, \vec{y} \in \text{null}(A)$. Then $A\vec{x} = \vec{0}_m$ and $A\vec{y} = \vec{0}_m$, so
$$A(\vec{x} + \vec{y}) = A\vec{x} + A\vec{y} = \vec{0}_m + \vec{0}_m = \vec{0}_m,$$
and thus $\vec{x} + \vec{y} \in \text{null}(A)$.
- Let $\vec{x} \in \text{null}(A)$ and $k \in \mathbb{R}$. Then $A\vec{x} = \vec{0}_m$, so
$$A(k\vec{x}) = k(A\vec{x}) = k\vec{0}_m = \vec{0}_m,$$
and thus $k\vec{x} \in \text{null}(A)$.

Therefore by the subspace test, $\text{null}(A)$ is a subspace of $\mathbb{R}^n$.

The proof that $\text{im}(A)$ is a subspace of $\mathbb{R}^m$ is similar and is left as an exercise to the reader.

We now wish to find a way to describe $\text{null}(A)$ for a matrix A. However, finding $\text{null}\,(A)$ is not new! There is just some new terminology being used, as $\text{null}\,(A)$ is simply the solution to the system $A\vec{x} = \vec{0}$.

Theorem 4.10.13: Basis of null(A)

Let A be an $m \times n$ matrix such that $\text{rank}(A) = r$. Then the system $A\vec{x} = \vec{0}_m$ has $n - r$ basic solutions, providing a basis of $\text{null}(A)$ with $\dim(\text{null}(A)) = n - r$.

Consider the following example.

Example 4.10.20: Null Space of A

Let

$$A = \begin{bmatrix} 1 & 2 & 1 \\ 0 & -1 & 1 \\ 2 & 3 & 3 \end{bmatrix}$$

Find $\text{null}\,(A)$ and $\text{im}\,(A)$.

Solution

In order to find $\text{null}\,(A)$, we simply need to solve the equation $A\vec{x} = \vec{0}$. This is the usual procedure of writing the augmented matrix, finding the reduced row-echelon form and then the solution. The augmented matrix and corresponding reduced row-echelon form are

$$\begin{bmatrix} 1 & 2 & 1 & 0 \\ 0 & -1 & 1 & 0 \\ 2 & 3 & 3 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & 3 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

The third column is not a pivot column, and therefore the solution will contain a parameter. The solution to the system $A\vec{x} = \vec{0}$ is given by

$$\begin{bmatrix} -3t \\ t \\ t \end{bmatrix} : t \in \mathbb{R}$$

which can be written as

$$t \begin{bmatrix} -3 \\ 1 \\ 1 \end{bmatrix} : t \in \mathbb{R}$$

Therefore, the null space of A is all multiples of this vector, which we can write as

$$\text{null}(A) = \text{span}\left\{ \begin{bmatrix} -3 \\ 1 \\ 1 \end{bmatrix} \right\}$$

Finally $\text{im}\,(A)$ is just $\left\{ A\vec{x} : \vec{x} \in \mathbb{R}^n \right\}$ and hence consists of the span of all columns of A, that is $\text{im}\,(A) = \text{col}(A)$.

Notice from the above calculation that that the first two columns of the reduced row-echelon form are pivot columns. Thus the column space is the span of the first two columns in the **original matrix**, and we get

$$\text{im}\,(A) = \text{col}(A) = \text{span}\left\{ \begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \\ 3 \end{bmatrix} \right\}$$

Here is a larger example, but the method is entirely similar.

Example 4.10.21: Null Space of A

Let

$$A = \begin{bmatrix} 1 & 2 & 1 & 0 & 1 \\ 2 & -1 & 1 & 3 & 0 \\ 3 & 1 & 2 & 3 & 1 \\ 4 & -2 & 2 & 6 & 0 \end{bmatrix}$$

Find the null space of A.

Solution

To find the null space, we need to solve the equation $AX = 0$. The augmented matrix and corresponding reduced row-echelon form are given by

$$\begin{bmatrix} 1 & 2 & 1 & 0 & 1 & 0 \\ 2 & -1 & 1 & 3 & 0 & 0 \\ 3 & 1 & 2 & 3 & 1 & 0 \\ 4 & -2 & 2 & 6 & 0 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & \frac{3}{5} & \frac{6}{5} & \frac{1}{5} & 0 \\ 0 & 1 & \frac{1}{5} & -\frac{3}{5} & \frac{2}{5} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

It follows that the first two columns are pivot columns, and the next three correspond to parameters. Therefore, $\text{null}\,(A)$ is given by

$$\begin{bmatrix} \left(-\frac{3}{5}\right)s + \left(-\frac{6}{5}\right)t + \left(\frac{1}{5}\right)r \\ \left(-\frac{1}{5}\right)s + \left(\frac{3}{5}\right)t + \left(-\frac{2}{5}\right)r \\ s \\ t \\ r \end{bmatrix} : s, t, r \in \mathbb{R}.$$

We write this in the form

$$s\begin{bmatrix} -\frac{3}{5} \\ -\frac{1}{5} \\ 1 \\ 0 \\ 0 \end{bmatrix} + t\begin{bmatrix} -\frac{6}{5} \\ \frac{3}{5} \\ 0 \\ 1 \\ 0 \end{bmatrix} + r\begin{bmatrix} \frac{1}{5} \\ -\frac{2}{5} \\ 0 \\ 0 \\ 1 \end{bmatrix} : s, t, r \in \mathbb{R}.$$

In other words, the null space of this matrix equals the span of the three vectors above. Thus

$$\text{null}\,(A) = \text{span}\left\{\begin{bmatrix} -\frac{3}{5} \\ -\frac{1}{5} \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} -\frac{6}{5} \\ \frac{3}{5} \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} \frac{1}{5} \\ -\frac{2}{5} \\ 0 \\ 0 \\ 1 \end{bmatrix}\right\}$$

Notice also that the three vectors above are linearly independent and so the dimension of $\text{null}\,(A)$ is 3. The following is true in general, the number of parameters in the solution of $AX = 0$ equals the dimension of the null space. Recall also that the number of leading ones in the reduced row-echelon form equals the number of pivot columns, which is the rank of the matrix, which is the same as the dimension of either the column or row space.

Before we proceed to an important theorem, we first define what is meant by the nullity of a matrix.

Definition 4.10.13: Nullity

The dimension of the null space of a matrix is called the **nullity**, denoted $\dim(\text{null}\,(A))$.

From our observation above we can now state an important theorem.

Theorem 4.10.14: Rank and Nullity

Let A be an $m \times n$ matrix. Then $\text{rank}\,(A) + \dim(\text{null}\,(A)) = n$.

Example 4.10.22: Rank and Nullity

Let

$$A = \begin{bmatrix} 1 & 2 & 1 \\ 0 & -1 & 1 \\ 2 & 3 & 3 \end{bmatrix}$$

Find $\text{rank}\,(A)$ and $\dim(\text{null}\,(A))$.

Solution

In the above Example 4.10.20 we determined that the reduced row-echelon form of A is given by

$$\begin{bmatrix} 1 & 0 & 3 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \end{bmatrix}$$

Therefore the rank of A is 2. We also determined that the null space of A is given by

$$\text{null}(A) = \text{span}\left\{ \begin{bmatrix} -3 \\ 1 \\ 1 \end{bmatrix} \right\}$$

Therefore the nullity of A is 1. It follows from Theorem 4.10.14 that $\text{rank}\,(A) + \dim(\text{null}\,(A)) = 2 + 1 = 3$, which is the number of columns of A.

We conclude this section with two similar, and important, theorems.

Theorem 4.10.15

Let A be an $m \times n$ matrix. The following are equivalent.

1. $\text{rank}(A) = n$.
2. $\text{row}(A) = \mathbb{R}^n$, i.e., the rows of A span $\mathbb{R}^n$.
3. The columns of A are independent in $\mathbb{R}^m$.
4. The $n \times n$ matrix $A^T A$ is invertible.
5. There exists an $n \times m$ matrix C so that $CA = I_n$.
6. If $A\vec{x} = \vec{0}_m$ for some $\vec{x} \in \mathbb{R}^n$, then $\vec{x} = \vec{0}_n$.

Theorem 4.10.16

Let A be an $m \times n$ matrix. The following are equivalent.

1. $\text{rank}(A) = m$.
2. $\text{col}(A) = \mathbb{R}^m$, i.e., the columns of A span $\mathbb{R}^m$.
3. The rows of A are independent in $\mathbb{R}^n$.
4. The $m \times m$ matrix AA^T is invertible.
5. There exists an $n \times m$ matrix C so that $AC = I_m$.
6. The system $A\vec{x} = \vec{b}$ is consistent for every $\vec{b} \in \mathbb{R}^m$.

Answers

Corollary 4.10.1: Linear Dependence in $\mathbb{R}^n$

Form the $n \times k$ matrix A having the vectors $\{\vec{u}_1, \cdots, \vec{u}_k\}$ as its columns and suppose $k > n$. Then A has rank $r \leq n < k$, so the system $AX = 0$ has a nontrivial solution and thus not linearly independent by Theorem 4.10.1.

Theorem 4.10.2**: Unique Linear Combination**

To prove this theorem, we will show that two linear combinations of vectors in U that equal $\vec{x}$ must be the same. Let $U = \{\vec{u}_1, \vec{u}_2, \ldots, \vec{u}_k\}$. Suppose that there is a vector $\vec{x} \in \text{span}(U)$ such that

$$\begin{aligned} \vec{x} &= s_1\vec{u}_1 + s_2\vec{u}_2 + \cdots + s_k\vec{u}_k, \text{ for some } s_1, s_2, \ldots, s_k \in \mathbb{R}, \text{ and} \\ \vec{x} &= t_1\vec{u}_1 + t_2\vec{u}_2 + \cdots + t_k\vec{u}_k, \text{ for some } t_1, t_2, \ldots, t_k \in \mathbb{R}. \end{aligned} \tag{4.10.5}$$

Then $\vec{0}_n = \vec{x} - \vec{x} = (s_1 - t_1)\vec{u}_1 + (s_2 - t_2)\vec{u}_2 + \cdots + (s_k - t_k)\vec{u}_k$.

Since U is independent, the only linear combination that vanishes is the trivial one, so $s_i - t_i = 0$ for all i, $1 \leq i \leq k$.

Therefore, $s_i = t_i$ for all i, $1 \leq i \leq k$, and the representation is unique.Let $U \subseteq \mathbb{R}^n$ be an independent set. Then any vector $\vec{x} \in \text{span}(U)$ can be written uniquely as a linear combination of vectors of U.

Theorem 4.10.5**: Subspaces are Spans**

We first show that if V is a subspace, then it can be written as $V = \text{span}\{\vec{u}_1, \cdots, \vec{u}_k\}$. Pick a vector $\vec{u}_1$ in V. If $V = \text{span}\{\vec{u}_1\}$, then you have found your list of vectors and are done. If $V \neq \text{span}\{\vec{u}_1\}$, then there exists $\vec{u}_2$ a vector of V which is not in $\text{span}\{\vec{u}_1\}$. Consider $\text{span}\{\vec{u}_1, \vec{u}_2\}$. If $V = \text{span}\{\vec{u}_1, \vec{u}_2\}$, we are done. Otherwise, pick $\vec{u}_3$ not in $\text{span}\{\vec{u}_1, \vec{u}_2\}$. Continue this way. Note that since V is a subspace, these spans are each contained in V. The process must stop with $\vec{u}_k$ for some $k \leq n$ by Corollary 4.10.1, and thus $V = \text{span}\{\vec{u}_1, \cdots, \vec{u}_k\}$.

Now suppose $V = \text{span}\{\vec{u}_1, \cdots, \vec{u}_k\}$, we must show this is a subspace. So let $\sum_{i=1}^k c_i\vec{u}_i$ and $\sum_{i=1}^k d_i\vec{u}_i$ be two vectors in V, and let a and b be two scalars. Then

$$a\sum_{i=1}^k c_i\vec{u}_i + b\sum_{i=1}^k d_i\vec{u}_i = \sum_{i=1}^k (ac_i + bd_i)\vec{u}_i$$

which is one of the vectors in $\text{span}\{\vec{u}_1, \cdots, \vec{u}_k\}$ and is therefore contained in V. This shows that $\text{span}\{\vec{u}_1, \cdots, \vec{u}_k\}$ has the properties of a subspace.

To prove that $V \subseteq W$, we prove that if $\vec{u}_i \in V$, then $\vec{u}_i \in W$.

Suppose $\vec{u} \in V$. Then $\vec{u} = a_1\vec{u}_1 + a_2\vec{u}_2 + \cdots + a_k\vec{u}_k$ for some $a_i \in \mathbb{R}$, $1 \leq i \leq k$. Since W contain each $\vec{u}_i$ and W is a vector space, it follows that $a_1\vec{u}_1 + a_2\vec{u}_2 + \cdots + a_k\vec{u}_k \in W$.

Theorem 4.10.6**: Exchange Theorem**

Since each $\vec{u}_j$ is in $\text{span}\{\vec{v}_1, \cdots, \vec{v}_s\}$, there exist scalars a_{ij} such that

$$\vec{u}_j = \sum_{i=1}^s a_{ij}\vec{v}_i$$

Suppose for a contradiction that $s < r$. Then the matrix $A = [a_{ij}]$ has fewer rows, s than columns, r. Then the system $AX = 0$ has a non trivial solution $\vec{d}$, that is there is a $\vec{d} \neq \vec{0}$ such that $A\vec{d} = \vec{0}$. In other words,

$$\sum_{j=1}^r a_{ij}d_j = 0, \ i = 1, 2, \cdots, s$$

Therefore,

$$\begin{aligned} \sum_{j=1}^r d_j\vec{u}_j &= \sum_{j=1}^r d_j \sum_{i=1}^s a_{ij}\vec{v}_i \\ &= \sum_{i=1}^s \left(\sum_{j=1}^r a_{ij}d_j\right)\vec{v}_i = \sum_{i=1}^s 0\vec{v}_i = 0 \end{aligned} \tag{4.10.6}$$

which contradicts the assumption that $\{\vec{u}_1, \cdots, \vec{u}_r\}$ is linearly independent, because not all the d_j are zero. Thus this contradiction indicates that $s \geq r$.

Theorem 4.10.7**: Bases of $\mathbb{R}^n$ are of the Same Size**

This follows right away from Theorem 9.4.4. Indeed observe that $B_1 = \{\vec{u}_1, \cdots, \vec{u}_s\}$ is a spanning set for V while $B_2 = \{\vec{v}_1, \cdots, \vec{v}_r\}$ is linearly independent, so $s \geq r$. Similarly $B_2 = \{\vec{v}_1, \cdots, \vec{v}_r\}$ is a spanning set for V while $B_1 = \{\vec{u}_1, \cdots, \vec{u}_s\}$ is linearly independent, so $r \geq s$.

Corollary 4.10.3**: Dimension of $\mathbb{R}^n$**

You only need to exhibit a basis for $\mathbb{R}^n$ which has n vectors. Such a basis is the standard basis $\{\vec{e}_1, \cdots, \vec{e}_n\}$.

Corollary 4.10.4**: Linearly Independent and Spanning Sets in $\mathbb{R}^n$**

Assume first that $\{\vec{u}_1, \cdots, \vec{u}_n\}$ is linearly independent, and we need to show that this set spans $\mathbb{R}^n$. To do so, let $\vec{v}$ be a vector of $\mathbb{R}^n$, and we need to write $\vec{v}$ as a linear combination of $\vec{u}_i$'s. Consider the matrix A having the vectors $\vec{u}_i$ as columns:

$$A = \begin{bmatrix} \vec{u}_1 & \cdots & \vec{u}_n \end{bmatrix}$$

By linear independence of the $\vec{u}_i$'s, the reduced row-echelon form of A is the identity matrix. Therefore the system $A\vec{x} = \vec{v}$ has a (unique) solution, so $\vec{v}$ is a linear combination of the $\vec{u}_i$'s.

To establish the second claim, suppose that $m < n$. Then letting $\vec{u}_{i_1}, \cdots, \vec{u}_{i_k}$ be the pivot columns of the matrix

$$\begin{bmatrix} \vec{u}_1 & \cdots & \vec{u}_m \end{bmatrix}$$

it follows $k \leq m < n$ and these k pivot columns would be a basis for $\mathbb{R}^n$ having fewer than n vectors, contrary to Corollary 4.10.3.

Finally consider the third claim. If $\{\vec{u}_1, \cdots, \vec{u}_n\}$ is not linearly independent, then replace this list with $\{\vec{u}_{i_1}, \cdots, \vec{u}_{i_k}\}$ where these are the pivot columns of the matrix

$$\begin{bmatrix} \vec{u}_1 & \cdots & \vec{u}_n \end{bmatrix}$$

Then $\{\vec{u}_{i_1}, \cdots, \vec{u}_{i_k}\}$ spans $\mathbb{R}^n$ and is linearly independent, so it is a basis having less than n vectors again contrary to Corollary 4.10.3.

Theorem 4.10.9**: Finding a Basis from a Span**

Let S denote the set of positive integers such that for $k \in S$, there exists a subset of $\{\vec{w}_1, \cdots, \vec{w}_m\}$ consisting of exactly k vectors which is a spanning set for W. Thus $m \in S$. Pick the smallest positive integer in S. Call it k. Then there exists $\{\vec{u}_1, \cdots, \vec{u}_k\} \subseteq \{\vec{w}_1, \cdots, \vec{w}_m\}$ such that $\text{span}\{\vec{u}_1, \cdots, \vec{u}_k\} = W$. If

$$\sum_{i=1}^k c_i\vec{w}_i = \vec{0}$$

and not all of the $c_i = 0$, then you could pick $c_j \neq 0$, divide by it and solve for $\vec{u}_j$ in terms of the others,

$$\vec{w}_j = \sum_{i \neq j} \left(-\frac{c_i}{c_j} \right) \vec{w}_i$$

Then you could delete $\vec{w}_j$ from the list and have the same span. Any linear combination involving $\vec{w}_j$ would equal one in which $\vec{w}_j$ is replaced with the above sum, showing that it could have been obtained as a linear combination of $\vec{w}_i$ for $i \neq j$. Thus $k-1 \in S$ contrary to the choice of k. Hence each $c_i = 0$ and so $\{\vec{u}_1, \cdots, \vec{u}_k\}$ is a basis for W consisting of vectors of $\{\vec{w}_1, \cdots, \vec{w}_m\}$.

Lemma $4.10.1$**: Effect of Row Operations on Row Space**

We will prove that the above is true for row operations, which can be easily applied to column operations.

Let $\vec{r}_1, \vec{r}_2, \ldots, \vec{r}_m$ denote the rows of A.

- If B is obtained from A by a interchanging two rows of A, then A and B have exactly the same rows, so $\text{row}(B) = \text{row}(A)$.
- Suppose $p \neq 0$, and suppose that for some j, $1 \leq j \leq m$, B is obtained from A by multiplying row j by p. Then

$$\text{row}(B) = \text{span}\{\vec{r}_1, \ldots, p\vec{r}_j, \ldots, \vec{r}_m\}.$$

Since

$$\{\vec{r}_1, \ldots, p\vec{r}_j, \ldots, \vec{r}_m\} \subseteq \text{row}(A),$$

it follows that $\text{row}(B) \subseteq \text{row}(A)$. Conversely, since

$$\{\vec{r}_1, \ldots, \vec{r}_m\} \subseteq \text{row}(B),$$

it follows that $\text{row}(A) \subseteq \text{row}(B)$. Therefore, $\text{row}(B) = \text{row}(A)$.

Suppose $p \neq 0$, and suppose that for some i and j, $1 \leq i, j \leq m$, B is obtained from A by adding p time row j to row i. Without loss of generality, we may assume $i < j$.

Then

$$\text{row}(B) = \text{span}\{\vec{r}_1, \ldots, \vec{r}_{i-1}, \vec{r}_i + p\vec{r}_j, \ldots, \vec{r}_j, \ldots, \vec{r}_m\}.$$

Since

$$\{\vec{r}_1, \ldots, \vec{r}_{i-1}, \vec{r}_i + p\vec{r}_j, \ldots, \vec{r}_m\} \subseteq \text{row}(A),$$

it follows that $\text{row}(B) \subseteq \text{row}(A)$.

Conversely, since

$$\{\vec{r}_1, \ldots, \vec{r}_m\} \subseteq \text{row}(B),$$

it follows that $\text{row}(A) \subseteq \text{row}(B)$. Therefore, $\text{row}(B) = \text{row}(A)$.

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4.11: ORTHOGONALITY

Outcomes

A. Determine if a given set is orthogonal or orthonormal.
B. Determine if a given matrix is orthogonal.
C. Given a linearly independent set, use the Gram-Schmidt Process to find corresponding orthogonal and orthonormal sets.
D. Find the orthogonal projection of a vector onto a subspace.
E. Find the least squares approximation for a collection of points.

In this section, we examine what it means for vectors (and sets of vectors) to be **orthogonal** and **orthonormal**. First, it is necessary to review some important concepts. You may recall the definitions for the span of a set of vectors and a linear independent set of vectors. We include the definitions and examples here for convenience.

Definition 4.11.1: Span of a Set of Vectors and Subspace

The collection of all linear combinations of a set of vectors $\{\vec{u}_1, \cdots, \vec{u}_k\}$ in $\mathbb{R}^n$ is known as the span of these vectors and is written as $\text{span}\{\vec{u}_1, \cdots, \vec{u}_k\}$.
We call a collection of the form $\text{span}\{\vec{u}_1, \cdots, \vec{u}_k\}$ a subspace of $\mathbb{R}^n$.

Consider the following example.

Example 4.11.1: Spanning Vectors

Describe the span of the vectors $\vec{u} = \begin{bmatrix} 1 & 1 & 0 \end{bmatrix}^T$ and $\vec{v} = \begin{bmatrix} 3 & 2 & 0 \end{bmatrix}^T \in \mathbb{R}^3$.

Solution

You can see that any linear combination of the vectors $\vec{u}$ and $\vec{v}$ yields a vector $\begin{bmatrix} x & y & 0 \end{bmatrix}^T$ in the XY-plane.

Moreover every vector in the XY-plane is in fact such a linear combination of the vectors $\vec{u}$ and $\vec{v}$. That's because

$$\begin{bmatrix} x \\ y \\ 0 \end{bmatrix} = (-2x + 3y) \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} + (x - y) \begin{bmatrix} 3 \\ 2 \\ 0 \end{bmatrix}$$

Thus $\text{span}\{\vec{u}, \vec{v}\}$ is precisely the XY-plane.

The span of a set of a vectors in $\mathbb{R}^n$ is what we call a **subspace of** $\mathbb{R}^n$. A subspace W is characterized by the feature that any linear combination of vectors of W is again a vector contained in W.

Another important property of sets of vectors is called **linear independence**.

Definition 4.11.2: Linear Independence

A set of non-zero vectors $\{\vec{u}_1, \cdots, \vec{u}_k\}$ in $\mathbb{R}^n$ is said to be **linearly independent** if no vector in that set is in the span of the other vectors of that set.

Here is an example.

Example 4.11.2: Linearly Independent Vectors

Consider vectors $\vec{u} = \begin{bmatrix} 1 & 1 & 0 \end{bmatrix}^T$, $\vec{v} = \begin{bmatrix} 3 & 2 & 0 \end{bmatrix}^T$, and $\vec{w} = \begin{bmatrix} 4 & 5 & 0 \end{bmatrix}^T \in \mathbb{R}^3$. Verify whether the set $\{\vec{u}, \vec{v}, \vec{w}\}$ is linearly independent.

Solution

We already verified in Example 4.11.1 that $\text{span}\{\vec{u}, \vec{v}\}$ is the XY-plane. Since $\vec{w}$ is clearly also in the XY-plane, then the set $\{\vec{u}, \vec{v}, \vec{w}\}$ is **not** linearly independent.

In terms of spanning, a set of vectors is linearly independent if it does not contain unnecessary vectors. In the previous example you can see that the vector $\vec{w}$ does not help to span any new vector not already in the span of the other two vectors. However you can verify that the set $\{\vec{u}, \vec{v}\}$ is linearly independent, since you will not get the XY-plane as the span of a single vector.

We can also determine if a set of vectors is linearly independent by examining linear combinations. A set of vectors is linearly independent if and only if whenever a linear combination of these vectors equals zero, it follows that all the coefficients equal zero. It is a good exercise to verify this equivalence, and this latter condition is often used as the (equivalent) definition of linear independence.

If a subspace is spanned by a linearly independent set of vectors, then we say that it is a basis for the subspace.

Definition 4.11.3: Basis

Let V be a subspace of $\mathbb{R}^n$. Then $\{\vec{u}_1, \cdots, \vec{u}_k\}$ is a **basis** for V if the following two conditions hold.

1. $\text{span}\{\vec{u}_1, \cdots, \vec{u}_k\} = V$
2. $\{\vec{u}_1, \cdots, \vec{u}_k\}$ is linearly independent

Thus the set of vectors $\{\vec{u}, \vec{v}\}$ from Example 4.11.2 is a basis for XY-plane in $\mathbb{R}^3$ since it is both linearly independent and spans the XY-plane.

Recall from the properties of the dot product of vectors that two vectors $\vec{u}$ and $\vec{v}$ are orthogonal if $\vec{u} \cdot \vec{v} = 0$. Suppose a vector is orthogonal to a spanning set of $\mathbb{R}^n$. What can be said about such a vector? This is the discussion in the following example.

Example 4.11.3: Orthogonal Vector to a Spanning Set

Let $\{\vec{x}_1, \vec{x}_2, \ldots, \vec{x}_k\} \in \mathbb{R}^n$ and suppose $\mathbb{R}^n = \text{span}\{\vec{x}_1, \vec{x}_2, \ldots, \vec{x}_k\}$. Furthermore, suppose that there exists a vector $\vec{u} \in \mathbb{R}^n$ for which $\vec{u} \cdot \vec{x}_j = 0$ for all j, $1 \leq j \leq k$. What type of vector is $\vec{u}$?

Solution

Write $\vec{u} = t_1\vec{x}_1 + t_2\vec{x}_2 + \cdots + t_k\vec{x}_k$ for some $t_1, t_2, \ldots, t_k \in \mathbb{R}$ (this is possible because $\vec{x}_1, \vec{x}_2, \ldots, \vec{x}_k$ span $\mathbb{R}^n$).

Then

$$\begin{aligned} \|\vec{u}\|^2 &= \vec{u} \cdot \vec{u} \\ &= \vec{u} \cdot (t_1\vec{x}_1 + t_2\vec{x}_2 + \cdots + t_k\vec{x}_k) \\ &= \vec{u} \cdot (t_1\vec{x}_1) + \vec{u} \cdot (t_2\vec{x}_2) + \cdots + \vec{u} \cdot (t_k\vec{x}_k) \\ &= t_1(\vec{u} \cdot \vec{x}_1) + t_2(\vec{u} \cdot \vec{x}_2) + \cdots + t_k(\vec{u} \cdot \vec{x}_k) \\ &= t_1(0) + t_2(0) + \cdots + t_k(0) = 0. \end{aligned} \tag{4.11.1}$$

Since $\|\vec{u}\|^2 = 0$, $\|\vec{u}\| = 0$. We know that $\|\vec{u}\| = 0$ if and only if $\vec{u} = \vec{0}_n$. Therefore, $\vec{u} = \vec{0}_n$. In conclusion, the only vector orthogonal to every vector of a spanning set of $\mathbb{R}^n$ is the zero vector.

We can now discuss what is meant by an orthogonal set of vectors.

Definition 4.11.4: Orthogonal Set of Vectors

Let $\{\vec{u}_1, \vec{u}_2, \cdots, \vec{u}_m\}$ be a set of vectors in $\mathbb{R}^n$. Then this set is called an **orthogonal set** if the following conditions hold:

1. $\vec{u}_i \cdot \vec{u}_j = 0$ for all $i \neq j$
2. $\vec{u}_i \neq \vec{0}$ for all i

If we have an orthogonal set of vectors and normalize each vector so they have length 1, the resulting set is called an **orthonormal set** of vectors. They can be described as follows.

Definition :5 Orthonormal Set of Vectors

A set of vectors, $\{\vec{w}_1, \cdots, \vec{w}_m\}$ is said to be an **orthonormal** set if

$$\vec{w}_i \cdot \vec{w}_j = \delta_{ij} = \begin{cases} 1 \text{ if } i = j \\ 0 \text{ if } i \neq j \end{cases}$$

Note that all orthonormal sets are orthogonal, but the reverse is not necessarily true since the vectors may not be normalized. In order to normalize the vectors, we simply need divide each one by its length.

Definition 4.11.6: Normalizing an Orthogonal Set

Normalizing an orthogonal set is the process of turning an orthogonal (but not orthonormal) set into an orthonormal set. If $\{\vec{u}_1, \vec{u}_2, \ldots, \vec{u}_k\}$ is an orthogonal subset of $\mathbb{R}^n$, then

$$\left\{ \frac{1}{\|\vec{u}_1\|}\vec{u}_1, \frac{1}{\|\vec{u}_2\|}\vec{u}_2, \ldots, \frac{1}{\|\vec{u}_k\|}\vec{u}_k \right\}$$

is an orthonormal set.

We illustrate this concept in the following example.

Example 4.11.4: Orthonormal Set

Consider the set of vectors given by

$$\{\vec{u}_1, \vec{u}_2\} = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \end{bmatrix} \right\}$$

Show that it is an orthogonal set of vectors but not an orthonormal one. Find the corresponding orthonormal set.

Solution

One easily verifies that $\vec{u}_1 \cdot \vec{u}_2 = 0$ and $\{\vec{u}_1, \vec{u}_2\}$ is an orthogonal set of vectors. On the other hand one can compute that $\|\vec{u}_1\| = \|\vec{u}_2\| = \sqrt{2} \neq 1$ and thus it is not an orthonormal set.

Thus to find a corresponding orthonormal set, we simply need to normalize each vector. We will write $\{\vec{w}_1, \vec{w}_2\}$ for the corresponding orthonormal set. Then,

$$\begin{aligned}\vec{w}_1 &= \frac{1}{\|\vec{u}_1\|}\vec{u}_1 \\ &= \frac{1}{\sqrt{2}}\begin{bmatrix} 1 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}\end{aligned} \tag{4.11.2}$$

Similarly,

$$\begin{aligned}\vec{w}_2 &= \frac{1}{\|\vec{u}_2\|}\vec{u}_2 \\ &= \frac{1}{\sqrt{2}}\begin{bmatrix} -1 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}\end{aligned} \tag{4.11.3}$$

Therefore the corresponding orthonormal set is

$$\{\vec{w}_1, \vec{w}_2\} = \left\{ \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}, \begin{bmatrix} -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix} \right\}$$

You can verify that this set is orthogonal.

Consider an orthogonal set of vectors in $\mathbb{R}^n$, written $\{\vec{w}_1, \cdots, \vec{w}_k\}$ with $k \leq n$. The span of these vectors is a subspace W of $\mathbb{R}^n$. If we could show that this orthogonal set is also linearly independent, we would have a basis of W. We will show this in the next theorem.

Theorem 4.11.1: Orthogonal Basis of a Subspace

Let $\{\vec{w}_1, \vec{w}_2, \cdots, \vec{w}_k\}$ be an orthonormal set of vectors in $\mathbb{R}^n$. Then this set is linearly independent and forms a basis for the subspace $W = \text{span}\{\vec{w}_1, \vec{w}_2, \cdots, \vec{w}_k\}$.

Proof available at the end of this section.

If an orthogonal set is a basis for a subspace, we call this an orthogonal basis. Similarly, if an orthonormal set is a basis, we call this an orthonormal basis.

We conclude this section with a discussion of Fourier expansions. Given any orthogonal basis B of $\mathbb{R}^n$ and an arbitrary vector $\vec{x} \in \mathbb{R}^n$, how do we express $\vec{x}$ as a linear combination of vectors in B? The solution is Fourier expansion.

Theorem 4.11.2: Fourier Expansion

Let V be a subspace of $\mathbb{R}^n$ and suppose $\{\vec{u}_1, \vec{u}_2, \ldots, \vec{u}_m\}$ is an orthogonal basis of V. Then for any $\vec{x} \in V$,

$$\vec{x} = \left(\frac{\vec{x} \cdot \vec{u}_1}{\|\vec{u}_1\|^2}\right)\vec{u}_1 + \left(\frac{\vec{x} \cdot \vec{u}_2}{\|\vec{u}_2\|^2}\right)\vec{u}_2 + \cdots + \left(\frac{\vec{x} \cdot \vec{u}_m}{\|\vec{u}_m\|^2}\right)\vec{u}_m$$

This expression is called the **Fourier expansion** of $\vec{x}$, and

$$\frac{\vec{x} \cdot \vec{u}_j}{\|\vec{u}_j\|^2},$$

$j = 1, 2, \ldots, m$ are the Fourier coefficients.

Consider the following example.

Example 4.11.5: Fourier Expansion

Let $\vec{u}_1 = \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix}, \vec{u}_2 = \begin{bmatrix} 0 \\ 2 \\ 1 \end{bmatrix}$, and $\vec{u}_3 = \begin{bmatrix} 5 \\ 1 \\ -2 \end{bmatrix}$, and let $\vec{x} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$.

Then $B = \{\vec{u}_1, \vec{u}_2, \vec{u}_3\}$ is an orthogonal basis of $\mathbb{R}^3$.

Compute the Fourier expansion of $\vec{x}$, thus writing $\vec{x}$ as a linear combination of the vectors of B.

Solution

Since B is a basis (verify!) there is a unique way to express $\vec{x}$ as a linear combination of the vectors of B. Moreover since B is an orthogonal basis (verify!), then this can be done by computing the Fourier expansion of $\vec{x}$.

That is:

$$\vec{x} = \left(\frac{\vec{x} \cdot \vec{u}_1}{\|\vec{u}_1\|^2}\right) \vec{u}_1 + \left(\frac{\vec{x} \cdot \vec{u}_2}{\|\vec{u}_2\|^2}\right) \vec{u}_2 + \left(\frac{\vec{x} \cdot \vec{u}_3}{\|\vec{u}_3\|^2}\right) \vec{u}_3.$$

We readily compute:

$$\frac{\vec{x} \cdot \vec{u}_1}{\|\vec{u}_1\|^2} = \frac{2}{6}, \ \frac{\vec{x} \cdot \vec{u}_2}{\|\vec{u}_2\|^2} = \frac{3}{5}, \text{ and } \frac{\vec{x} \cdot \vec{u}_3}{\|\vec{u}_3\|^2} = \frac{4}{30}.$$

Therefore,

$$\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix} + \frac{3}{5} \begin{bmatrix} 0 \\ 2 \\ 1 \end{bmatrix} + \frac{2}{15} \begin{bmatrix} 5 \\ 1 \\ -2 \end{bmatrix}.$$

Orthogonal Matrices

Recall that the process to find the inverse of a matrix was often cumbersome. In contrast, it was very easy to take the transpose of a matrix. Luckily for some special matrices, the transpose equals the inverse. When an $n \times n$ matrix has all real entries and its transpose equals its inverse, the matrix is called an **orthogonal matrix**.

The precise definition is as follows.

Definition 4.11.7: Orthogonal Matrices

A real $n \times n$ matrix U is called an **orthogonal** matrix if

$$UU^T = U^T U = I.$$

Note since U is assumed to be a square matrix, it suffices to verify only one of these equalities $UU^T = I$ or $U^T U = I$ holds to guarantee that U^T is the inverse of U.

Consider the following example.

Example 4.11.6: Orthogonal Matrix

Orthogonal Matrix Show the matrix

$$U = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix}$$

is orthogonal.

Solution

All we need to do is verify (one of the equations from) the requirements of Definition 4.11.7.

$$UU^T = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Since $UU^T = I$, this matrix is orthogonal.

Here is another example.

Example 4.11.7: Orthogonal Matrix

Orthogonal Matrix Let $U = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & -1 & 0 \end{bmatrix}$. Is U orthogonal?

Solution

Again the answer is yes and this can be verified simply by showing that $U^T U = I$:

$$\begin{aligned} U^T U &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & -1 & 0 \end{bmatrix}^T \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & -1 & 0 \end{bmatrix} \\ &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & -1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & -1 & 0 \end{bmatrix} \\ &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \end{aligned} \tag{4.11.4}$$

When we say that U is orthogonal, we are saying that $UU^T = I$, meaning that

$$\sum_j u_{ij} u_{jk}^T = \sum_j u_{ij} u_{kj} = \delta_{ik}$$

where δ_{ij} is the **Kronecker symbol** defined by

$$\delta_{ij} = \begin{cases} 1 \text{ if } i = j \\ 0 \text{ if } i \neq j \end{cases}$$

In words, the product of the i^{th} row of U with the k^{th} row gives 1 if $i = k$ and 0 if $i \neq k$. The same is true of the columns because $U^T U = I$ also. Therefore,

$$\sum_j u_{ij}^T u_{jk} = \sum_j u_{ji} u_{jk} = \delta_{ik}$$

which says that the product of one column with another column gives 1 if the two columns are the same and 0 if the two columns

are different.

More succinctly, this states that if $\vec{u}_1, \cdots, \vec{u}_n$ are the columns of U, an orthogonal matrix, then

$$\vec{u}_i \cdot \vec{u}_j = \delta_{ij} = \begin{cases} 1 \text{ if } i = j \\ 0 \text{ if } i \neq j \end{cases}$$

We will say that the columns form an orthonormal set of vectors, and similarly for the rows. Thus a matrix is **orthogonal** if its rows (or columns) form an **orthonormal** set of vectors. Notice that the convention is to call such a matrix orthogonal rather than orthonormal (although this may make more sense!).

Proposition 4.11.1: Orthonormal Basis

The rows of an $n \times n$ orthogonal matrix form an orthonormal basis of $\mathbb{R}^n$. Further, any orthonormal basis of $\mathbb{R}^n$ can be used to construct an $n \times n$ orthogonal matrix.

Proof available at the end of this section.

Consider the following proposition.

Proposition 4.11.2: Determinant of Orthogonal Matrices

Det Suppose U is an orthogonal matrix. Then $\det(U) = \pm 1$.

Proof available at the end of this section.

Orthogonal matrices are divided into two classes, proper and improper. The proper orthogonal matrices are those whose determinant equals 1 and the improper ones are those whose determinant equals -1. The reason for the distinction is that the improper orthogonal matrices are sometimes considered to have no physical significance. These matrices cause a change in orientation which would correspond to material passing through itself in a non physical manner. Thus in considering which coordinate systems must be considered in certain applications, you only need to consider those which are related by a proper orthogonal transformation. Geometrically, the linear transformations determined by the proper orthogonal matrices correspond to the composition of rotations.

We conclude this section with two useful properties of orthogonal matrices.

Example 4.11.8: Product and Inverse of Orthogonal Matrices

Suppose A and B are orthogonal matrices. Then AB and A^{-1} both exist and are orthogonal.

Solution

First we examine the product AB.

$$(AB)(B^T A^T) = A(BB^T)A^T = AA^T = I$$

Since AB is square, $B^T A^T = (AB)^T$ is the inverse of AB, so AB is invertible, and $(AB)^{-1} = (AB)^T$ Therefore, AB is orthogonal.

Next we show that $A^{-1} = A^T$ is also orthogonal.

$$(A^{-1})^{-1} = A = (A^T)^T = (A^{-1})^T$$

Therefore A^{-1} is also orthogonal.

Gram-Schmidt Process

The Gram-Schmidt process is an algorithm to transform a set of vectors into an orthonormal set spanning the same subspace, that is generating the same collection of linear combinations (see Definition 9.2.2).

The goal of the Gram-Schmidt process is to take a linearly independent set of vectors and transform it into an orthonormal set with the same span. The first objective is to construct an orthogonal set of vectors with the same span, since from there an orthonormal set can be obtained by simply dividing each vector by its length.

Algorithm 4.11.1: Gram-Schmidt Process

Let $\{\vec{u}_1, \cdots, \vec{u}_n\}$ be a set of linearly independent vectors in $\mathbb{R}^n$.

I: Construct a new set of vectors $\{\vec{v}_1, \cdots, \vec{v}_n\}$ as follows:

$$\begin{aligned}
\vec{v}_1 &= \vec{u}_1 \\
\vec{v}_2 &= \vec{u}_2 - \left(\frac{\vec{u}_2 \cdot \vec{v}_1}{\|\vec{v}_1\|^2}\right)\vec{v}_1 \\
\vec{v}_3 &= \vec{u}_3 - \left(\frac{\vec{u}_3 \cdot \vec{v}_1}{\|\vec{v}_1\|^2}\right)\vec{v}_1 - \left(\frac{\vec{u}_3 \cdot \vec{v}_2}{\|\vec{v}_2\|^2}\right)\vec{v}_2 \\
&\vdots \\
\vec{v}_n &= \vec{u}_n - \left(\frac{\vec{u}_n \cdot \vec{v}_1}{\|\vec{v}_1\|^2}\right)\vec{v}_1 - \left(\frac{\vec{u}_n \cdot \vec{v}_2}{\|\vec{v}_2\|^2}\right)\vec{v}_2 - \cdots - \left(\frac{\vec{u}_n \cdot \vec{v}_{n-1}}{\|\vec{v}_{n-1}\|^2}\right)\vec{v}_{n-1}
\end{aligned}$$

II: Now let $\vec{w}_i = \dfrac{\vec{v}_i}{\|\vec{v}_i\|}$ for $i = 1, \cdots, n$.

Then

1. $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is an orthogonal set.
2. $\{\vec{w}_1, \cdots, \vec{w}_n\}$ is an orthonormal set.
3. $\operatorname{span}\{\vec{u}_1, \cdots, \vec{u}_n\} = \operatorname{span}\{\vec{v}_1, \cdots, \vec{v}_n\} = \operatorname{span}\{\vec{w}_1, \cdots, \vec{w}_n\}$.

Solution

The full proof of this algorithm is beyond this material, however here is an indication of the arguments.

To show that $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is an orthogonal set, let

$$a_2 = \frac{\vec{u}_2 \cdot \vec{v}_1}{\|\vec{v}_1\|^2}$$

then:

$$\begin{aligned}
\vec{v}_1 \cdot \vec{v}_2 &= \vec{v}_1 \cdot (\vec{u}_2 - a_2\vec{v}_1) \\
&= \vec{v}_1 \cdot \vec{u}_2 - a_2(\vec{v}_1 \cdot \vec{v}_1 \\
&= \vec{v}_1 \cdot \vec{u}_2 - \frac{\vec{u}_2 \cdot \vec{v}_1}{\|\vec{v}_1\|^2}\|\vec{v}_1\|^2 \\
&= (\vec{v}_1 \cdot \vec{u}_2) - (\vec{u}_2 \cdot \vec{v}_1) = 0
\end{aligned}$$

Now that you have shown that $\{\vec{v}_1, \vec{v}_2\}$ is orthogonal, use the same method as above to show that $\{\vec{v}_1, \vec{v}_2, \vec{v}_3\}$ is also orthogonal, and so on.

Then in a similar fashion you show that $\operatorname{span}\{\vec{u}_1, \cdots, \vec{u}_n\} = \operatorname{span}\{\vec{v}_1, \cdots, \vec{v}_n\}$.

Finally defining $\vec{w}_i = \dfrac{\vec{v}_i}{\|\vec{v}_i\|}$ for $i = 1, \cdots, n$ does not affect orthogonality and yields vectors of length 1, hence an orthonormal set. You can also observe that it does not affect the span either and the proof would be complete.

Consider the following example.

Example 4.11.9: Find Orthonormal Set with Same Span

Consider the set of vectors $\{\vec{u}_1, \vec{u}_2\}$ given as in Example 4.11.1. That is

$$\vec{u}_1 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \vec{u}_2 = \begin{bmatrix} 3 \\ 2 \\ 0 \end{bmatrix} \in \mathbb{R}^3$$

Use the Gram-Schmidt algorithm to find an orthonormal set of vectors $\{\vec{w}_1, \vec{w}_2\}$ having the same span.

Solution

We already remarked that the set of vectors in $\{\vec{u}_1, \vec{u}_2\}$ is linearly independent, so we can proceed with the Gram-Schmidt algorithm:

$$\begin{aligned} \vec{v}_1 &= \vec{u}_1 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \\ \vec{v}_2 &= \vec{u}_2 - \left(\frac{\vec{u}_2 \cdot \vec{v}_1}{\|\vec{v}_1\|^2} \right) \vec{v}_1 \\ &= \begin{bmatrix} 3 \\ 2 \\ 0 \end{bmatrix} - \frac{5}{2} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \\ &= \begin{bmatrix} \frac{1}{2} \\ -\frac{1}{2} \\ 0 \end{bmatrix} \end{aligned} \tag{4.11.5}$$

Now to normalize simply let

$$\begin{aligned} \vec{w}_1 &= \frac{\vec{v}_1}{\|\vec{v}_1\|} = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ 0 \end{bmatrix} \\ \vec{w}_2 &= \frac{\vec{v}_2}{\|\vec{v}_2\|} = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} \\ 0 \end{bmatrix} \end{aligned} \tag{4.11.6}$$

You can verify that $\{\vec{w}_1, \vec{w}_2\}$ is an orthonormal set of vectors having the same span as $\{\vec{u}_1, \vec{u}_2\}$, namely the XY-plane.

In this example, we began with a linearly independent set and found an orthonormal set of vectors which had the same span. It turns out that if we start with a basis of a subspace and apply the Gram-Schmidt algorithm, the result will be an orthogonal basis of the same subspace. We examine this in the following example.

Example 4.11.10: Find a Corresponding Orthogonal Basis

Let

$$\vec{x}_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \vec{x}_2 = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}, \text{ and } \vec{x}_3 = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix},$$

and let $U = \text{span}\{\vec{x}_1, \vec{x}_2, \vec{x}_3\}$. Use the Gram-Schmidt Process to construct an orthogonal basis B of U.

Solution

First $\vec{f}_1 = \vec{x}_1$.

Next,

$$\vec{f}_2 = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix} - \frac{2}{2} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}.$$

Finally,

$$\vec{f}_3 = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} - \frac{1}{2} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} - \frac{0}{1} \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1/2 \\ 1 \\ -1/2 \\ 0 \end{bmatrix}.$$

Therefore,

$$\left\{ \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1/2 \\ 1 \\ -1/2 \\ 0 \end{bmatrix} \right\}$$

is an orthogonal basis of U. However, it is sometimes more convenient to deal with vectors having integer entries, in which case we take

$$B = \left\{ \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ -1 \\ 0 \end{bmatrix} \right\}.$$

Orthogonal Projections

An important use of the Gram-Schmidt Process is in orthogonal projections, the focus of this section.

You may recall that a subspace of $\mathbb{R}^n$ is a set of vectors which contains the zero vector, and is closed under addition and scalar multiplication. Let's call such a subspace W. In particular, a plane in $\mathbb{R}^n$ which contains the origin, $(0, 0, \cdots, 0)$, is a subspace of $\mathbb{R}^n$.

Suppose a point Y in $\mathbb{R}^n$ is not contained in W, then what point Z in W is closest to Y? Using the Gram-Schmidt Process, we can find such a point. Let $\vec{y}, \vec{z}$ represent the position vectors of the points Y and Z respectively, with $\vec{y} - \vec{z}$ representing the vector connecting the two points Y and Z. It will follow that if Z is the point on W closest to Y, then $\vec{y} - \vec{z}$ will be perpendicular to W (can you see why?); in other words, $\vec{y} - \vec{z}$ is orthogonal to W (and to every vector contained in W) as in the following diagram.

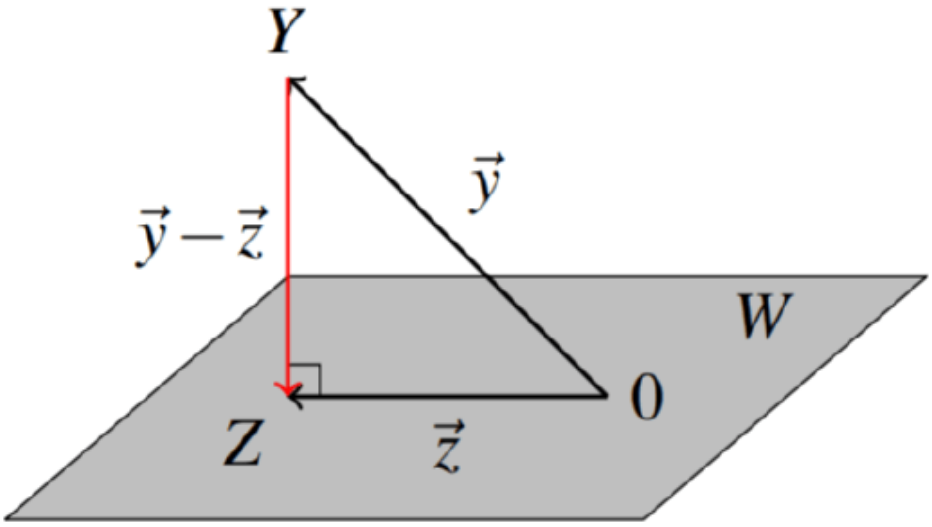


Figure 4.11.1

The vector $\vec{z}$ is called the **orthogonal projection** of $\vec{y}$ on W. The definition is given as follows.

Definition 4.11.8: Orthogonal Projection

Let W be a subspace of $\mathbb{R}^n$, and Y be any point in $\mathbb{R}^n$. Then the orthogonal projection of Y onto W is given by

$$\vec{z} = \text{proj}_W(\vec{y}) = \left(\frac{\vec{y}\cdot\vec{w}_1}{\|\vec{w}_1\|^2}\right)\vec{w}_1 + \left(\frac{\vec{y}\cdot\vec{w}_2}{\|\vec{w}_2\|^2}\right)\vec{w}_2 + \cdots + \left(\frac{\vec{y}\cdot\vec{w}_m}{\|\vec{w}_m\|^2}\right)\vec{w}_m$$

where $\{\vec{w}_1, \vec{w}_2, \cdots, \vec{w}_m\}$ is any orthogonal basis of W.

Therefore, in order to find the orthogonal projection, we must first find an orthogonal basis for the subspace. Note that one could use an orthonormal basis, but it is not necessary in this case since as you can see above the normalization of each vector is included in the formula for the projection.

Before we explore this further through an example, we show that the orthogonal projection does indeed yield a point Z (the point whose position vector is the vector $\vec{z}$ above) which is the point of W closest to Y.

Theorem 4.11.3: Approximation Theorem

Let W be a subspace of $\mathbb{R}^n$ and Y any point in $\mathbb{R}^n$. Let Z be the point whose position vector is the orthogonal projection of Y onto W.

Then, Z is the point in W closest to Y.

Proof available at the end of this section.

Consider the following example.

Example 4.11.11: Orthogonal Projection

Let W be the plane through the origin given by the equation $x - 2y + z = 0$. Find the point in W closest to the point $Y = (1, 0, 3)$.

Solution

We must first find an orthogonal basis for W. Notice that W is characterized by all points (a,b,c) where $c=2b-a$. In other words,

$$W=\begin{bmatrix} a \\ b \\ 2b-a \end{bmatrix} = a\begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} + b\begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix},\ a,b\in\mathbb{R}$$

We can thus write W as

$$\begin{aligned} W &= \text{span}\left\{\vec{u}_1,\vec{u}_2\right\} \\ &= \text{span}\left\{\begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix}\right\} \end{aligned} \tag{4.11.7}$$

Notice that this span is a basis of W as it is linearly independent. We will use the Gram-Schmidt Process to convert this to an orthogonal basis, $\{\vec{w}_1,\vec{w}_2\}$. In this case, as we remarked it is only necessary to find an orthogonal basis, and it is not required that it be orthonormal.

$$\begin{aligned} \vec{w}_1 = \vec{u}_1 &= \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \\ \vec{w}_2 = \vec{u}_2 - \left(\frac{\vec{u}_2\cdot\vec{w}_1}{\|\vec{w}_1\|^2}\right)\vec{w}_1 & \\ &= \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix} - \left(\frac{-2}{2}\right)\begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \\ &= \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \\ &= \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \end{aligned} \tag{4.11.8}$$

Therefore an orthogonal basis of W is

$$\{\vec{w}_1,\vec{w}_2\} = \left\{\begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}\right\}$$

We can now use this basis to find the orthogonal projection of the point $Y=(1,0,3)$ on the subspace W. We will write the position vector $\vec{y}$ of Y as $\vec{y}=\begin{bmatrix} 1 \\ 0 \\ 3 \end{bmatrix}$. Using Definition 4.11.8, we compute the projection as follows:

$$\begin{aligned} \vec{z} &= \text{proj}_W\left(\vec{y}\right) \\ &= \left(\frac{\vec{y}\cdot\vec{w}_1}{\|\vec{w}_1\|^2}\right)\vec{w}_1 + \left(\frac{\vec{y}\cdot\vec{w}_2}{\|\vec{w}_2\|^2}\right)\vec{w}_2 \\ &= \left(\frac{-2}{2}\right)\begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} + \left(\frac{4}{3}\right)\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} \frac{1}{3} \\ \frac{4}{3} \\ \frac{7}{3} \end{bmatrix} \end{aligned} \tag{4.11.9}$$

Therefore the point Z on W closest to the point $(1,0,3)$ is $\left(\frac{1}{3},\frac{4}{3},\frac{7}{3}\right)$.

Recall that the vector $\vec{y} - \vec{z}$ is perpendicular (orthogonal) to all the vectors contained in the plane W. Using a basis for W, we can in fact find all such vectors which are perpendicular to W. We call this set of vectors the **orthogonal complement** of W and denote it $W^\perp$.

Definition 4.11.9: Orthogonal Complement

Let W be a subspace of $\mathbb{R}^n$. Then the orthogonal complement of W, written $W^\perp$, is the set of all vectors $\vec{x}$ such that $\vec{x} \cdot \vec{z} = 0$ for all vectors $\vec{z}$ in W.

$$W^\perp = \{\vec{x} \in \mathbb{R}^n \text{ such that } \vec{x} \cdot \vec{z} = 0 \text{ for all } \vec{z} \in W\}$$

The orthogonal complement is defined as the set of all vectors which are orthogonal to all vectors in the original subspace. It turns out that it is sufficient that the vectors in the orthogonal complement be orthogonal to a spanning set of the original space.

Proposition 4.11.3: Orthogonal to Spanning Set

Let W be a subspace of $\mathbb{R}^n$ such that $W = \text{span}\{\vec{w}_1, \vec{w}_2, \cdots, \vec{w}_m\}$. Then $W^\perp$ is the set of all vectors which are orthogonal to each $\vec{w}_i$ in the spanning set.

The following proposition demonstrates that the orthogonal complement of a subspace is itself a subspace.

Proposition 4.11.4: The Orthogonal Complement

Let W be a subspace of $\mathbb{R}^n$. Then the orthogonal complement $W^\perp$ is also a subspace of $\mathbb{R}^n$.

Consider the following proposition.

Proposition 4.11.5: Orthogonal Complement of $\mathbb{R}^n$

The complement of $\mathbb{R}^n$ is the set containing the zero vector:

$$(\mathbb{R}^n)^\perp = \left\{\vec{0}\right\}$$

Similarly,

$$\left\{\vec{0}\right\}^\perp = (\mathbb{R}^n).$$

Proof available at the end of this section.

In the next example, we will look at how to find $W^\perp$.

Example 4.11.12: Orthogonal Complement

Let W be the plane through the origin given by the equation $x - 2y + z = 0$. Find a basis for the orthogonal complement of W.

Solution

From Example 4.11.11 we know that we can write W as

$$W = \text{span}\{\vec{u}_1, \vec{u}_2\} = \text{span}\left\{\begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix}\right\}$$

In order to find $W^\perp$, we need to find all $\vec{x}$ which are orthogonal to every vector in this span.

Let $\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$. In order to satisfy $\vec{x} \cdot \vec{u}_1 = 0$, the following equation must hold.

$$x_1 - x_3 = 0$$

In order to satisfy $\vec{x} \cdot \vec{u}_2 = 0$, the following equation must hold.

$$x_2 + 2x_3 = 0$$

Both of these equations must be satisfied, so we have the following system of equations.

$$\begin{aligned} x_1 - x_3 &= 0 \\ x_2 + 2x_3 &= 0 \end{aligned}$$

To solve, set up the augmented matrix.

$$\begin{bmatrix} 1 & 0 & -1 & 0 \\ 0 & 1 & 2 & 0 \end{bmatrix}$$

Using Gaussian Elimination, we find that $W^\perp = \text{span}\left\{\begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}\right\}$, and hence $\left\{\begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}\right\}$ is a basis for $W^\perp$.

The following results summarize the important properties of the orthogonal projection.

Theorem 4.11.4: Orthogonal Projection

Let W be a subspace of $\mathbb{R}^n$, Y be any point in $\mathbb{R}^n$, and let Z be the point in W closest to Y. Then,

1. The position vector $\vec{z}$ of the point Z is given by $\vec{z} = \text{proj}_W(\vec{y})$
2. $\vec{z} \in W$ and $\vec{y} - \vec{z} \in W^\perp$
3. $|Y - Z| < |Y - Z_1|$ for all $Z_1 \neq Z \in W$

Consider the following example of this concept.

Example 4.11.13: Find a Vector Closest to a Given Vector

Let

$$\vec{x}_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \vec{x}_2 = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}, \vec{x}_3 = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \text{ and } \vec{v} = \begin{bmatrix} 4 \\ 3 \\ -2 \\ 5 \end{bmatrix}.$$

We want to find the vector in $W = \text{span}\{\vec{x}_1, \vec{x}_2, \vec{x}_3\}$ closest to $\vec{y}$.

Solution

We will first use the Gram-Schmidt Process to construct the orthogonal basis, B, of W:

$$B = \left\{\begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ -1 \\ 0 \end{bmatrix}\right\}.$$

By Theorem 4.11.4,

$$\text{proj}_U(\vec{v}) = \frac{2}{2}\begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} + \frac{5}{1}\begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} + \frac{12}{6}\begin{bmatrix} 1 \\ 2 \\ -1 \\ 0 \end{bmatrix} = \begin{bmatrix} 3 \\ 4 \\ -1 \\ 5 \end{bmatrix}$$

is the vector in U closest to $\vec{y}$.

Consider the next example.

Example 4.11.14: Vector Written as a Sum of Two Vectors

Let W be a subspace given by $W = \text{span}\left\{\begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 2 \end{bmatrix}\right\}$, and $Y = (1, 2, 3, 4)$.
Find the point Z in W closest to Y, and moreover write $\vec{y}$ as the sum of a vector in W and a vector in $W^\perp$.

Solution

From Theorem 4.11.3 the point Z in W closest to Y is given by $\vec{z} = \text{proj}_W(\vec{y})$.

Notice that since the above vectors already give an orthogonal basis for W, we have:

$$\begin{aligned} \vec{z} &= \text{proj}_W(\vec{y}) \\ &= \left(\frac{\vec{y}\cdot\vec{w}_1}{\|\vec{w}_1\|^2}\right)\vec{w}_1 + \left(\frac{\vec{y}\cdot\vec{w}_2}{\|\vec{w}_2\|^2}\right)\vec{w}_2 \\ &= \left(\frac{4}{2}\right)\begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} + \left(\frac{10}{5}\right)\begin{bmatrix} 0 \\ 1 \\ 0 \\ 2 \end{bmatrix} \\ &= \begin{bmatrix} 2 \\ 2 \\ 2 \\ 4 \end{bmatrix} \end{aligned} \tag{4.11.10}$$

Therefore the point in W closest to Y is $Z = (2, 2, 2, 4)$.
Now, we need to write $\vec{y}$ as the sum of a vector in W and a vector in $W^\perp$. This can easily be done as follows:

$$\vec{y} = \vec{z} + (\vec{y} - \vec{z})$$

since $\vec{z}$ is in W and as we have seen $\vec{y} - \vec{z}$ is in $W^\perp$.
The vector $\vec{y} - \vec{z}$ is given by

$$\vec{y} - \vec{z} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix} - \begin{bmatrix} 2 \\ 2 \\ 2 \\ 4 \end{bmatrix} = \begin{bmatrix} -1 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

Therefore, we can write $\vec{y}$ as

$$\begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \\ 2 \\ 4 \end{bmatrix} + \begin{bmatrix} -1 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

Example 4.11.15: Point in a Plane Closest to a Given Point

Find the point Z in the plane $3x + y - 2z = 0$ that is closest to the point $Y = (1, 1, 1)$.

Solution

The solution will proceed as follows.

1. Find a basis X of the subspace W of $\mathbb{R}^3$ defined by the equation $3x + y - 2z = 0$.
2. Orthogonalize the basis X to get an orthogonal basis B of W.
3. Find the projection on W of the position vector of the point Y.

We now begin the solution.

1. $3x + y - 2z = 0$ is a system of one equation in three variables. Putting the augmented matrix in reduced row-echelon form:
$$\begin{bmatrix} 3 & 1 & -2 & 0 \end{bmatrix} \to \begin{bmatrix} 1 & \frac{1}{3} & -\frac{2}{3} & 0 \end{bmatrix}$$
gives general solution $x = \frac{1}{3}s + \frac{2}{3}t$, $y = s$, $z = t$ for any $s, t \in \mathbb{R}$. Then
$$W = \text{span}\left\{ \begin{bmatrix} -\frac{1}{3} \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} \frac{2}{3} \\ 0 \\ 1 \end{bmatrix} \right\}$$
Let $X = \left\{ \begin{bmatrix} -1 \\ 3 \\ 0 \end{bmatrix}, \begin{bmatrix} 2 \\ 0 \\ 3 \end{bmatrix} \right\}$. Then X is linearly independent and $\text{span}(X) = W$, so X is a basis of W.
2. Use the Gram-Schmidt Process to get an orthogonal basis of W:
$$\vec{f}_1 = \begin{bmatrix} -1 \\ 3 \\ 0 \end{bmatrix} \text{ and } \vec{f}_2 = \begin{bmatrix} 2 \\ 0 \\ 3 \end{bmatrix} - \frac{-2}{10} \begin{bmatrix} -1 \\ 3 \\ 0 \end{bmatrix} = \frac{1}{5} \begin{bmatrix} 9 \\ 3 \\ 15 \end{bmatrix}.$$
Therefore $B = \left\{ \begin{bmatrix} -1 \\ 3 \\ 0 \end{bmatrix}, \begin{bmatrix} 3 \\ 1 \\ 5 \end{bmatrix} \right\}$ is an orthogonal basis of W.
3. To find the point Z on W closest to $Y = (1, 1, 1)$, compute
$$\begin{aligned} \text{proj}_W \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} &= \frac{2}{10} \begin{bmatrix} -1 \\ 3 \\ 0 \end{bmatrix} + \frac{9}{35} \begin{bmatrix} 3 \\ 1 \\ 5 \end{bmatrix} \\ &= \frac{1}{7} \begin{bmatrix} 4 \\ 6 \\ 9 \end{bmatrix}. \end{aligned} \tag{4.11.11}$$
Therefore, $Z = \left(\frac{4}{7}, \frac{6}{7}, \frac{9}{7}\right)$.

Least Squares Approximation

It should not be surprising to hear that many problems do not have a perfect solution, and in these cases the objective is always to try to do the best possible. For example what does one do if there are no solutions to a system of linear equations $A\vec{x} = \vec{b}$? It turns out that what we do is find $\vec{x}$ such that $A\vec{x}$ is as close to $\vec{b}$ as possible. A very important technique that follows from orthogonal projections is that of the least square approximation, and allows us to do exactly that.

We begin with a lemma.

Recall that we can form the image of an $m \times n$ matrix A by $\text{im}(A) == \{A\vec{x} : \vec{x} \in \mathbb{R}^n\}$. Rephrasing Theorem 4.11.4 using the subspace $W = \text{im}(A)$ gives the equivalence of an orthogonality condition with a minimization condition. The following picture

illustrates this orthogonality condition and geometric meaning of this theorem.

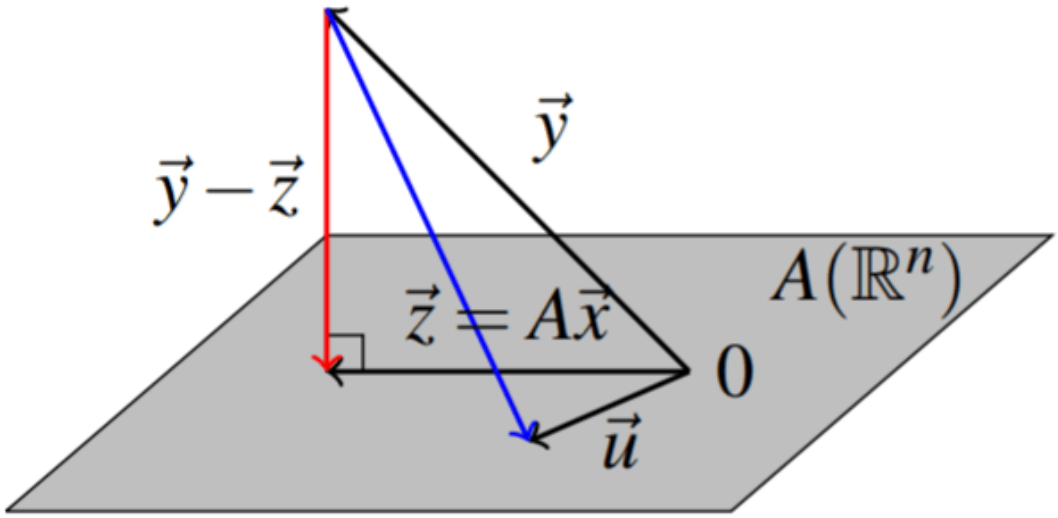


Figure 4.11.2

Theorem 4.11.5: Existence of Minimizers

Let $\vec{y} \in \mathbb{R}^m$ and let A be an $m \times n$ matrix.

Choose $\vec{z} \in W = \text{im}\,(A)$ given by $\vec{z} = \text{proj}_W\,(\vec{y})$, and let $\vec{x} \in \mathbb{R}^n$ such that $\vec{z} = A\vec{x}$.

Then

1. $\vec{y} - A\vec{x} \in W^\perp$
2. $\|\vec{y} - A\vec{x}\| < \|\vec{y} - \vec{u}\|$ for all $\vec{u} \neq \vec{z} \in W$

We note a simple but useful observation.

Lemma 4.11.1: Transpose and Dot Product

Let A be an $m \times n$ matrix. Then

$$A\vec{x} \cdot \vec{y} = \vec{x} \cdot A^T\vec{y}$$

Proof available at the end of this section.

The next corollary gives the technique of least squares.

Corollary 4.11.1: Least Squares and Normal Equation

A specific value of $\vec{x}$ which solves the problem of Theorem 4.11.5 is obtained by solving the equation

$$A^TA\vec{x} = A^T\vec{y}$$

Furthermore, there always exists a solution to this system of equations.

Proof available at the end of this section.

Note that $\vec{x}$ might not be unique but $A\vec{x}$, the closest point of $A(\mathbb{R}^n)$ to $\vec{y}$ is unique as was shown in the above argument.

Consider the following example.

Example 4.11.16: Least Squares Solution to a System

Find a least squares solution to the system

$$\begin{bmatrix} 2 & 1 \\ -1 & 3 \\ 4 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix}$$

Solution

First, consider whether there exists a real solution. To do so, set up the augmnented matrix given by

$$\begin{bmatrix} 2 & 1 & 2 \\ -1 & 3 & 1 \\ 4 & 5 & 1 \end{bmatrix}$$

The reduced row-echelon form of this augmented matrix is

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

It follows that there is no real solution to this system. Therefore we wish to find the least squares solution. The normal equations are

$$A^T A\vec{x} = A^T\vec{y}$$

$$\begin{bmatrix} 2 & -1 & 4 \\ 1 & 3 & 5 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ -1 & 3 \\ 4 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2 & -1 & 4 \\ 1 & 3 & 5 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix} \tag{4.11.12}$$

and so we need to solve the system

$$\begin{bmatrix} 21 & 19 \\ 19 & 35 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 7 \\ 10 \end{bmatrix}$$

This is a familiar exercise and the solution is

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \frac{5}{34} \\ \frac{7}{34} \end{bmatrix}$$

Consider another example.

Example 4.11.17: Least Squares Solution to a System

Find a least squares solution to the system

$$\begin{bmatrix} 2 & 1 \\ -1 & 3 \\ 4 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 3 \\ 2 \\ 9 \end{bmatrix}$$

Solution

First, consider whether there exists a real solution. To do so, set up the augmnented matrix given by

$$\begin{bmatrix} 2 & 1 & 3 \\ -1 & 3 & 2 \\ 4 & 5 & 9 \end{bmatrix}$$

The reduced row-echelon form of this augmented matrix is

$$\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

It follows that the system has a solution given by $x = y = 1$. However we can also use the normal equations and find the least squares solution.

$$\begin{bmatrix} 2 & -1 & 4 \\ 1 & 3 & 5 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ -1 & 3 \\ 4 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2 & -1 & 4 \\ 1 & 3 & 5 \end{bmatrix} \begin{bmatrix} 3 \\ 2 \\ 9 \end{bmatrix}$$

Then

$$\begin{bmatrix} 21 & 19 \\ 19 & 35 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 40 \\ 54 \end{bmatrix}$$

The least squares solution is

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

which is the same as the solution found above.

An important application of Corollary 4.11.1 is the problem of finding the least squares regression line in statistics. Suppose you are given points in the xy plane

$$\{(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)\}$$

and you would like to find constants m and b such that the line $\vec{y} = m\vec{x} + b$ goes through all these points. Of course this will be impossible in general. Therefore, we try to find m, b such that the line will be as close as possible. The desired system is

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} x_1 & 1 \\ \vdots & \vdots \\ x_n & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix}$$

which is of the form $\vec{y} = A\vec{x}$. It is desired to choose m and b to make

$$\left\| A \begin{bmatrix} m \\ b \end{bmatrix} - \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \right\|^2$$

as small as possible. According to Theorem 4.11.5 and Corollary 4.11.1, the best values for m and b occur as the solution to

$$A^T A \begin{bmatrix} m \\ b \end{bmatrix} = A^T \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}, \quad \text{where } A = \begin{bmatrix} x_1 & 1 \\ \vdots & \vdots \\ x_n & 1 \end{bmatrix}$$

Thus, computing $A^T A$,

$$\begin{bmatrix} \sum_{i=1}^n x_i^2 & \sum_{i=1}^n x_i \\ \sum_{i=1}^n x_i & n \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^n x_i y_i \\ \sum_{i=1}^n y_i \end{bmatrix}$$

Solving this system of equations for m and b (using Cramer's rule for example) yields:

$$m = \frac{-\left(\sum_{i=1}^n x_i\right)\left(\sum_{i=1}^n y_i\right) + \left(\sum_{i=1}^n x_i y_i\right) n}{\left(\sum_{i=1}^n x_i^2\right) n - \left(\sum_{i=1}^n x_i\right)^2}$$

and

$$b = \frac{-\left(\sum_{i=1}^{n} x_i\right)\sum_{i=1}^{n} x_i y_i + \left(\sum_{i=1}^{n} y_i\right)\sum_{i=1}^{n} x_i^2}{\left(\sum_{i=1}^{n} x_i^2\right) n - \left(\sum_{i=1}^{n} x_i\right)^2}.$$

Consider the following example.

Example 4.11.18: Least Squares Regression

Find the least squares regression line $\vec{y} = m\vec{x} + b$ for the following set of data points:

$$\{(0,1),(1,2),(2,2),(3,4),(4,5)\}$$

Solution

In this case we have $n = 5$ data points and we obtain:

$$\sum_{i=1}^{5} x_i = 10 \qquad \sum_{i=1}^{5} y_i = 14$$

$$\sum_{i=1}^{5} x_i y_i = 38 \quad \sum_{i=1}^{5} x_i^2 = 30$$

and hence

$$m = \frac{-10 * 14 + 5 * 38}{5 * 30 - 10^2} = 1.00$$

$$b = \frac{-10 * 38 + 14 * 30}{5 * 30 - 10^2} = 0.80 \tag{4.11.13}$$

The least squares regression line for the set of data points is:

$$\vec{y} = \vec{x} + .8$$

One could use this line to approximate other values for the data. For example for $x = 6$ one could use $y(6) = 6 + .8 = 6.8$ as an approximate value for the data.

The following diagram shows the data points and the corresponding regression line.

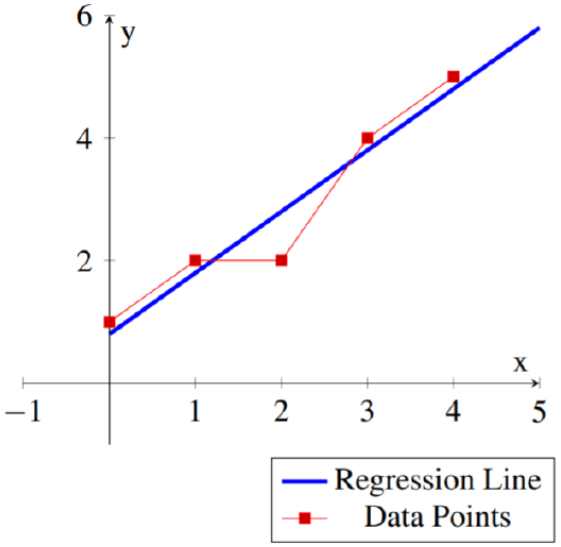


Figure 4.11.3

One could clearly do a least squares fit for curves of the form $y = ax^2 + bx + c$ in the same way. In this case you want to solve as well as possible for a, b, and c the system

$$\begin{bmatrix} x_1^2 & x_1 & 1 \\ \vdots & \vdots & \vdots \\ x_n^2 & x_n & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$$

and one would use the same technique as above. Many other similar problems are important, including many in higher dimensions and they are all solved the same way.

Answers

Theorem 4.11.1**: Orthogonal Basis of a Subspace**

To show it is a linearly independent set, suppose a linear combination of these vectors equals $\vec{0}$, such as:

$$a_1\vec{w}_1 + a_2\vec{w}_2 + \cdots + a_k\vec{w}_k = \vec{0}, a_i \in \mathbb{R}$$

We need to show that all $a_i = 0$. To do so, take the dot product of each side of the above equation with the vector $\vec{w}_i$ and obtain the following.

$$\begin{aligned} \vec{w}_i \cdot (a_1\vec{w}_1 + a_2\vec{w}_2 + \cdots + a_k\vec{w}_k) &= \vec{w}_i \cdot \vec{0} \\ a_1(\vec{w}_i \cdot \vec{w}_1) + a_2(\vec{w}_i \cdot \vec{w}_2) + \cdots + a_k(\vec{w}_i \cdot \vec{w}_k) &= 0 \end{aligned} \tag{4.11.14}$$

Now since the set is orthogonal, $\vec{w}_i \cdot \vec{w}_m = 0$ for all $m \neq i$, so we have:

$$a_1(0) + \cdots + a_i(\vec{w}_i \cdot \vec{w}_i) + \cdots + a_k(0) = 0$$

$$a_i\|\vec{w}_i\|^2 = 0$$

Since the set is orthogonal, we know that $\|\vec{w}_i\|^2 \neq 0$. It follows that $a_i = 0$. Since the a_i was chosen arbitrarily, the set $\{\vec{w}_1, \vec{w}_2, \cdots, \vec{w}_k\}$ is linearly independent.

Finally since $W = \text{span}\{\vec{w}_1, \vec{w}_2, \cdots, \vec{w}_k\}$, the set of vectors also spans W and therefore forms a basis of W.

Proposition 4.11.1**: Orthonormal Basis**

Recall from Theorem 4.11.1 that an orthonormal set is linearly independent and forms a basis for its span. Since the rows of an $n \times n$ orthogonal matrix form an orthonormal set, they must be linearly independent. Now we have n linearly independent vectors, and it follows that their span equals $\mathbb{R}^n$. Therefore these vectors form an orthonormal basis for $\mathbb{R}^n$.

Suppose now that we have an orthonormal basis for $\mathbb{R}^n$. Since the basis will contain n vectors, these can be used to construct an $n \times n$ matrix, with each vector becoming a row. Therefore the matrix is composed of orthonormal rows, which by our above discussion, means that the matrix is orthogonal. Note we could also have construct a matrix with each vector becoming a column instead, and this would again be an orthogonal matrix. In fact this is simply the transpose of the previous matrix.

Proposition 4.11.2**: Determinant of Orthogonal Matrices**

This result follows from the properties of determinants. Recall that for any matrix A, $\det(A)^T = \det(A)$. Now if U is orthogonal, then:

$$(\det(U))^2 = \det(U^T)\det(U) = \det(U^TU) = \det(I) = 1$$

Therefore $(\det(U))^2 = 1$ and it follows that $\det(U) = \pm 1$.

Theorem 4.11.3**: Approximation Theorem**

First Z is certainly a point in W since it is in the span of a basis of W.

To show that Z is the point in W closest to Y, we wish to show that $|\vec{y} - \vec{z}_1| > |\vec{y} - \vec{z}|$ for all $\vec{z}_1 \neq \vec{z} \in W$. We begin by writing $\vec{y} - \vec{z}_1 = (\vec{y} - \vec{z}) + (\vec{z} - \vec{z}_1)$. Now, the vector $\vec{y} - \vec{z}$ is orthogonal to W, and $\vec{z} - \vec{z}_1$ is contained in W. Therefore these vectors are orthogonal to each other. By the Pythagorean Theorem, we have that

$$\|\vec{y} - \vec{z}_1\|^2 = \|\vec{y} - \vec{z}\|^2 + \|\vec{z} - \vec{z}_1\|^2 > \|\vec{y} - \vec{z}\|^2$$

This follows because $\vec{z} \neq \vec{z}_1$ so $\|\vec{z} - \vec{z}_1\|^2 > 0$.

Hence, $\|\vec{y} - \vec{z}_1\|^2 > \|\vec{y} - \vec{z}\|^2$. Taking the square root of each side, we obtain the desired result.

Proposition 4.11.5**: Orthogonal Complement of** $\mathbb{R}^n$

Here, $\vec{0}$ is the zero vector of $\mathbb{R}^n$. Since $\vec{x} \cdot \vec{0} = 0$ for all $\vec{x} \in \mathbb{R}^n$, $\mathbb{R}^n \subseteq \{\vec{0}\}^\perp$. Since $\{\vec{0}\}^\perp \subseteq \mathbb{R}^n$, the equality follows, i.e., $\{\vec{0}\}^\perp = \mathbb{R}^n$.

Again, since $\vec{x} \cdot \vec{0} = 0$ for all $\vec{x} \in \mathbb{R}^n$, $\vec{0} \in (\mathbb{R}^n)^\perp$, so $\{\vec{0}\} \subseteq (\mathbb{R}^n)^\perp$. Suppose $\vec{x} \in \mathbb{R}^n$, $\vec{x} \neq \vec{0}$. Since $\vec{x} \cdot \vec{x} = ||\vec{x}||^2$ and $\vec{x} \neq \vec{0}$, $\vec{x} \cdot \vec{x} \neq 0$, so $\vec{x} \notin (\mathbb{R}^n)^\perp$. Therefore $(\mathbb{R}^n)^\perp \subseteq \{\vec{0}\}$, and thus $(\mathbb{R}^n)^\perp = \{\vec{0}\}$.

Lemma 4.11.1**: Transpose and Dot Product**

This follows from the definitions:

$$A\vec{x} \cdot \vec{y} = \sum_{i,j} a_{ij}x_jy_i = \sum_{i,j} x_ja_{ji}y_i = \vec{x} \cdot A^T\vec{y}$$

Corollary 4.11.1**: Least Squares and Normal Equation**

For $\vec{x}$ the minimizer of Theorem 4.11.5, $(\vec{y} - A\vec{x}) \cdot A\vec{u} = 0$ for all $\vec{u} \in \mathbb{R}^n$ and from Lemma 4.11.1, this is the same as saying

$$A^T(\vec{y} - A\vec{x}) \cdot \vec{u} = 0$$

for all $u \in \mathbb{R}^n$. This implies

$$A^T\vec{y} - A^TA\vec{x} = \vec{0}.$$

Therefore, there is a solution to the equation of this corollary, and it solves the minimization problem of Theorem 4.11.5.

Vector Projection GeoGebra Demo SKKU - Matrix - Lab

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Vector Projection GeoGebra Demo SKKU - Matrix - Lab

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4.12: Applications

Applications

Outcomes

A. Apply the concepts of vectors in $\mathbb{R}^n$ to the applications of physics and work.

Vectors and Physics

Suppose you push on something. Then, your push is made up of two components, how hard you push and the direction you push. This illustrates the concept of force.

Definition 4.12.1: Force

Force is a vector. The magnitude of this vector is a measure of how hard it is pushing. It is measured in units such as Newtons or pounds or tons. The direction of this vector is the direction in which the push is taking place.

Vectors are used to model force and other physical vectors like velocity. As with all vectors, a vector modeling force has two essential ingredients, its magnitude and its direction.

Recall the special vectors which point along the coordinate axes. These are given by

$$\vec{e}_i = [0 \cdots 0\ 1\ 0 \cdots 0]^T$$

where the 1 is in the i^{th} slot and there are zeros in all the other spaces. The direction of $\vec{e}_i$ is referred to as the i^{th} direction.

Consider the following picture which illustrates the case of $\mathbb{R}^3$. Recall that in $\mathbb{R}^3$, we may refer to these vectors as $\vec{i}, \vec{j}$, and $\vec{k}$.

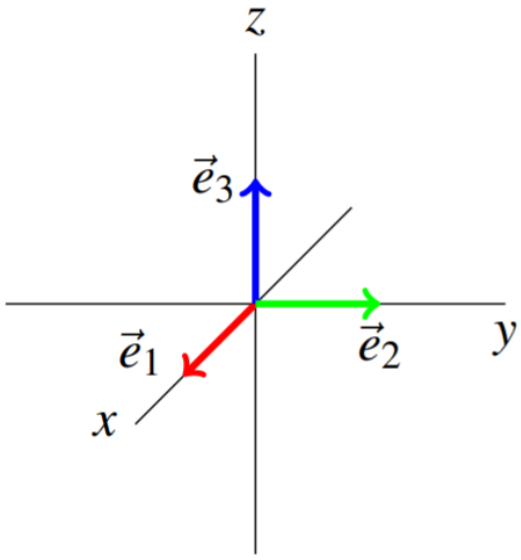


Figure 4.12.1

Given a vector $\vec{u} = [u_1 \cdots u_n]^T$, it follows that

$$\vec{u} = u_1\vec{e}_1 + \cdots + u_n\vec{e}_n = \sum_{k=1}^{n} u_i\vec{e}_i$$

What does addition of vectors mean physically? Suppose two forces are applied to some object. Each of these would be represented by a force vector and the two forces acting together would yield an overall force acting on the object which would also be a force vector known as the resultant. Suppose the two vectors are $\vec{u} = \sum_{k=1}^{n} u_i\vec{e}_i$ and $\vec{v} = \sum_{k=1}^{n} v_i\vec{e}_i$. Then the vector $\vec{u}$ involves a component in the i^{th} direction given by $u_i\vec{e}_i$, while the component in the i^{th} direction of $\vec{v}$ is $v_i\vec{e}_i$. Then the vector $\vec{u}+\vec{v}$ should have a component in the i^{th} direction equal to $(u_i + v_i)\,\vec{e}_i$. This is exactly what is obtained when the vectors, $\vec{u}$ and $\vec{v}$ are added.

$$\begin{aligned} \vec{u}+\vec{v} &= [u_1 + v_1 \cdots u_n + v_n]^T \\ &= \sum_{i=1}^{n} (u_i + v_i)\,\vec{e}_i \end{aligned} \tag{4.12.1}$$

Thus the addition of vectors according to the rules of addition in $\mathbb{R}^n$ which were presented earlier, yields the appropriate vector which duplicates the cumulative effect of all the vectors in the sum.

Consider now some examples of vector addition.

Example 4.12.1: The Resultant of Three Forces

There are three ropes attached to a car and three people pull on these ropes. The first exerts a force of $\vec{F}_1 = 2\vec{i} + 3\vec{j} - 2\vec{k}$ Newtons, the second exerts a force of $\vec{F}_2 = 3\vec{i} + 5\vec{j} + \vec{k}$ Newtons and the third exerts a force of $5\vec{i} - \vec{j} + 2\vec{k}$ Newtons. Find the total force in the direction of $\vec{i}$.

Solution

To find the total force, we add the vectors as described above. This is given by

$$\begin{aligned} &(2\vec{i} + 3\vec{j} - 2\vec{k}) + (3\vec{i} + 5\vec{j} + \vec{k}) + (5\vec{i} - \vec{j} + 2\vec{k}) \\ &= (2+3+5)\vec{i} + (3+5+-1)\vec{j} + (-2+1+2)\vec{k} \\ &= 10\vec{i} + 7\vec{j} + \vec{k} \end{aligned} \tag{4.12.2}$$

Hence, the total force is $10\vec{i} + 7\vec{j} + \vec{k}$ Newtons. Therefore, the force in the $\vec{i}$ direction is 10 Newtons.

Consider another example.

Example 4.12.2: Finding a Vector from Geometric Description

An airplane flies North East at 100 miles per hour. Write this as a vector.

Solution

A picture of this situation follows.

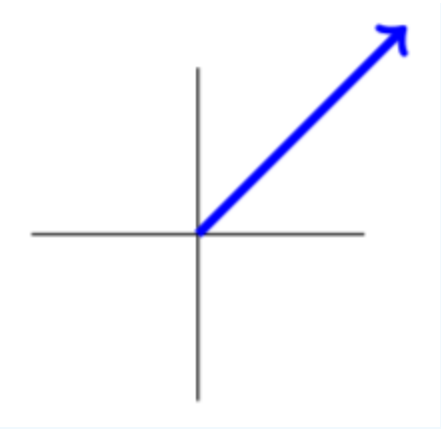


Figure 4.12.2

Therefore, we need to find the vector $\vec{u}$ which has length 100 and direction as shown in this diagram. We can consider the vector $\vec{u}$ as the hypotenuse of a right triangle having equal sides, since the direction of $\vec{u}$ corresponds with the 45° line. The sides, corresponding to the $\vec{i}$ and $\vec{j}$ directions, should be each of length $100/\sqrt{2}$. Therefore, the vector is given by

$$\vec{u} = \frac{100}{\sqrt{2}}\vec{i} + \frac{100}{\sqrt{2}}\vec{j} = \left[\begin{array}{cc} 0.05in\frac{100}{\sqrt{2}} & 0.05in\frac{100}{\sqrt{2}} \end{array}\right]^T$$

This example also motivates the concept of **velocity**, defined below.

Definition 4.12.2: Speed and Velocity

The **speed** of an object is a measure of how fast it is going. It is measured in units of length per unit time. For example, miles per hour, kilometers per minute, feet per second. The **velocity** is a vector having the speed as the magnitude but also specifying the direction.

Thus the velocity vector in the above example is $0.05in\frac{100}{\sqrt{2}}\vec{i} + 0.05in\frac{100}{\sqrt{2}}\vec{j}$, while the speed is 100 miles per hour.

Consider the following example.

The velocity of an airplane is $100\vec{i} + \vec{j} + \vec{k}$ measured in kilometers per hour and at a certain instant of time its position is $(1,2,1)$.

Find the position of this airplane one minute later.

Solution

Here imagine a Cartesian coordinate system in which the third component is altitude and the first and second components are measured on a line from West to East and a line from South to North.

Consider the vector $\left[\begin{array}{ccc} 1 & 2 & 1 \end{array}\right]^T$, which is the initial position vector of the airplane. As the plane moves, the position vector changes according to the velocity vector. After one minute (considered as $\frac{1}{60}$ of an hour) the airplane has moved in the $\vec{i}$ direction a distance of $100 \times \frac{1}{60} = \frac{5}{3}$ kilometer. In the $\vec{j}$ direction it has moved $\frac{1}{60}$ kilometer during this same time, while it moves $\frac{1}{60}$ kilometer in the $\vec{k}$ direction. Therefore, the new displacement vector for the airplane is

$$\left[\begin{array}{ccc} 1 & 2 & 1 \end{array}\right]^T + \left[\begin{array}{ccc} \frac{5}{3} & \frac{1}{60} & \frac{1}{60} \end{array}\right]^T = \left[\begin{array}{ccc} \frac{8}{3} & \frac{121}{60} & \frac{121}{60} \end{array}\right]^T$$

Now consider an example which involves combining two velocities.

Example 4.12.4: Sum of Two Velocities

A certain river is one half kilometer wide with a current flowing at 4 kilometers per hour from East to West. A man swims directly toward the opposite shore from the South bank of the river at a speed of 3 kilometers per hour. How far down the river does he find himself when he has swam across? How far does he end up swimming?

Solution

Consider the following picture which demonstrates the above scenario.

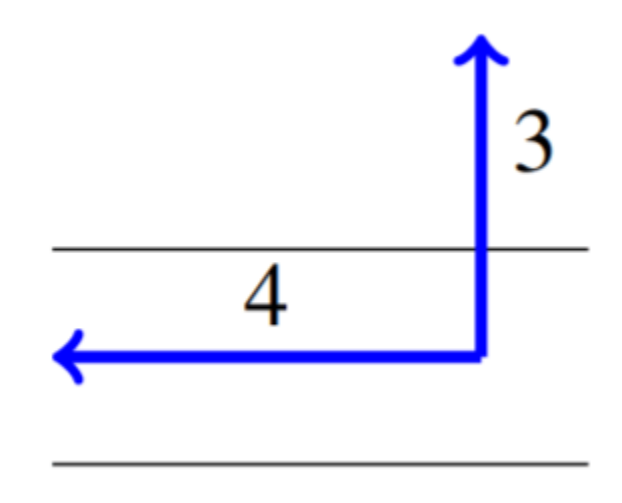


Figure 4.12.3

First we want to know the total time of the swim across the river. The velocity in the direction across the river is 3 kilometers per hour, and the river is $\frac{1}{2}$ kilometer wide. It follows the trip takes $1/6$ hour or 10 minutes.

Now, we can compute how far downstream he will end up. Since the river runs at a rate of 4 kilometers per hour, and the trip takes $1/6$ hour, the distance traveled downstream is given by $4\left(\frac{1}{6}\right)=\frac{2}{3}$ kilometers.

The distance traveled by the swimmer is given by the hypotenuse of a right triangle. The two arms of the triangle are given by the distance across the river, $\frac{1}{2}$km, and the distance traveled downstream, $\frac{2}{3}$ km. Then, using the Pythagorean Theorem, we can calculate the total distance d traveled.

$$d=\sqrt{\left(\frac{2}{3}\right)^2+\left(\frac{1}{2}\right)^2}=\frac{5}{6}\text{km}$$

Therefore, the swimmer travels a total distance of $\frac{5}{6}$ kilometers.

Work

The mathematical concept of work is an application of vectors in $\mathbb{R}^n$. The physical concept of work differs from the notion of work employed in ordinary conversation. For example, suppose you were to slide a 150 pound weight off a table which is three feet high and shuffle along the floor for 50 yards, keeping the height always three feet and then deposit this weight on another three foot high table. The physical concept of work would indicate that the force exerted by your arms did no work during this project. The reason for this definition is that even though your arms exerted considerable force on the weight, the direction of motion was at right angles to the force they exerted. The only part of a force which does work in the sense of physics is the component of the force in the direction of motion.

Work is defined to be the magnitude of the component of this force times the distance over which it acts, when the component of force points in the direction of motion. In the case where the force points in exactly the opposite direction of motion work is given by (-1) times the magnitude of this component times the distance. Thus the work done by a force on an object as the

object moves from one point to another is a measure of the extent to which the force contributes to the motion. This is illustrated in the following picture in the case where the given force contributes to the motion.

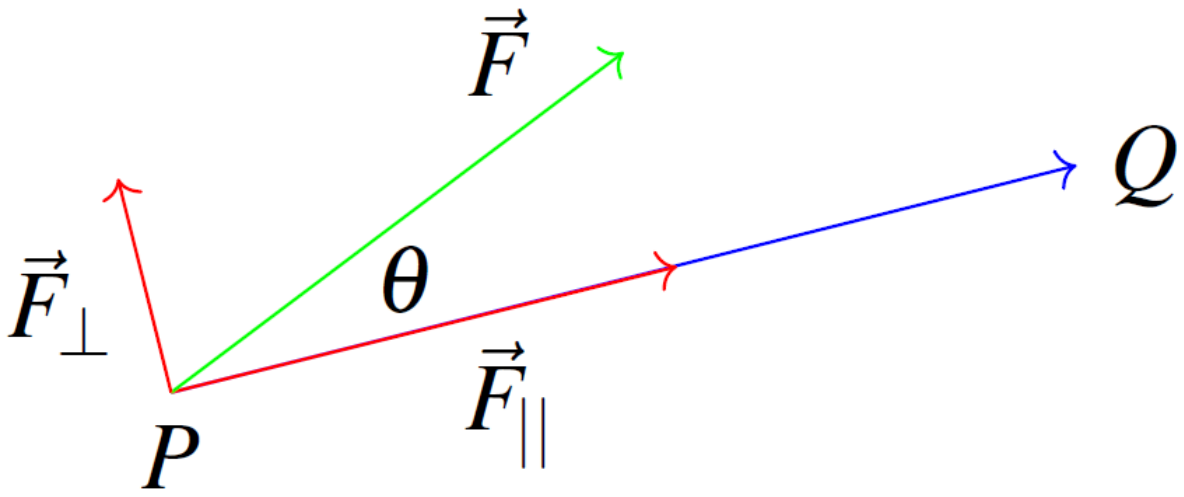


Figure 4.12.4

Recall that for any vector $\vec{u}$ in $\mathbb{R}^n$, we can write $\vec{u}$ as a sum of two vectors, as in

$$\vec{u} = \vec{u}_{||} + \vec{u}_{\perp}$$

For any force $\vec{F}$, we can write this force as the sum of a vector in the direction of the motion and a vector perpendicular to the motion. In other words,

$$\vec{F} = \vec{F}_{||} + \vec{F}_{\perp}$$

In the above picture the force, $\vec{F}$ is applied to an object which moves on the straight line from P to Q. There are two vectors shown, $\vec{F}_{||}$ and $\vec{F}_{\perp}$ and the picture is intended to indicate that when you add these two vectors you get $\vec{F}$. In other words, $\vec{F} = \vec{F}_{||} + \vec{F}_{\perp}$. Notice that $\vec{F}_{||}$ acts in the direction of motion and $\vec{F}_{\perp}$ acts perpendicular to the direction of motion. Only $\vec{F}_{||}$ contributes to the work done by $\vec{F}$ on the object as it moves from P to Q. $\vec{F}_{||}$ is called the component of the force in the direction of motion. From trigonometry, you see the magnitude of $\vec{F}_{||}$ should equal $\|\vec{F}\| \, |\cos\theta|$. Thus, since $\vec{F}_{||}$ points in the direction of the vector from P to Q, the total work done should equal

$$\|\vec{F}\| \|\vec{PQ}\| \cos\theta = \|\vec{F}\| \|\vec{q} - \vec{p}\| \cos\theta$$

Now, suppose the included angle had been obtuse. Then the work done by the force $\vec{F}$ on the object would have been negative because $\vec{F}_{||}$ would point in -1 times the direction of the motion. In this case, $\cos\theta$ would also be negative and so it is still the case that the work done would be given by the above formula. Thus from the geometric description of the dot product given above, the work equals

$$\|\vec{F}\| \|\vec{q} - \vec{p}\| \cos\theta = \vec{F} \bullet (\vec{q} - \vec{p})$$

This explains the following definition.

Definition 4.12.3: Work Done on an Object by a Force

Let $\vec{F}$ be a force acting on an object which moves from the point P to the point Q, which have position vectors given by $\vec{p}$ and $\vec{q}$ respectively. Then the **work** done on the object by the given force equals $\vec{F} \bullet (\vec{q} - \vec{p})$.

Consider the following example.

Example 4.12.4: Finding Work

Let $\vec{F} = \begin{bmatrix} 2 & 7 & -3 \end{bmatrix}^T$ Newtons. Find the work done by this force in moving from the point $(1,2,3)$ to the point $(-9,-3,4)$ along the straight line segment joining these points where distances are measured in meters.

Solution

First, compute the vector $\vec{q} - \vec{p}$, given by

$$\begin{bmatrix} -9 & -3 & 4 \end{bmatrix}^T - \begin{bmatrix} 1 & 2 & 3 \end{bmatrix}^T = \begin{bmatrix} -10 & -5 & 1 \end{bmatrix}^T$$

According to Definition 4.12.3 the work done is

$$\begin{aligned} \begin{bmatrix} 2 & 7 & 3 \end{bmatrix}^T \bullet \begin{bmatrix} -10 & -5 & 1 \end{bmatrix}^T &= -20 + (-35) + (-3) \\ &= -58 \text{ Newton meters} \end{aligned} \tag{4.12.3}$$

Note that if the force had been given in pounds and the distance had been given in feet, the units on the work would have been foot pounds. In general, work has units equal to units of a force times units of a length. Recall that 1 Newton meter is equal to 1 Joule. Also notice that the work done by the force can be negative as in the above example.

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4.E: Exercises

Exercise $4.E.1$

Find $-3\begin{bmatrix} 5 \\ -1 \\ 2 \\ -3 \end{bmatrix} + 5\begin{bmatrix} -8 \\ 2 \\ -3 \\ 6 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $4.E.2$

Find $-7\begin{bmatrix} 6 \\ 0 \\ 4 \\ -1 \end{bmatrix} + 6\begin{bmatrix} -13 \\ -1 \\ 1 \\ 6 \end{bmatrix}$.

Exercise $4.E.3$

Decide whether

$$\vec{v} = \begin{bmatrix} 4 \\ 4 \\ -3 \end{bmatrix}$$

is a linear combination of the vectors

$$\vec{u}_1 = \begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix} \quad \text{and} \quad \vec{u}_2 = \begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix}.$$

Answer available at the end of this section.

Exercise $4.E.4$

Decide whether

$$\vec{v} = \begin{bmatrix} 4 \\ 4 \\ 4 \end{bmatrix}$$

is a linear combination of the vectors

$$\vec{u}_1 = \begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix} \quad \text{and} \quad \vec{u}_2 = \begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix}.$$

Answer available at the end of this section.

Exercise $4.E.5$

Find the vector equation for the line through $(-7, 6, 0)$ and $(-1, 1, 4)$. Then, find the parametric equations for this line.

Exercise $4.E.6$

Find parametric equations for the line through the point $(7, 7, 1)$ with a direction vector $\vec{d} = \begin{bmatrix} 1 \\ 6 \\ 2 \end{bmatrix}$.

Exercise $4.E.7$

Parametric equations of the line are

$$\begin{aligned} x &= t + 2 \\ y &= 6 - 3t \\ x &= -t = 6 \end{aligned} \tag{4.E.1}$$

Find a direction vector for the line and a point on the line.

Exercise $4.E.8$

Find the vector equation for the line through the two points $(-5, 5, 1),\ \ (2, 2, 4)$. Then, find the parametric equations.

Exercise $4.E.9$

The equation of a line in two dimensions is written as $y = x - 5$. Find parametric equations for this line.

Exercise $4.E.10$

Find parametric equations for the line through $(6, 5, -2)$ and $(5, 1, 2)$.

Exercise $4.E.11$

Find the vector equation and parametric equations for the line through the point $(-7, 10, -6)$ with a direction vector $\vec{d} = \begin{bmatrix} 1 \\ 1 \\ 3 \end{bmatrix}$.

Exercise $4.E.12$

Parametric equations of the line are

$$\begin{aligned} x &= 2t + 2 \\ y &= 5 - 4t \\ z &= -t - 3 \end{aligned} \tag{4.E.2}$$

Find a direction vector for the line and a point on the line, and write the vector equation of the line.

Exercise $4.E.13$

Find the vector equation and parametric equations for the line through the two points $(4,10,0),\ \ (1,-5,-6)$.

Exercise $4.E.14$

Find the point on the line segment from $P=(-4,7,5)$ to $Q=(2,-2,-3)$ which is $\frac{1}{7}$ of the way from P to Q.

Exercise $4.E.15$

Suppose a triangle in $\mathbb{R}^n$ has vertices at $P_1,\ \ P_2$, and P_3. Consider the lines which are drawn from a vertex to the mid point of the opposite side. Show these three lines intersect in a point and find the coordinates of this point.

Exercise $4.E.16$

Find $\begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix} \bullet \begin{bmatrix} 2 \\ 0 \\ 1 \\ 3 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $4.E.17$

Use the formula given in Proposition 4.7.2 to verify the Cauchy Schwarz inequality and to show that equality occurs if and only if one of the vectors is a scalar multiple of the other

Answer available at the end of this section.

Exercise $4.E.18$

For $\vec{u}$, $\vec{v}$ vectors in $\mathbb{R}^3$, define the product, $\vec{u}*\vec{v}=u_1v_1+2u_2v_2+3u_3v_3$. Show the axioms for a dot product all hold for this product. Prove

$$||\vec{u}*\vec{v}||\leq(\vec{u}*\vec{u})^{1/2}(\vec{v}*\vec{v})^{1/2}$$

Answer available at the end of this section.

Exercise $4.E.19$

Let $\vec{a}$, $\vec{b}$ be vectors. Show that $\left(\vec{a}\bullet\vec{b}\right)=\frac{1}{4}\left(||\vec{a}+\vec{b}||^2-||\vec{a}-\vec{b}||^2\right)$.

Exercise $4.E.20$

Using the axioms of the dot product, prove the parallelogram identity:

$$||\vec{a}+\vec{b}||^2+||\vec{a}-\vec{b}||^2=2||\vec{a}||^2+2||\vec{b}||^2$$

Exercise $4.E.21$

Let A be a real $m \times n$ matrix and let $\vec{u} \in \mathbb{R}^n$ and $\vec{v} \in \mathbb{R}^m$. Show $A\vec{u} \bullet \vec{v} = \vec{u} \bullet A^T\vec{v}$. Hint: Use the definition of matrix multiplication to do this.

Answer available at the end of this section.

Exercise $4.E.22$

Use the result of Problem $4.E.21$ to verify directly that $(AB)^T = B^T A^T$ without making any reference to subscripts.

Answer available at the end of this section.

Exercise $4.E.23$

Find the angle between the vectors

$$\vec{u} = \begin{bmatrix} 3 \\ -1 \\ -1 \end{bmatrix}, \vec{v} = \begin{bmatrix} 1 \\ 4 \\ 2 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $4.E.24$

Find the angle between the vectors

$$\vec{u} = \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}, \vec{v} = \begin{bmatrix} 1 \\ 2 \\ -7 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $4.E.25$

Find $\text{proj}_{\vec{v}}(\vec{w})$ where $\vec{w} = \begin{bmatrix} 1 \\ 0 \\ -2 \end{bmatrix}$ and $\vec{v} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $4.E.26$

Find $\text{proj}_{\vec{v}}(\vec{w})$ where $\vec{w} = \begin{bmatrix} 1 \\ 2 \\ -2 \end{bmatrix}$ and $\vec{v} = \begin{bmatrix} 1 \\ 0 \\ 3 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $4.E.27$

Find $\text{proj}_{\vec{v}}(\vec{w})$ where $\vec{w} = \begin{bmatrix} 1 \\ 2 \\ -2 \\ 1 \end{bmatrix}$ and $\vec{v} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 0 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $4.E.28$

Let $P = (1, 2, 3)$ be a point in $\mathbb{R}^3$. Let L be the line through the point $P_0 = (1, 4, 5)$ with direction vector $\vec{d} = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$. Find the shortest distance from P to L, and find the point Q on L that is closest to P.

Exercise $4.E.29$

Let $P = (0, 2, 1)$ be a point in $\mathbb{R}^3$. Let L be the line through the point $P_0 = (1, 1, 1)$ with direction vector $\vec{d} = \begin{bmatrix} 3 \\ 0 \\ 1 \end{bmatrix}$. Find the shortest distance from P to L, and find the point Q on L that is closest to P.

Exercise $4.E.30$

Does it make sense to speak of $\text{proj}_{\vec{0}}(\vec{w})$?

Answer available at the end of this section.

Exercise $4.E.31$

Prove the Cauchy Schwarz inequality in $\mathbb{R}^n$ as follows. For $\vec{u}$,$\vec{v}$ vectors, consider

$$(\vec{w} - \text{proj}_{\vec{v}}\vec{w}) \bullet (\vec{w} - \text{proj}_{\vec{v}}\vec{w}) \geq 0$$

Simplify using the axioms of the dot product and then put in the formula for the projection. Notice that this expression equals 0 and you get equality in the Cauchy Schwarz inequality if and only if $\vec{w} = \text{proj}_{\vec{v}}\vec{w}$. What is the geometric meaning of $\vec{w} = \text{proj}_{\vec{v}}\vec{w}$?

Answer available at the end of this section.

Exercise $4.E.32$

Let $\vec{v}$, $\vec{w}$, $\vec{u}$ be vectors. Show that $(\vec{w} + \vec{u})_{\perp} = \vec{w}_{\perp} + \vec{u}_{\perp}$ where $\vec{w}_{\perp} = \vec{w} - \text{proj}_{\vec{v}}(\vec{w})$.

Answer available at the end of this section.

Exercise $4.E.33$

Show that

$$(\vec{v} - \text{proj}_{\vec{u}}(\vec{v}), \vec{u}) = (\vec{v} - \text{proj}_{\vec{u}}(\vec{v})) \bullet \vec{u} = 0$$

and conclude every vector in $\mathbb{R}^n$ can be written as the sum of two vectors, one which is perpendicular and one which is parallel to the given vector.

Answer available at the end of this section.

Exercise $4.E.34$

Show that if $\vec{a} \times \vec{u} = \vec{0}$ for any unit vector $\vec{u}$, then $\vec{a} = \vec{0}$.

Answer available at the end of this section.

Exercise $4.E.35$

Find the area of the triangle determined by the three points $(1, 2, 3),\ (4, 2, 0)$ and $(-3, 2, 1)$.

Answer available at the end of this section.

Exercise $4.E.36$

Find the area of the triangle determined by the three points $(1, 0, 3),\ (4, 1, 0)$ and $(-3, 1, 1)$.

Answer available at the end of this section.

Exercise $4.E.37$

Find the area of the triangle determined by the three points, $(1, 2, 3),\ (2, 3, 4)$ and $(3, 4, 5)$. Did something interesting happen here? What does it mean geometrically?

Answer available at the end of this section.

Exercise $4.E.38$

Find the area of the parallelogram determined by the vectors $\begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}, \begin{bmatrix} 3 \\ -2 \\ 1 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $4.E.39$

Find the area of the parallelogram determined by the vectors $\begin{bmatrix} 1 \\ 0 \\ 3 \end{bmatrix}, \begin{bmatrix} 4 \\ -2 \\ 1 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $4.E.40$

Is $\vec{u} \times (\vec{v} \times \vec{w}) = (\vec{u} \times \vec{v}) \times \vec{w}$? What is the meaning of $\vec{u} \times \vec{v} \times \vec{w}$? Explain. Hint: Try $\left(\vec{i} \times \vec{j}\right) \times \vec{k}$.

Answer available at the end of this section.

Exercise $4.E.41$

Verify directly that the coordinate description of the cross product, $\vec{u} \times \vec{v}$ has the property that it is perpendicular to both $\vec{u}$ and $\vec{v}$. Then show by direct computation that this coordinate description satisfies

$$\begin{aligned} ||\vec{u} \times \vec{v}||^2 &= ||\vec{u}||^2||\vec{v}||^2 - (\vec{u} \bullet \vec{v})^2 \\ &= ||\vec{u}||^2||\vec{v}||^2(1 - \cos^2(\theta)) \end{aligned} \tag{4.E.3}$$

where θ is the angle included between the two vectors. Explain why $||\vec{u} \times \vec{v}||$ has the correct magnitude.

Answer available at the end of this section.

Exercise $4.E.42$

Suppose A is a 3×3 skew symmetric matrix such that $A^T = -A$. Show there exists a vector $\vec{\Omega}$ such that for all $\vec{u} \in \mathbb{R}^3$

$$A\vec{u} = \vec{\Omega} \times \vec{u}$$

Hint: Explain why since A is skew symmetric it is of the form

$$A = \begin{bmatrix} 0 & -\omega_3 & \omega_2 \\ \omega_3 & 0 & -\omega_1 \\ -\omega_2 & \omega_1 & 0 \end{bmatrix}$$

where the ω_i are numbers. Then consider $\omega_1\vec{i} + \omega_2\vec{j} + \omega_3\vec{k}$.

Exercise $4.E.43$

Find the volume of the parallelepiped determined by the vectors $\begin{bmatrix} 1 \\ -7 \\ -5 \end{bmatrix}$, $\begin{bmatrix} 1 \\ -2 \\ -6 \end{bmatrix}$, and $\begin{bmatrix} 3 \\ 2 \\ 3 \end{bmatrix}$.

Answer available at the end of this section.

Exercise $4.E.44$

Suppose $\vec{u}$, $\vec{v}$, and $\vec{w}$ are three vectors whose components are all integers. Can you conclude the volume of the parallelepiped determined from these three vectors will always be an integer?

Answer available at the end of this section.

Exercise $4.E.45$

What does it mean geometrically if the box product of three vectors gives zero?

Answer available at the end of this section.

Exercise $4.E.46$

Using Problem $4.E.45$, find an equation of a plane containing the two position vectors, $\vec{p}$ and $\vec{q}$ and the point 0. Hint: If (x, y, z) is a point on this plane, the volume of the parallelepiped determined by (x, y, z) and the vectors $\vec{p}$, $\vec{q}$ equals 0.

Answer available at the end of this section.

Exercise $4.E.47$

Using the notion of the box product yielding either plus or minus the volume of the parallelepiped determined by the given three vectors, show that

$$(\vec{u} \times \vec{v}) \bullet \vec{w} = \vec{u} \bullet (\vec{v} \times \vec{w})$$

In other words, the dot and the cross can be switched as long as the order of the vectors remains the same. Hint: There are two ways to do this, by the coordinate description of the dot and cross product and by geometric reasoning.

Exercise $4.E.48$

Simplify $(\vec{u} \times \vec{v}) \bullet (\vec{v} \times \vec{w}) \times (\vec{w} \times \vec{z})$.

Answer available at the end of this section.

Exercise $4.E.49$

Simplify $||\vec{u} \times \vec{v}||^2 + (\vec{u} \bullet \vec{v})^2 - ||\vec{u}||^2 ||\vec{v}||^2$.

Answer available at the end of this section.

Exercise $4.E.50$

For $\vec{u},\ \vec{v},\ \vec{w}$ functions of t, prove the following product rules:

$$\begin{aligned} (\vec{u} \times \vec{v})' &= \vec{u}' \times \vec{v} + \vec{u} \times \vec{v}' \\ (\vec{u} \bullet \vec{v})' &= \vec{u}' \bullet \vec{v} + \vec{u} \bullet \vec{v}' \end{aligned} \tag{4.E.4}$$

Answer available at the end of this section.

Exercise $4.E.51$

Here are some vectors.

$$\begin{bmatrix} 1 \\ 1 \\ -2 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ -2 \end{bmatrix}, \begin{bmatrix} 2 \\ 7 \\ -4 \end{bmatrix}, \begin{bmatrix} 5 \\ 7 \\ -10 \end{bmatrix}, \begin{bmatrix} 12 \\ 17 \\ -24 \end{bmatrix}$$

Describe the span of these vectors as the span of as few vectors as possible.

Exercise $4.E.52$

Here are some vectors.

$$\left[\begin{array}{r}1\\2\\-2\end{array}\right], \left[\begin{array}{r}12\\29\\-24\end{array}\right], \left[\begin{array}{r}1\\3\\-2\end{array}\right], \left[\begin{array}{r}2\\9\\-4\end{array}\right], \left[\begin{array}{r}5\\12\\-10\end{array}\right].$$

Describe the span of these vectors as the span of as few vectors as possible.

Exercise $4.E.53$

Here are some vectors.

$$\left[\begin{array}{r}1\\2\\-2\end{array}\right], \left[\begin{array}{r}1\\3\\-2\end{array}\right], \left[\begin{array}{r}1\\-2\\-2\end{array}\right], \left[\begin{array}{r}-1\\0\\2\end{array}\right], \left[\begin{array}{r}1\\3\\-1\end{array}\right]$$

Describe the span of these vectors as the span of as few vectors as possible.

Exercise $4.E.54$

Here are some vectors.

$$\left[\begin{array}{r}1\\1\\-2\end{array}\right], \left[\begin{array}{r}1\\2\\-2\end{array}\right], \left[\begin{array}{r}1\\-3\\-2\end{array}\right], \left[\begin{array}{r}-1\\1\\2\end{array}\right]$$

Now here is another vector:

$$\left[\begin{array}{r}1\\2\\-1\end{array}\right]$$

Is this vector in the span of the first four vectors? If it is, exhibit a linear combination of the first four vectors which equals this vector, using as few vectors as possible in the linear combination.

Exercise $4.E.55$

Here are some vectors.

$$\left[\begin{array}{r}1\\1\\-2\end{array}\right], \left[\begin{array}{r}1\\2\\-2\end{array}\right], \left[\begin{array}{r}1\\-3\\-2\end{array}\right], \left[\begin{array}{r}-1\\1\\2\end{array}\right]$$

Now here is another vector:

$$\left[\begin{array}{r}2\\-3\\-4\end{array}\right]$$

Is this vector in the span of the first four vectors? If it is, exhibit a linear combination of the first four vectors which equals this vector, using as few vectors as possible in the linear combination.

Exercise $4.E.56$

Here are some vectors.

$$\left[\begin{array}{r}1\\1\\-2\end{array}\right], \left[\begin{array}{r}1\\2\\-2\end{array}\right], \left[\begin{array}{r}1\\-3\\-2\end{array}\right], \left[\begin{array}{r}1\\2\\-1\end{array}\right]$$

Now here is another vector:

$$\begin{bmatrix} 1 \\ 9 \\ 1 \end{bmatrix}$$

Is this vector in the span of the first four vectors? If it is, exhibit a linear combination of the first four vectors which equals this vector, using as few vectors as possible in the linear combination.

Exercise $4.E.57$

Here are some vectors,

$$\begin{bmatrix} 1 \\ -1 \\ -2 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ -2 \end{bmatrix}, \begin{bmatrix} 1 \\ -5 \\ -2 \end{bmatrix}, \begin{bmatrix} -1 \\ 5 \\ 2 \end{bmatrix}$$

Now here is another vector:

$$\begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}$$

Is this vector in the span of the first four vectors? If it is, exhibit a linear combination of the first four vectors which equals this vector, using as few vectors as possible in the linear combination.

Exercise $4.E.58$

Here are some vectors.

$$\begin{bmatrix} 1 \\ -1 \\ -2 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ -2 \end{bmatrix}, \begin{bmatrix} 1 \\ -5 \\ -2 \end{bmatrix}, \begin{bmatrix} -1 \\ 5 \\ 2 \end{bmatrix}$$

Now here is another vector:

$$\begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}$$

Is this vector in the span of the first four vectors? If it is, exhibit a linear combination of the first four vectors which equals this vector, using as few vectors as possible in the linear combination.

Exercise $4.E.59$

Here are some vectors.

$$\begin{bmatrix} 1 \\ 0 \\ -2 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ -2 \end{bmatrix}, \begin{bmatrix} 2 \\ -2 \\ -3 \end{bmatrix}, \begin{bmatrix} -1 \\ 4 \\ 2 \end{bmatrix}$$

Now here is another vector:

$$\begin{bmatrix} -1 \\ -4 \\ 2 \end{bmatrix}$$

Is this vector in the span of the first four vectors? If it is, exhibit a linear combination of the first four vectors which equals this vector, using as few vectors as possible in the linear combination.

Exercise $4.E.60$

Suppose $\{\vec{x}_1, \cdots, \vec{x}_k\}$ is a set of vectors from $\mathbb{R}^n$. Show that $\vec{0}$ is in $span\{\vec{x}_1, \cdots, \vec{x}_k\}$.

Answer available at the end of this section.

Exercise $4.E.61$

Are the following vectors linearly independent? If they are, explain why and if they are not, exhibit one of them as a linear combination of the others. Also give a linearly independent set of vectors which has the same span as the given vectors.

$$\begin{bmatrix} 1 \\ 3 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 10 \\ 2 \\ 1 \end{bmatrix}$$

Exercise $4.E.62$

Are the following vectors linearly independent? If they are, explain why and if they are not, exhibit one of them as a linear combination of the others. Also give a linearly independent set of vectors which has the same span as the given vectors.

$$\begin{bmatrix} -1 \\ -2 \\ 2 \\ 3 \end{bmatrix}, \begin{bmatrix} -3 \\ -4 \\ 3 \\ 3 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 4 \\ 3 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 6 \\ 4 \end{bmatrix}$$

Exercise $4.E.63$

Are the following vectors linearly independent? If they are, explain why and if they are not, exhibit one of them as a linear combination of the others. Also give a linearly independent set of vectors which has the same span as the given vectors.

$$\begin{bmatrix} 1 \\ 5 \\ -2 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 6 \\ -3 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ -4 \\ 1 \\ -1 \end{bmatrix}, \begin{bmatrix} 1 \\ 6 \\ -2 \\ 1 \end{bmatrix}$$

Exercise $4.E.64$

Are the following vectors linearly independent? If they are, explain why and if they are not, exhibit one of them as a linear combination of the others. Also give a linearly independent set of vectors which has the same span as the given vectors.

$$\begin{bmatrix} 1 \\ -1 \\ 3 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 6 \\ 34 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 7 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 8 \\ 1 \end{bmatrix}$$

Exercise $4.E.65$

Are the following vectors linearly independent? If they are, explain why and if they are not, exhibit one of them as a linear combination of the others.

$$\begin{bmatrix} 1 \\ 3 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} -3 \\ -10 \\ 3 \\ -3 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ 0 \\ 1 \end{bmatrix}$$

Exercise 4.E.66

Are the following vectors linearly independent? If they are, explain why and if they are not, exhibit one of them as a linear combination of the others. Also give a linearly independent set of vectors which has the same span as the given vectors.

$$\begin{bmatrix} 1 \\ 3 \\ -3 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ -5 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ -4 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 10 \\ -14 \\ 1 \end{bmatrix}$$

Exercise 4.E.67

Are the following vectors linearly independent? If they are, explain why and if they are not, exhibit one of them as a linear combination of the others. Also give a linearly independent set of vectors which has the same span as the given vectors.

$$\begin{bmatrix} 1 \\ 0 \\ 3 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 8 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 7 \\ 34 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 7 \\ 1 \end{bmatrix}$$

Exercise 4.E.68

Are the following vectors linearly independent? If they are, explain why and if they are not, exhibit one of them as a linear combination of the others. Also give a linearly independent set of vectors which has the same span as the given vectors.

$$\begin{bmatrix} 1 \\ 4 \\ -2 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 5 \\ -3 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 7 \\ -5 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 5 \\ -2 \\ 1 \end{bmatrix}$$

Exercise 4.E.69

Are the following vectors linearly independent? If they are, explain why and if they are not, exhibit one of them as a linear combination of the others.

$$\begin{bmatrix} 1 \\ 2 \\ 2 \\ -4 \end{bmatrix}, \begin{bmatrix} 3 \\ 4 \\ 1 \\ -4 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 0 \\ 4 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ -2 \\ 5 \end{bmatrix}$$

Exercise 4.E.70

Are the following vectors linearly independent? If they are, explain why and if they are not, exhibit one of them as a linear combination of the others. Also give a linearly independent set of vectors which has the same span as the given vectors.

$$\left[\begin{array}{r}2\\3\\1\\-3\end{array}\right],\left[\begin{array}{r}-5\\-6\\0\\3\end{array}\right],\left[\begin{array}{r}-1\\-2\\1\\3\end{array}\right],\left[\begin{array}{r}-1\\-2\\0\\4\end{array}\right]$$

Exercise $4.E.71$

Here are some vectors in $\mathbb{R}^4$.

$$\left[\begin{array}{r}1\\1\\-1\\1\end{array}\right],\left[\begin{array}{r}1\\2\\-1\\1\end{array}\right],\left[\begin{array}{r}1\\-2\\-1\\1\end{array}\right],\left[\begin{array}{r}1\\2\\0\\1\end{array}\right],\left[\begin{array}{r}1\\-1\\-1\\1\end{array}\right]$$

These vectors can't possibly be linearly independent. Tell why. Next obtain a linearly independent subset of these vectors which has the same span as these vectors. In other words, find a basis for the span of these vectors.

Exercise $4.E.72$

Here are some vectors in $\mathbb{R}^4$.

$$\left[\begin{array}{r}1\\2\\-2\\1\end{array}\right],\left[\begin{array}{r}1\\3\\-3\\1\end{array}\right],\left[\begin{array}{r}1\\3\\-2\\1\end{array}\right],\left[\begin{array}{r}4\\3\\-1\\4\end{array}\right],\left[\begin{array}{r}1\\3\\-2\\1\end{array}\right]$$

These vectors can't possibly be linearly independent. Tell why. Next obtain a linearly independent subset of these vectors which has the same span as these vectors. In other words, find a basis for the span of these vectors.

Exercise $4.E.73$

Here are some vectors in $\mathbb{R}^4$.

$$\left[\begin{array}{r}1\\1\\0\\1\end{array}\right],\left[\begin{array}{r}1\\2\\1\\1\end{array}\right],\left[\begin{array}{r}1\\-2\\-3\\1\end{array}\right],\left[\begin{array}{r}2\\-5\\-7\\2\end{array}\right],\left[\begin{array}{r}1\\2\\2\\1\end{array}\right]$$

These vectors can't possibly be linearly independent. Tell why. Next obtain a linearly independent subset of these vectors which has the same span as these vectors. In other words, find a basis for the span of these vectors.

Exercise $4.E.74$

Here are some vectors in $\mathbb{R}^4$.

$$\left[\begin{array}{r}1\\2\\-2\\1\end{array}\right],\left[\begin{array}{r}1\\3\\-3\\1\end{array}\right],\left[\begin{array}{r}1\\-1\\1\\1\end{array}\right],\left[\begin{array}{r}2\\-3\\3\\2\end{array}\right],\left[\begin{array}{r}1\\3\\-2\\1\end{array}\right]$$

These vectors can't possibly be linearly independent. Tell why. Next obtain a linearly independent subset of these vectors which has the same span as these vectors. In other words, find a basis for the span of these vectors.

Exercise $4.E.75$

Here are some vectors in $\mathbb{R}^4$.

$$\begin{bmatrix} 1 \\ 4 \\ -2 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 5 \\ -3 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 5 \\ -2 \\ 1 \end{bmatrix}, \begin{bmatrix} 4 \\ 11 \\ -1 \\ 4 \end{bmatrix}, \begin{bmatrix} 1 \\ 5 \\ -3 \\ 1 \end{bmatrix}$$

These vectors can't possibly be linearly independent. Tell why. Next obtain a linearly independent subset of these vectors which has the same span as these vectors. In other words, find a basis for the span of these vectors.

Exercise $4.E.76$

Here are some vectors in $\mathbb{R}^4$.

$$\begin{bmatrix} 1 \\ 3 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} -\frac{3}{2} \\ -\frac{9}{2} \\ \frac{3}{2} \\ -\frac{3}{2} \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \\ -2 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ 0 \\ 1 \end{bmatrix}$$

These vectors can't possibly be linearly independent. Tell why. Next obtain a linearly independent subset of these vectors which has the same span as these vectors. In other words, find a basis for the span of these vectors.

Exercise $4.E.77$

Here are some vectors in $\mathbb{R}^4$.

$$\begin{bmatrix} 1 \\ 3 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \\ -2 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ 0 \\ 1 \end{bmatrix}$$

These vectors can't possibly be linearly independent. Tell why. Next obtain a linearly independent subset of these vectors which has the same span as these vectors. In other words, find a basis for the span of these vectors

Exercise $4.E.78$

Here are some vectors in $\mathbb{R}^4$.

$$\begin{bmatrix} 1 \\ 4 \\ -2 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 5 \\ -3 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ 3 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 5 \\ -2 \\ 1 \end{bmatrix}$$

These vectors can't possibly be linearly independent. Tell why. Next obtain a linearly independent subset of these vectors which has the same span as these vectors. In other words, find a basis for the span of these vectors.

Exercise $4.E.79$

Here are some vectors in $\mathbb{R}^4$.

$$\left[\begin{array}{r}1\\-1\\3\\1\end{array}\right],\left[\begin{array}{r}1\\0\\7\\1\end{array}\right],\left[\begin{array}{r}1\\0\\8\\1\end{array}\right],\left[\begin{array}{r}4\\-9\\-6\\4\end{array}\right],\left[\begin{array}{r}1\\0\\8\\1\end{array}\right]$$

These vectors can't possibly be linearly independent. Tell why. Next obtain a linearly independent subset of these vectors which has the same span as these vectors. In other words, find a basis for the span of these vectors.

Exercise $4.E.80$

Here are some vectors in $\mathbb{R}^4$.

$$\left[\begin{array}{r}1\\-1\\-1\\1\end{array}\right],\left[\begin{array}{r}-3\\3\\3\\-3\end{array}\right],\left[\begin{array}{r}1\\0\\-1\\1\end{array}\right],\left[\begin{array}{r}2\\-9\\-2\\2\end{array}\right],\left[\begin{array}{r}1\\0\\0\\1\end{array}\right]$$

These vectors can't possibly be linearly independent. Tell why. Next obtain a linearly independent subset of these vectors which has the same span as these vectors. In other words, find a basis for the span of these vectors.

Exercise $4.E.81$

Here are some vectors in $\mathbb{R}^4$.

$$\left[\begin{array}{r}1\\b+1\\a\\1\end{array}\right],\left[\begin{array}{r}3\\3b+3\\3a\\3\end{array}\right],\left[\begin{array}{r}1\\b+2\\2a+1\\1\end{array}\right],\left[\begin{array}{r}2\\2b-5\\-5a-7\\2\end{array}\right],\left[\begin{array}{r}1\\b+2\\2a+2\\1\end{array}\right]$$

These vectors can't possibly be linearly independent. Tell why. Next obtain a linearly independent subset of these vectors which has the same span as these vectors. In other words, find a basis for the span of these vectors.

Exercise $4.E.82$

Let $H = span\left\{\left[\begin{array}{r}2\\1\\1\\1\end{array}\right],\left[\begin{array}{r}-1\\0\\-1\\-1\end{array}\right],\left[\begin{array}{r}5\\2\\3\\3\end{array}\right],\left[\begin{array}{r}-1\\1\\-2\\-2\end{array}\right]\right\}$. Find the dimension of H and determine a basis.

Exercise $4.E.83$

Let H denote $span\left\{\left[\begin{array}{r}0\\1\\1\\-1\end{array}\right],\left[\begin{array}{r}-1\\-1\\-2\\2\end{array}\right],\left[\begin{array}{r}2\\3\\5\\-5\end{array}\right],\left[\begin{array}{r}0\\1\\2\\-2\end{array}\right]\right\}$. Find the dimension of H and determine a basis.

Exercise $4.E.84$

Let H denote $span\left\{\left[\begin{array}{r}-2\\1\\1\\-3\end{array}\right],\left[\begin{array}{r}-9\\4\\3\\-9\end{array}\right],\left[\begin{array}{r}-33\\15\\12\\-36\end{array}\right],\left[\begin{array}{r}-22\\10\\8\\-24\end{array}\right]\right\}$. Find the dimension of H and determine a basis.

Exercise $4.E.85$

Let H denote $span\left\{\begin{bmatrix}-1\\1\\-1\\-2\end{bmatrix},\begin{bmatrix}-4\\3\\-2\\-4\end{bmatrix},\begin{bmatrix}-3\\2\\-1\\-2\end{bmatrix},\begin{bmatrix}-1\\1\\-2\\-4\end{bmatrix},\begin{bmatrix}-7\\5\\-3\\-6\end{bmatrix}\right\}$. Find the dimension of H and determine a basis.

Exercise $4.E.86$

Let H denote $span\left\{\begin{bmatrix}2\\3\\2\\1\end{bmatrix},\begin{bmatrix}8\\15\\6\\3\end{bmatrix},\begin{bmatrix}3\\6\\2\\1\end{bmatrix},\begin{bmatrix}4\\6\\6\\3\end{bmatrix},\begin{bmatrix}8\\15\\6\\3\end{bmatrix}\right\}$. Find the dimension of H and determine a basis.

Exercise $4.E.87$

Let H denote $span\left\{\begin{bmatrix}0\\2\\0\\-1\end{bmatrix},\begin{bmatrix}-1\\6\\0\\-2\end{bmatrix},\begin{bmatrix}-2\\16\\0\\-6\end{bmatrix},\begin{bmatrix}-3\\22\\0\\-8\end{bmatrix}\right\}$. Find the dimension of H and determine a basis.

Exercise $4.E.88$

Let H denote $span\left\{\begin{bmatrix}5\\1\\1\\4\end{bmatrix},\begin{bmatrix}14\\3\\2\\8\end{bmatrix},\begin{bmatrix}38\\8\\6\\24\end{bmatrix},\begin{bmatrix}47\\10\\7\\28\end{bmatrix},\begin{bmatrix}10\\2\\3\\12\end{bmatrix}\right\}$. Find the dimension of H and determine a basis.

Exercise $4.E.89$

Let H denote $span\left\{\begin{bmatrix}6\\1\\1\\5\end{bmatrix},\begin{bmatrix}17\\3\\2\\10\end{bmatrix},\begin{bmatrix}52\\9\\7\\35\end{bmatrix},\begin{bmatrix}18\\3\\4\\20\end{bmatrix}\right\}$. Find the dimension of H and determine a basis.

Exercise $4.E.90$

Let $M=\left\{\vec{u}=\begin{bmatrix}u_1\\u_2\\u_3\\u_4\end{bmatrix}\in\mathbb{R}^4:\sin(u_1)=1\right\}$. Is M a subspace? Explain.

Answer available at the end of this section.

Exercise $4.E.91$

Let $M = \left\{ \vec{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \in \mathbb{R}^4 : ||u_1|| \leq 4 \right\}$. Is M a subspace? Explain.

Answer available at the end of this section.

Exercise $4.E.92$

Let $M = \left\{ \vec{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \in \mathbb{R}^4 : u_1 \geq 0 \text{ for each } i = 1, 2, 3, 4 \right\}$. Is M a subspace? Explain.

Answer available at the end of this section.

Exercise $4.E.93$

Let $\vec{w}$, $\vec{w}_1$ be given vectors in $\mathbb{R}^4$ and define

$$M = \left\{ \vec{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \in \mathbb{R}^4 : \vec{w} \bullet \vec{u} = 0 \text{ and } \vec{w}_1 \bullet \vec{u} = 0 \right\}.$$

Is M a subspace? Explain.

Answer available at the end of this section.

Exercise $4.E.94$

Let $\vec{w} \in \mathbb{R}^4$ and let $M = \left\{ \vec{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \in \mathbb{R}^4 : \vec{w} \bullet \vec{u} = 0 \right\}$. Is M a subspace? Explain.

Answer available at the end of this section.

Exercise $4.E.95$

Let $M = \left\{ \vec{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \in \mathbb{R}^4 : u_3 \geq u_1 \right\}$. Is M a subspace? Explain.

Answer available at the end of this section.

Exercise $4.E.96$

Let $M = \left\{ \vec{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \in \mathbb{R}^4 : u_3 = u_1 = 0 \right\}$. Is M a subspace? Explain.

Answer available at the end of this section.

Exercise $4.E.97$

Consider the set of vectors S given by

$$S = \left\{ \begin{bmatrix} 4u + v - 5w \\ 12u + 6v - 6w \\ 4u + 4v + 4w \end{bmatrix} : u, v, w \in \mathbb{R} \right\}.$$

Is S a subspace of $\mathbb{R}^3$? If so, explain why, give a basis for the subspace and find its dimension.

Exercise $4.E.98$

Consider the set of vectors S given by

$$S = \left\{ \begin{bmatrix} 2u + 6v + 7w \\ -3u - 9v - 12w \\ 2u + 6v + 6w \\ u + 3v + 3w \end{bmatrix} : u, v, w \in \mathbb{R} \right\}.$$

Is S a subspace of $\mathbb{R}^4$? If so, explain why, give a basis for the subspace and find its dimension.

Exercise $4.E.99$

Consider the set of vectors S given by

$$S = \left\{ \begin{bmatrix} 2u + v \\ 6v - 3u + 3w \\ 3v - 6u + 3w \end{bmatrix} : u, v, w \in \mathbb{R} \right\}.$$

Is this set of vectors a subspace of $\mathbb{R}^3$? If so, explain why, give a basis for the subspace and find its dimension.

Exercise $4.E.100$

Consider the vectors of the form

$$\left\{ \begin{bmatrix} 2u + v + 7w \\ u - 2v + w \\ -6v - 6w \end{bmatrix} : u, v, w \in \mathbb{R} \right\}.$$

Is this set of vectors a subspace of $\mathbb{R}^3$? If so, explain why, give a basis for the subspace and find its dimension.

Exercise $4.E.101$

Consider the vectors of the form

$$\left\{ \begin{bmatrix} 3u+v+11w \\ 18u+6v+66w \\ 28u+8v+100w \end{bmatrix} : u,v,w \in \mathbb{R} \right\}.$$

Is this set of vectors a subspace of $\mathbb{R}^3$? If so, explain why, give a basis for the subspace and find its dimension.

Exercise $4.E.102$

Consider the vectors of the form

$$\left\{ \begin{bmatrix} 3u+v \\ 2w-4u \\ 2w-2v-8u \end{bmatrix} : u,v,w \in \mathbb{R} \right\}.$$

Is this set of vectors a subspace of $\mathbb{R}^3$? If so, explain why, give a basis for the subspace and find its dimension.

Exercise $4.E.103$

Consider the set of vectors S given by

$$\left\{ \begin{bmatrix} u+v+w \\ 2u+2v+4w \\ u+v+w \\ 0 \end{bmatrix} : u,v,w \in \mathbb{R} \right\}.$$

Is S is a subspace of $\mathbb{R}^4$? If so, explain why, give a basis for the subspace and find its dimension.

Exercise $4.E.104$

Consider the set of vectors S given by

$$\left\{ \begin{bmatrix} v \\ -3u-3w \\ 8u-4v+4w \end{bmatrix} : u,v,w \in \mathbb{R} \right\}.$$

Is S is a subspace of $\mathbb{R}^4$? If so, explain why, give a basis for the subspace and find its dimension.

Exercise $4.E.105$

If you have 5 vectors in $\mathbb{R}^5$ and the vectors are linearly independent, can it always be concluded they span $\mathbb{R}^5$? Explain.

Answer available at the end of this section.

Exercise $4.E.106$

If you have 6 vectors in $\mathbb{R}^5$, is it possible they are linearly independent? Explain.

Answer available at the end of this section.

Exercise $4.E.107$

Suppose A is an $m \times n$ matrix and $\{\vec{w}_1, \cdots, \vec{w}_k\}$ is a linearly independent set of vectors in $A(\mathbb{R}^n) \subseteq \mathbb{R}^m$. Now suppose $A\vec{z}_i = \vec{w}_i$. Show $\{\vec{z}_1, \cdots, \vec{z}_k\}$ is also independent.

Answer available at the end of this section.

Exercise $4.E.108$

Suppose $V,\ W$ are subspaces of $\mathbb{R}^n$. Let $V \cap W$ be all vectors which are in both V and W. Show that $V \cap W$ is a subspace also.

Answer available at the end of this section.

Exercise $4.E.109$

Suppose V and W both have dimension equal to 7 and they are subspaces of $\mathbb{R}^{10}$. What are the possibilities for the dimension of $V \cap W$? Hint: Remember that a linear independent set can be extended to form a basis.

Exercise $4.E.110$

Suppose V has dimension p and W has dimension q and they are each contained in a subspace, U which has dimension equal to n where $n > \max(p, q)$. What are the possibilities for the dimension of $V \cap W$? Hint: Remember that a linearly independent set can be extended to form a basis.

Answer available at the end of this section.

Exercise $4.E.111$

Suppose A is an $m \times n$ matrix and B is an $n \times p$ matrix. Show that

$$\dim(\ker(AB)) \leq \dim(\ker(A)) + \dim(\ker(B)).$$

Consider the subspace, $B(\mathbb{R}^p) \cap \ker(A)$ and suppose a basis for this subspace is $\{\vec{w}_1, \cdots, \vec{w}_k\}$. Now suppose $\{\vec{u}_1, \cdots, \vec{u}_r\}$ is a basis for $\ker(B)$. Let $\{\vec{z}_1, \cdots, \vec{z}_k\}$ be such that $B\vec{z}_1 = \vec{w}_i$ and argue that

$$\ker(AB) \subseteq span\{\vec{u}_1, \cdots, \vec{u}_r, \vec{z}_1, \cdots, \vec{z}_k\}.$$

Answer available at the end of this section.

Exercise $4.E.112$

Show that if A is an $m \times n$ matrix, then $\ker(A)$ is a subspace of $\mathbb{R}^n$.

Answer available at the end of this section.

Exercise $4.E.113$

Find the rank of the following matrix. Also find a basis for the row and column spaces.

$$\begin{bmatrix} 1 & 3 & 0 & -2 & 0 & 3 \\ 3 & 9 & 1 & -7 & 0 & 8 \\ 1 & 3 & 1 & -3 & 1 & -1 \\ 1 & 3 & -1 & -1 & -2 & 10 \end{bmatrix}$$

Exercise $4.E.114$

Find the rank of the following matrix. Also find a basis for the row and column spaces.

$$\begin{bmatrix} 1 & 3 & 0 & -2 & 7 & 3 \\ 3 & 9 & 1 & -7 & 23 & 8 \\ 1 & 3 & 1 & -3 & 9 & 2 \\ 1 & 3 & -1 & -1 & 5 & 4 \end{bmatrix}$$

Exercise $4.E.115$

Find the rank of the following matrix. Also find a basis for the row and column spaces.

$$\begin{bmatrix} 1 & 0 & 3 & 0 & 7 & 0 \\ 3 & 1 & 10 & 0 & 23 & 0 \\ 1 & 1 & 4 & 1 & 7 & 0 \\ 1 & -1 & 2 & -2 & 9 & 1 \end{bmatrix}$$

Exercise $4.E.116$

Find the rank of the following matrix. Also find a basis for the row and column spaces.

$$\begin{bmatrix} 1 & 0 & 3 \\ 3 & 1 & 10 \\ 1 & 1 & 4 \\ 1 & -1 & 2 \end{bmatrix}$$

Exercise $4.E.117$

Find the rank of the following matrix. Also find a basis for the row and column spaces.

$$\begin{bmatrix} 0 & 0 & -1 & 0 & 1 \\ 1 & 2 & 3 & -2 & -18 \\ 1 & 2 & 2 & -1 & -11 \\ -1 & -2 & -2 & 1 & 11 \end{bmatrix}$$

Exercise $4.E.118$

Find the rank of the following matrix. Also find a basis for the row and column spaces.

$$\begin{bmatrix} 1 & 0 & 3 & 0 \\ 3 & 1 & 10 & 0 \\ -1 & 1 & -2 & 1 \\ 1 & -1 & 2 & -2 \end{bmatrix}$$

Exercise $4.E.119$

Find $\ker(A)$ for the following matrices.

a. $A = \begin{bmatrix} 2 & 3 \\ 4 & 6 \end{bmatrix}$

b. $A = \begin{bmatrix} 1 & 0 & -1 \\ -1 & 1 & 3 \\ 3 & 2 & 1 \end{bmatrix}$

c. $A = \begin{bmatrix} 2 & 4 & 0 \\ 3 & 6 & -2 \\ 1 & 2 & -2 \end{bmatrix}$

d. $A = \begin{bmatrix} 2 & -1 & 3 & 5 \\ 2 & 0 & 1 & 2 \\ 6 & 4 & -5 & -6 \\ 0 & 2 & -4 & -6 \end{bmatrix}$

Answer available at the end of this section.

Exercise $4.E.120$

Determine whether the following set of vectors is orthogonal. If it is orthogonal, determine whether it is also orthonormal.

$$\begin{bmatrix} \frac{1}{6}\sqrt{2}\sqrt{3} \\ \frac{1}{3}\sqrt{2}\sqrt{3} \\ -\frac{1}{6}\sqrt{2}\sqrt{3} \end{bmatrix}, \begin{bmatrix} \frac{1}{2}\sqrt{2} \\ 0 \\ \frac{1}{2}\sqrt{2} \end{bmatrix}, \begin{bmatrix} -\frac{1}{3}\sqrt{3} \\ \frac{1}{3}\sqrt{3} \\ \frac{1}{3}\sqrt{3} \end{bmatrix}$$

If the set of vectors is orthogonal but not orthonormal, give an orthonormal set of vectors which has the same span.

Exercise $4.E.121$

Determine whether the following set of vectors is orthogonal. If it is orthogonal, determine whether it is also orthonormal.

$$\begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix}$$

If the set of vectors is orthogonal but not orthonormal, give an orthonormal set of vectors which has the same span.

Exercise $4.E.122$

Determine whether the following set of vectors is orthogonal. If it is orthogonal, determine whether it is also orthonormal.

$$\begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

If the set of vectors is orthogonal but not orthonormal, give an orthonormal set of vectors which has the same span.

Exercise $4.E.123$

Determine whether the following set of vectors is orthogonal. If it is orthogonal, determine whether it is also orthonormal.

$$\begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$$

If the set of vectors is orthogonal but not orthonormal, give an orthonormal set of vectors which has the same span.

Exercise $4.E.124$

Determine whether the following set of vectors is orthogonal. If it is orthogonal, determine whether it is also orthonormal.

$$\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

If the set of vectors is orthogonal but not orthonormal, give an orthonormal set of vectors which has the same span.

Exercise $4.E.125$

Here are some matrices. Label according to whether they are symmetric, skew symmetric, or orthogonal.

a. $\begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$

b. $\begin{bmatrix} 1 & 2 & -3 \\ 2 & 1 & 4 \\ -3 & 4 & 7 \end{bmatrix}$

c. $\begin{bmatrix} 0 & -2 & -3 \\ 2 & 0 & -4 \\ 3 & 4 & 0 \end{bmatrix}$

Answer available at the end of this section.

Exercise $4.E.126$

For U an orthogonal matrix, explain why $||U\vec{x}|| = ||\vec{x}||$ for any vector $\vec{x}$. Next explain why if U is an $n \times n$ matrix with the property that $||U\vec{x}|| = ||\vec{x}||$ for all vectors, $\vec{x}$, then U must be orthogonal. Thus the orthogonal matrices are exactly those which preserve length.

Answer available at the end of this section.

Exercise $4.E.127$

Suppose U is an orthogonal $n \times n$ matrix. Explain why $rank(U) = n$.

Answer available at the end of this section.

Exercise $4.E.128$

Fill in the missing entries to make the matrix orthogonal.

$$\begin{bmatrix} \frac{-1}{\sqrt{2}} & \frac{-1}{\sqrt{6}} & \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{2}} & - & - \\ - & \frac{\sqrt{6}}{3} & - \end{bmatrix}.$$

Answer available at the end of this section.

Exercise $4.E.129$

Fill in the missing entries to make the matrix orthogonal.

$$\begin{bmatrix} \frac{2}{3} & \frac{\sqrt{2}}{2} & \frac{1}{6}\sqrt{2} \\ \frac{2}{3} & - & - \\ - & 0 & - \end{bmatrix}$$

Answer available at the end of this section.

Exercise $4.E.130$

Fill in the missing entries to make the matrix orthogonal.

$$\begin{bmatrix} \frac{1}{3} & -\frac{2}{\sqrt{5}} & - \\ \frac{2}{3} & 0 & - \\ - & - & \frac{4}{15}\sqrt{5} \end{bmatrix}$$

Answer available at the end of this section.

Exercise $4.E.131$

Find an orthonormal basis for the span of each of the following sets of vectors.

a. $\begin{bmatrix} 3 \\ -4 \\ 0 \end{bmatrix}, \begin{bmatrix} 7 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 7 \\ 1 \end{bmatrix}$

b. $\begin{bmatrix} 3 \\ 0 \\ -4 \end{bmatrix}, \begin{bmatrix} 11 \\ 0 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 7 \end{bmatrix}$

c. $\begin{bmatrix} 3 \\ 0 \\ -4 \end{bmatrix}, \begin{bmatrix} 5 \\ 0 \\ 10 \end{bmatrix}, \begin{bmatrix} -7 \\ 1 \\ 1 \end{bmatrix}$

Answer available at the end of this section.

Exercise $4.E.132$

Using the Gram Schmidt process find an orthonormal basis for the following span:

$$span\left\{\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \\ 3 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}\right\}$$

Answer available at the end of this section.

Exercise $4.E.133$

Using the Gram Schmidt process find an orthonormal basis for the following span:

$$span\left\{\begin{bmatrix}1\\2\\1\\0\end{bmatrix},\begin{bmatrix}2\\-1\\3\\1\end{bmatrix},\begin{bmatrix}1\\0\\0\\1\end{bmatrix}\right\}$$

Answer available at the end of this section.

Exercise 4.E.134

The set $V=\left\{\begin{bmatrix}x\\y\\z\end{bmatrix}:2x+3y-z=0\right\}$ is a subspace of $\mathbb{R}^3$. Find an orthonormal basis for this subspace.

Answer available at the end of this section.

Exercise 4.E.135

Consider the following scalar equation of a plane.

$$2x-3y+z=0$$

Find the orthogonal complement of the vector $\vec{v}=\begin{bmatrix}3\\4\\1\end{bmatrix}$. Also find the point on the plane which is closest to $(3,4,1)$.

Exercise 4.E.136

Consider the following scalar equation of a plane.

$$x+3y+z=0$$

Find the orthogonal complement of the vector $\vec{v}=\begin{bmatrix}1\\2\\1\end{bmatrix}$. Also find the point on the plane which is closest to $(3,4,1)$.

Exercise 4.E.137

Let $\vec{v}$ be a vector and let $\vec{n}$ be a normal vector for a plane through the origin. Find the equation of the line through the point determined by $\vec{v}$ which has direction vector $\vec{n}$. Show that it intersects the plane at the point determined by $\vec{v}-proj_{\vec{n}}\vec{v}$. Hint: The line:$\vec{v}+t\vec{n}$. It is in the plane if $\vec{n}\bullet(\vec{v}+t\vec{n})=0$. Determine t. Then substitute in to the equation of the line.

Exercise 4.E.138

As shown in the above problem, one can find the closest point to~v in a plane through the origin by finding the intersection of the line through $\vec{v}$ having direction vector equal to the normal vector to the plane with the plane. If the plane does not pass through the origin, this will still work to find the point on the plane closest to the point determined by $\vec{v}$. Here is a relation which defines a plane

$$2x+y+z=11$$

and here is a point: $(1,1,2)$. Find the point on the plane which is closest to this point. Then determine the distance from the point to the plane by taking the distance between these two points. Hint: Line: $(x,y,z)=(1,1,2)+t(2,1,1)$. Now require that it intersect the plane.

Exercise $4.E.139$

In general, you have a point (x_0, y_0, z_0) and a scalar equation for a plane $ax + by + cz = d$ where $a^2 + b^2 + c^2 > 0$. Determine a formula for the closest point on the plane to the given point. Then use this point to get a formula for the distance from the given point to the plane. Hint: Find the line perpendicular to the plane which goes through the given point: $(x, y, z) = (x_0, y_0, z_0) + t(a, b, c)$. Now require that this point satisfy the equation for the plane to determine t.

Exercise $4.E.140$

Find the least squares solution to the following system.

$$\begin{aligned} x + 2y &= 1 \\ 2x + 3y &= 2 \\ 3x + 5y &= 4 \end{aligned} \tag{4.E.5}$$

Answer available at the end of this section.

Exercise $4.E.141$

You are doing experiments and have obtained the ordered pairs,

$$(0, 1), (1, 2), (2, 3.5), (3, 4)$$

Find m and b such that $\vec{y} = m\vec{x} + b$ approximates these four points as well as possible.

Exercise $4.E.142$

Suppose you have several ordered triples, (x_i, y_i, z_i). Describe how to find a polynomial such as

$$z = a + bx + cy + dxy + ex^2 + fy^2$$

giving the best fit to the given ordered triples.

Exercise $4.E.143$

The wind blows from the South at 20 kilometers per hour and an airplane which flies at 600 kilometers per hour in still air is heading East. Find the velocity of the airplane and its location after two hours.

Exercise $4.E.144$

The wind blows from the West at 30 kilometers per hour and an airplane which flies at 400 kilometers per hour in still air is heading North East. Find the velocity of the airplane and its position after two hours.

Exercise $4.E.145$

The wind blows from the North at 10 kilometers per hour. An airplane which flies at 300 kilometers per hour in still air is supposed to go to the point whose coordinates are at $(100, 100)$. In what direction should the airplane fly?

Exercise $4.E.146$

Three forces act on an object. Two are $\begin{bmatrix} 3 \\ -1 \\ -1 \end{bmatrix}$ and $\begin{bmatrix} 1 \\ -3 \\ 4 \end{bmatrix}$ Newtons. Find the third force if the object is not to move.

Exercise $4.E.147$

Three forces act on an object. Two are $\begin{bmatrix} 6 \\ -3 \\ 3 \end{bmatrix}$ and $\begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix}$ Newtons. Find the third force if the total force on the object is to be $\begin{bmatrix} 7 \\ 1 \\ 3 \end{bmatrix}$.

Exercise $4.E.148$

A river flows West at the rate of b miles per hour. A boat can move at the rate of 8 miles per hour. Find the smallest value of b such that it is not possible for the boat to proceed directly across the river.

Exercise $4.E.149$

The wind blows from West to East at a speed of 50 miles per hour and an airplane which travels at 400 miles per hour in still air is heading North West. What is the velocity of the airplane relative to the ground? What is the component of this velocity in the direction North?

Answer available at the end of this section.

Exercise $4.E.150$

The wind blows from West to East at a speed of 60 miles per hour and an airplane can travel travels at 100 miles per hour in still air. How many degrees West of North should the airplane head in order to travel exactly North?

Exercise $4.E.151$

The wind blows from West to East at a speed of 50 miles per hour and an airplane which travels at 400 miles per hour in still air heading somewhat West of North so that, with the wind, it is flying due North. It uses 30.0 gallons of gas every hour. If it has to travel 600.0 miles due North, how much gas will it use in flying to its destination?

Exercise $4.E.152$

An airplane is flying due north at 150.0 miles per hour but it is not actually going due North because there is a wind which is pushing the airplane due east at 40.0 miles per hour. After one hour, the plane starts flying 30° East of North. Assuming the plane starts at $(0,0)$, where is it after 2 hours? Let North be the direction of the positive y axis and let East be the direction of the positive x axis.

Answer available at the end of this section.

Exercise $4.E.153$

City A is located at the origin $(0,0)$ while city B is located at $(300,500)$ where distances are in miles. An airplane flies at 250 miles per hour in still air. This airplane wants to fly from city A to city B but the wind is blowing in the direction of the positive y axis at a speed of 50 miles per hour. Find a unit vector such that if the plane heads in this direction, it will end up at city B having flown the shortest possible distance. How long will it take to get there?

Answer available at the end of this section.

Exercise $4.E.154$

A certain river is one half mile wide with a current flowing at 2 miles per hour from East to West. A man swims directly toward the opposite shore from the South bank of the river at a speed of 3 miles per hour. How far down the river does he find himself when he has swam across? How far does he end up traveling?

Answer available at the end of this section.

Exercise $4.E.155$

A certain river is one half mile wide with a current flowing at 2 miles per hour from East to West. A man can swim at 3 miles per hour in still water. In what direction should he swim in order to travel directly across the river? What would the answer to this problem be if the river flowed at 3 miles per hour and the man could swim only at the rate of 2 miles per hour?

Answer available at the end of this section.

Exercise $4.E.156$

Three forces are applied to a point which does not move. Two of the forces are $2\vec{i}+2\vec{j}-6\vec{k}$ Newtons and $8\vec{i}+8\vec{j}+3\vec{k}$ Newtons. Find the third force.

Exercise $4.E.157$

The total force acting on an object is to be $4\vec{i}+2\vec{j}-3\vec{k}$ Newtons. A force of $-3\vec{i}-1\vec{j}+8\vec{k}$ Newtons is being applied. What other force should be applied to achieve the desired total force?

Exercise $4.E.158$

A bird flies from its nest 8 km in the direction $\frac{5}{6}\pi$ north of east where it stops to rest on a tree. It then flies 1 km in the direction due southeast and lands atop a telephone pole. Place an xy coordinate system so that the origin is the bird's nest, and the positive x axis points east and the positive y axis points north. Find the displacement vector from the nest to the telephone pole.

Exercise $4.E.159$

If $\vec{F}$ is a force and $\vec{D}$ is a vector, show $\text{proj}_{\vec{D}}\left(\vec{F}\right)=\left(\|\vec{F}\|\cos\theta\right)\vec{u}$ where $\vec{u}$ is the unit vector in the direction of $\vec{D}$, where $\vec{u}=\vec{D}/\|\vec{D}\|$ and θ is the included angle between the two vectors, $\vec{F}$ and $\vec{D}$. $\|\vec{F}\|\cos\theta$ is sometimes called the component of the force, $\vec{F}$ in the direction, $\vec{D}$.

Answer available at the end of this section.

Exercise $4.E.160$

A boy drags a sled for 100 feet along the ground by pulling on a rope which is 20 degrees from the horizontal with a force of 40 pounds. How much work does this force do?

Answer available at the end of this section.

Exercise $4.E.161$

A girl drags a sled for 200 feet along the ground by pulling on a rope which is 30 degrees from the horizontal with a force of 20 pounds. How much work does this force do?

Answer available at the end of this section.

Exercise $4.E.162$

A large dog drags a sled for 300 feet along the ground by pulling on a rope which is 45 degrees from the horizontal with a force of 20 pounds. How much work does this force do?

Answer available at the end of this section.

Exercise $4.E.163$

How much work does it take to slide a crate 20 meters along a loading dock by pulling on it with a 200 Newton force at an angle of 30° from the horizontal? Express your answer in Newton meters.

Answer available at the end of this section.

Exercise $4.E.164$

An object moves 10 meters in the direction of $\vec{j}$. There are two forces acting on this object, $\vec{F}_1 = \vec{i} + \vec{j} + 2\vec{k}$, and $\vec{F}_2 = -5\vec{i} + 2\vec{j} - 6\vec{k}$. Find the total work done on the object by the two forces. **Hint:** You can take the work done by the resultant of the two forces or you can add the work done by each force. Why?

Answer available at the end of this section.

Exercise $4.E.165$

An object moves 10 meters in the direction of $\vec{j} + \vec{i}$. There are two forces acting on this object, $\vec{F}_1 = \vec{i} + 2\vec{j} + 2\vec{k}$, and $\vec{F}_2 = 5\vec{i} + 2\vec{j} - 6\vec{k}$. Find the total work done on the object by the two forces. **Hint:** You can take the work done by the resultant of the two forces or you can add the work done by each force. Why?

Answer available at the end of this section.

Exercise $4.E.166$

An object moves 20 meters in the direction of $\vec{k}+\vec{j}$. There are two forces acting on this object, $\vec{F}_1=\vec{i}+\vec{j}+2\vec{k}$, and $\vec{F}_2=\vec{i}+2\vec{j}-6\vec{k}$. Find the total work done on the object by the two forces. **Hint:** You can take the work done by the resultant of the two forces or you can add the work done by each force.

Answer available at the end of this section.

Answers

Exercise $4.E.1$

$$\begin{bmatrix} -55 \\ 13 \\ -21 \\ 39 \end{bmatrix}$$

Exercise $4.E.3$

$$\begin{bmatrix} 4 \\ 4 \\ -3 \end{bmatrix} = 2\begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix} - \begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix}$$

Exercise $4.E.4$

The system

$$\begin{bmatrix} 4 \\ 4 \\ 4 \end{bmatrix} = a_1\begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix} + a_2\begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix}$$

has no solution.

Exercise $4.E.16$

$$\begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix} \bullet \begin{bmatrix} 2 \\ 0 \\ 1 \\ 3 \end{bmatrix} = 17$$

Exercise $4.E.17$

This formula says that $\vec{u}\bullet\vec{v} = ||\vec{u}||\ ||\vec{v}||\cos\theta$ where θ is the included angle between the two vectors. Thus

$$||\vec{u}\bullet\vec{v}|| = ||\vec{u}||\,||\vec{v}||\,|\cos\theta| \leq ||\vec{u}||\,||\vec{v}||$$

and equality holds if and only if $\theta = 0$ or π. This means that the two vectors either point in the same direction or opposite directions. Hence one is a multiple of the other.

Exercise $4.E.18$

This follows from the Cauchy Schwarz inequality and the proof of Theorem 4.7.1 which only used the properties of the dot product. Since this new product has the same properties the Cauchy Schwarz inequality holds for it as well.

Exercise $4.E.21$

$A\vec{x}\bullet\vec{y} = \sum_k (A\vec{x})_k y_k = \sum_k \sum_i A_{ki}x_i y_k = \sum_i \sum_k A^T_{ik}x_i y_k = \vec{x}\bullet A^T\vec{y}$

Exercise $4.E.22$

$$\begin{aligned} AB\vec{x}\bullet\vec{y} &= B\vec{x}\bullet A^T\vec{y} \\ &= \vec{x}\bullet B^TA^T\vec{y} \\ &= \vec{x}\bullet (AB)^T\vec{y} \end{aligned} \tag{4.E.6}$$

Since this is true for all $\vec{x}$, it follows that, in particular, it holds for

$$\vec{x} = B^TA^T\vec{y} - (AB)^T\vec{y}$$

and so from the axioms of the dot product,

$$\left(B^TA^T\vec{y} - (AB)^T\vec{y}\right)\bullet\left(B^TA^T\vec{y} - (AB)^T\vec{y}\right) = 0$$

and so $B^TA^T\vec{y} - (AB)^T\vec{y} = \vec{0}$. However, this is true for all $\vec{y}$ and so $B^TA^T - (AB)^T = 0$.

Exercise $4.E.23$

$\frac{\begin{bmatrix} 3 & -1 & -1 \end{bmatrix}^T \bullet \begin{bmatrix} 1 & 4 & 2 \end{bmatrix}^T}{\sqrt{9+1+1}\sqrt{1+16+4}} = \frac{-3}{\sqrt{11}\sqrt{21}} = -0.19739 = \cos\theta$ Therefore we need to solve

$$-0.19739 = \cos\theta$$

Thus $\theta = 1.7695$ radians.

Exercise $4.E.24$

$\frac{-10}{\sqrt{1+4+1}\sqrt{1+4+49}} = -0.55555 = \cos\theta$ Therefore we need to solve $-0.55555 = \cos\theta$, which gives $\theta = 2.0313$ radians.

Exercise $4.E.25$

$\frac{\vec{u}\bullet\vec{v}}{\vec{u}\bullet\vec{u}}\vec{u} = \frac{-5}{14}\begin{bmatrix}1\\2\\3\end{bmatrix} = \begin{bmatrix}-\frac{5}{14}\\-\frac{5}{7}\\-\frac{15}{14}\end{bmatrix}$

Exercise $4.E.26$

$\frac{\vec{u}\bullet\vec{v}}{\vec{u}\bullet\vec{u}}\vec{u} = \frac{-5}{10}\begin{bmatrix}1\\0\\3\end{bmatrix} = \begin{bmatrix}-\frac{1}{2}\\0\\-\frac{3}{2}\end{bmatrix}$

Exercise $4.E.27$

$\frac{\vec{u}\bullet\vec{v}}{\vec{u}\bullet\vec{u}}\vec{u} = \frac{\begin{bmatrix}1&2&-2&1\end{bmatrix}^T\bullet\begin{bmatrix}1&2&3&0\end{bmatrix}^T}{1+4+9}\begin{bmatrix}1\\2\\3\\0\end{bmatrix} = \begin{bmatrix}-\frac{1}{14}\\-\frac{1}{7}\\-\frac{3}{14}\\0\end{bmatrix}$

Exercise $4.E.30$

No, it does not. The 0 vector has no direction. The formula for $\text{proj}_{\vec{0}}(\vec{w})$ doesn't make sense either.

Exercise $4.E.31$

$$\left(\vec{u} - \frac{\vec{u}\bullet\vec{v}}{||\vec{v}||^2}\vec{v}\right)\bullet\left(\vec{u} - \frac{\vec{u}\bullet\vec{v}}{||\vec{v}||^2}\vec{v}\right) = ||\vec{u}||^2 - 2(\vec{u}\bullet\vec{v})^2\frac{1}{||\vec{v}||^2} + (\vec{u}\bullet\vec{v})^2\frac{1}{||\vec{v}||^2} \geq 0$$

And so

$$||\vec{u}||^2||\vec{v}||^2 \geq (\vec{u}\bullet\vec{v})^2$$

You get equality exactly when $\vec{u} = \text{proj}_{\vec{v}}\vec{u} = \frac{\vec{u}\bullet\vec{v}}{||\vec{v}||^2}\vec{v}$ in other words, when $\vec{u}$ is a multiple of $\vec{v}$.

Exercise $4.E.32$

$$\begin{aligned}\vec{w} - \text{proj}_{\vec{v}}(\vec{w}) + \vec{u} - \text{proj}_{\vec{v}}(\vec{u}) &= \vec{w} + \vec{u} - (\text{proj}_{\vec{v}}(\vec{w}) + \text{proj}_{\vec{v}}(\vec{u}))\\ &= \vec{w} + \vec{u} - \text{proj}_{\vec{v}}(\vec{w}+\vec{u})\end{aligned} \tag{4.E.7}$$

This follows because

$$\begin{aligned}\text{proj}_{\vec{v}}(\vec{w}) + \text{proj}_{\vec{v}}(\vec{u}) &= \frac{\vec{u}\bullet\vec{v}}{||\vec{v}||^2}\vec{v} + \frac{\vec{w}\bullet\vec{v}}{||\vec{v}||^2}\vec{v}\\ &= \frac{(\vec{u}+\vec{w})\bullet\vec{v}}{||\vec{v}||^2}\vec{v}\\ &= \text{proj}_{\vec{v}}(\vec{w}+\vec{u})\end{aligned} \tag{4.E.8}$$

Exercise $4.E.33$

$(\vec{v} - \text{proj}_{\vec{u}}(\vec{v}))\bullet\vec{u} = \vec{v}\bullet\vec{u} - \left(\frac{(\vec{v}\cdot\vec{u}}{||\vec{u}||^2}\vec{u}\right)\bullet\vec{u} = \vec{v}\bullet\vec{u} - \vec{v}\bullet\vec{u} = 0$. Therefore, $\vec{v} = \vec{v} - \text{proj}_{\vec{u}}(\vec{v}) + \text{proj}_{\vec{u}}(\vec{v})$. The first is perpendicular to $\vec{u}$ and the second is a multiple of $\vec{u}$ so it is parallel to $\vec{u}$.

Exercise $4.E.34$

If $\vec{a} \neq \vec{0}$, then the condition says that $||\vec{a}\times\vec{u}|| = ||\vec{a}||\sin\theta = 0$ for all angles θ. Hence $\vec{a} = \vec{0}$ after all.

Exercise $4.E.35$

$\begin{bmatrix}3\\0\\-3\end{bmatrix}\times\begin{bmatrix}-4\\0\\-2\end{bmatrix} = \begin{bmatrix}0\\18\\0\end{bmatrix}$. So the area is 9.

Exercise $4.E.36$

$\begin{bmatrix}3\\1\\-3\end{bmatrix}\times\begin{bmatrix}-4\\1\\-2\end{bmatrix} = \begin{bmatrix}1\\18\\7\end{bmatrix}$. The area is given by

$$\frac{1}{2}\sqrt{1+(18)^2+49} = \frac{1}{2}\sqrt{374}$$

Exercise $4.E.37$

$\begin{bmatrix}1&1&1\end{bmatrix}\times\begin{bmatrix}2&2&2\end{bmatrix} = \begin{bmatrix}0&0&0\end{bmatrix}$. The area is 0. It means the three points are on the same line.

Exercise $4.E.38$

$\begin{bmatrix}1\\2\\3\end{bmatrix}\times\begin{bmatrix}3\\-2\\1\end{bmatrix} = \begin{bmatrix}8\\8\\-8\end{bmatrix}$. The area is $8\sqrt{3}$.

Exercise $4.E.39$

$\begin{bmatrix}1\\0\\3\end{bmatrix}\times\begin{bmatrix}4\\-2\\1\end{bmatrix} = \begin{bmatrix}6\\11\\-2\end{bmatrix}$. The area is $\sqrt{36+121+4} = \sqrt{161}$.

Exercise $4.E.40$

$\left(\vec{i}\times\vec{j}\right)\times\vec{j} = \vec{k}\times\vec{j} = i\vec{i}$. However, $\vec{i}\times\left(\vec{j}\times\vec{j}\right) = \vec{0}$ and so the cross product is not associative.

Exercise $4.E.41$

Verify directly from the coordinate description of the cross product that the right hand rule applies to the vectors $\vec{i},\vec{j},\vec{k}$. Next verify that the distributive law holds

for the coordinate description of the cross product. This gives another way to approach the cross product. First define it in terms of coordinates and then get the geometric properties from this. However, this approach does not yield the right hand rule property very easily. From the coordinate description,

$$\vec{a}\times\vec{b}\cdot\vec{a}=\epsilon_{ijk}a_jb_ka_i=-\epsilon_{jik}a_kb_ka_i=-\epsilon_{jik}b_ka_ia_j=-\vec{a}\times\vec{b}\cdot\vec{a}$$

and so $\vec{a}\times\vec{b}$ is perpendicular to $\vec{a}$. Similarly, $\vec{a}\times\vec{b}$ is perpendicular to $\vec{b}$. Now we need that

$$||\vec{a}\times\vec{b}||^2=||\vec{a}||^2||\vec{b}||^2(1-\cos^2\theta)=||\vec{a}||^2||\vec{b}||^2\sin^2\theta$$

and so $||\vec{a}\times\vec{b}||=||\vec{a}||\ \ ||\vec{b}||\sin\theta$, the area of the parallelogram determined by $\vec{a}$, $\vec{b}$. Only the right hand rule is a little problematic. However, you can see right away from the component definition that the right hand rule holds for each of the standard unit vectors. Thus $\vec{i}\times\vec{j}=\vec{k}$ etc.

$$\begin{vmatrix}\vec{i}&\vec{j}&\vec{k}\\1&0&0\\0&1&0\end{vmatrix}=\vec{k}$$

Exercise $4.E.43$

$$\begin{vmatrix}1&-7&-5\\1&-2&-6\\3&2&3\end{vmatrix}=113$$

Exercise $4.E.44$

Yes. It will involve the sum of product of integers and so it will be an integer.

Exercise $4.E.45$

It means that if you place them so that they all have their tails at the same point, the three will lie in the same plane.

Exercise $4.E.46$

$\vec{x}\bullet\left(\vec{a}\times\vec{b}\right)=0$

Exercise $4.E.48$

Here $[\vec{v},\vec{w},\vec{z}]$ denotes the box product. Consider the cross product term. From the above,

$$\begin{aligned}(\vec{v}\times\vec{w})\times(\vec{w}\times\vec{z})&=[\vec{v},\vec{w},\vec{z}]\vec{w}-[\vec{w},\vec{w},\vec{z}]\vec{v}\\&=[\vec{v},\vec{w},\vec{z}]\vec{w}\end{aligned}\tag{4.E.9}$$

Thus it reduces to

$$(\vec{u}\times\vec{v})\bullet[\vec{v},\vec{w},\vec{z}]\vec{w}=[\vec{v},\vec{w},\vec{z}][\vec{u},\vec{v},\vec{w}]$$

Exercise $4.E.49$

$$\begin{aligned}||\vec{u}\times\vec{v}||^2&=\epsilon_{ijk}u_jv_k\epsilon_{irs}u_rv_s=(\delta_{jr}\delta_{ks}-\delta_{kr}\delta_{js})u_rv_su_jv_k\\&=u_jv_ku_jv_k-u_kv_ju_jv_k=||\vec{u}||^2||\vec{v}||^2-(\vec{u}\bullet\vec{v})^2\end{aligned}\tag{4.E.10}$$

It follows that the expression reduces to 0. You can also do the following.

$$\begin{aligned}||\vec{u}\times\vec{v}||^2&=||\vec{u}||^2||\vec{v}||^2\sin^2\theta\\&=||\vec{u}||^2||\vec{v}||^2(1-\cos^2\theta)\\&=||\vec{u}||^2||\vec{v}||^2-||\vec{u}||^2||\vec{v}||^2\cos^2\theta\\&=||\vec{u}||^2||\vec{v}||^2-(\vec{u}\bullet\vec{v})^2\end{aligned}\tag{4.E.11}$$

which implies the expression equals 0.

Exercise $4.E.50$

We will show it using the summation convention and permutation symbol

$$\begin{aligned}((\vec{u}\times\vec{v})')_i&=((\vec{u}\times\vec{v})_i)'=(\epsilon_{ijk}u_jv_k)'\\&=\epsilon_{ijk}u_j'v_k+\epsilon_{ijk}u_kv_k'=(\vec{u}'\times\vec{v}+\vec{u}\times\vec{v}')_i\end{aligned}\tag{4.E.12}$$

and so $(\vec{u}\times\vec{v})'=\vec{u}'\times\vec{v}+\vec{u}\times\vec{v}'$.

Exercise $4.E.60$

$\sum_{i=1}^{k}0\vec{x}_k=\vec{0}$

Exercise $4.E.90$

No. Let $\vec{u}=\begin{bmatrix}\frac{\pi}{2}\\0\\0\\0\end{bmatrix}$. Then $2\vec{u}\notin M$ although $\vec{u}\in M$.

Exercise $4.E.91$

No. $\begin{bmatrix}1\\0\\0\\0\end{bmatrix}\in M$ but $10\begin{bmatrix}1\\0\\0\\0\end{bmatrix}\notin M$.

Exercise $4.E.92$

This is not a subspace. $\begin{bmatrix}1\\1\\1\\1\end{bmatrix}$ is in it. However, $(-1)\begin{bmatrix}1\\1\\1\\1\end{bmatrix}$ is not.

Exercise $4.E.93$

This is a subspace because it is closed with respect to vector addition and scalar multiplication.

Exercise $4.E.94$

Yes, this is a subspace because it is closed with respect to vector addition and scalar multiplication.

Exercise $4.E.95$

This is not a subspace. $\begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$ is in it. However $(-1)\begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ -1 \\ 0 \end{bmatrix}$ is not.

Exercise $4.E.96$

This is a subspace. It is closed with respect to vector addition and scalar multiplication.

Exercise $4.E.105$

Yes. If not, there would exist a vector not in the span. But then you could add in this vector and obtain a linearly independent set of vectors with more vectors than a basis.

Exercise $4.E.106$

They can't be.

Exercise $4.E.107$

Say $\sum_{i=1}^{k} c_i \vec{z}_i = \vec{0}$. Then apply A to it as follows.

$$\sum_{i=1}^{k} c_a A\vec{z}_i = \sum_{i=1}^{k} c_i \vec{w}_i = \vec{0}$$

and so, by linear independence of the $\vec{w}_i$, it follows that each $c_i = 0$.

Exercise $4.E.108$

If $\vec{x}, \vec{y} \in V \cap W$, then for scalars α, β, the linear combination $\alpha\vec{x} + \beta\vec{y}$ must be in both V and W since they are both subspaces.

Exercise $4.E.110$

Let $\{x_1, \cdots, x_k\}$ be a basis for $V \cap W$. Then there is a basis for V and W which are respectively

$$\{x_1, \cdots, x_k, y_{k+1}, \cdots, y_p\},\ \{x_1, \cdots, x_k, z_{k+1}, \cdots z_q\}$$

It follows that you must have $k + p - k + q - k \leq n$ and so you must have

$$p + q - n \leq k$$

Exercise $4.E.111$

Here is how you do this. Suppose $AB\vec{x} = \vec{0}$. Then $B\vec{x} \in \ker(A) \cap B(\mathbb{R}^p)$ and so $B\vec{x} = \sum_{i=1}^{k} B\vec{z}_i$ showing that

$$\vec{x} - \sum_{i=1}^{k} \vec{z}_i \in \ker(B)$$

Consider $B(\mathbb{R}^p) \cap \ker(A)$ and let a basis be $\{\vec{w}_1, \cdots, \vec{w}_k\}$. Then each $\vec{w}_i$ is of the form $B\vec{z}_i = \vec{w}_i$. Therefore, $\{\vec{z}_1, \cdots, \vec{z}_k\}$ is linearly independent and $AB\vec{z}_i = 0$. Now let $\{\vec{u}_1, \cdots, \vec{u}_r\}$ be a basis for $\ker(B)$. If $AB\vec{x} = \vec{0}$, then $B\vec{x} \in \ker(A) \cap B(\mathbb{R}^p)$ and so $B\vec{x} = \sum_{i=1}^{k} c_i B\vec{z}_1$ which implies

$$\vec{x} - \sum_{i=1}^{k} c_i \vec{z}_i \in \ker(B)$$

and so it is of the form

$$\vec{x} - \sum_{i=1}^{k} c_i \vec{z}_i = \sum_{j=1}^{r} d_j \vec{u}_j$$

It follows that if $AB\vec{x} = \vec{0}$ so that $\vec{x} \in \ker(AB)$, then

$$\vec{x} \in span(\vec{z}_1, \cdots, \vec{z}_k, \vec{u}_1, \cdots, \vec{u}_r).$$

Therefore,

$$\begin{aligned} \dim(\ker(AB)) &\leq k + r = \dim(B(\mathbb{R}^p) \cap \ker(A)) + \dim(\ker(B)) \\ &\leq \dim(\ker(A)) + \dim(\ker(B)) \end{aligned} \tag{4.E.13}$$

Exercise $4.E.112$

If $\vec{x}$, $\vec{y} \in \ker(A)$ then

$$A(a\vec{x} + b\vec{y}) = aA\vec{x} + bA\vec{y} = a\vec{0} + b\vec{0} = \vec{0}$$

and so $\ker(A)$ is closed under linear combinations. Hence it is a subspace.

Exercise $4.E.119$

Exercise $4.E.125$

a. Orthogonal
b. Symmetric
c. Skew Symmetric

Exercise $4.E.126$

$||U\vec{x}||^2 = U\vec{x} \bullet U\vec{x} = U^T U\vec{x} \bullet \vec{x} = I\vec{x} \bullet \vec{x} = ||\vec{x}||^2$. Next suppose distance is preserved by U. Then

$$\begin{aligned}(U(\vec{x}+\vec{y}))\bullet(U(\vec{x}+\vec{y})) &= ||Ux||^2+||Uy||^2+2(Ux\bullet Uy)\\ &= ||\vec{x}||^2+||\vec{y}||^2+2(U^TU\vec{x}\bullet\vec{y})\end{aligned} \tag{4.E.14}$$

But since U preserves distances, it is also the case that

$$(U(\vec{x}+\vec{y})\bullet U(\vec{x}+\vec{y})) = ||\vec{x}||^2+||\vec{y}||^2+2(\vec{x}\bullet\vec{y})$$

Hence

$$\vec{x}\bullet\vec{y} = U^TU\vec{x}\bullet\vec{y}$$

and so

$$((U^TU-I)\vec{x})\bullet\vec{y}=0$$

Since y is arbitrary, it follows that $U^TU-I=0$. Thus U is orthogonal.

Exercise $4.E.127$

You could observe that $\det(UU^T)=(\det(U))^2-1$ so $\det(U)\neq 0$.

Exercise $4.E.128$

$$\begin{aligned}&\begin{bmatrix}\frac{-1}{\sqrt{2}} & \frac{-1}{\sqrt{6}} & \frac{1}{\sqrt{3}}\\ \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{6}} & a\\ 0 & \frac{\sqrt{6}}{3} & b\end{bmatrix}\begin{bmatrix}\frac{-1}{\sqrt{2}} & \frac{-1}{\sqrt{6}} & \frac{1}{\sqrt{3}}\\ \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{6}} & a\\ 0 & \frac{\sqrt{6}}{3} & b\end{bmatrix}^T\\ &=\begin{bmatrix}1 & \frac{1}{3}\sqrt{3}a-\frac{1}{3} & \frac{1}{3}\sqrt{3}b-\frac{1}{3}\\ \frac{1}{3}\sqrt{3}a-\frac{1}{3} & a^2+\frac{2}{3} & ab-\frac{1}{3}\\ \frac{1}{3}\sqrt{3}b-\frac{1}{3} & ab-\frac{1}{3} & b^2+\frac{2}{3}\end{bmatrix}\end{aligned} \tag{4.E.15}$$

This requires, $a=1/\sqrt{3}, b=1/\sqrt{3}$.

$$\begin{bmatrix}\frac{-1}{\sqrt{2}} & \frac{-1}{\sqrt{6}} & \frac{1}{\sqrt{3}}\\ \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{6}} & 1/\sqrt{3}\\ 0 & \frac{\sqrt{6}}{3} & 1/\sqrt{3}\end{bmatrix}\begin{bmatrix}\frac{-1}{\sqrt{2}} & \frac{-1}{\sqrt{6}} & \frac{1}{\sqrt{3}}\\ \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{6}} & 1/\sqrt{3}\\ 0 & \frac{\sqrt{6}}{3} & 1/\sqrt{3}\end{bmatrix}^T=\begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix}$$

Exercise $4.E.129$

$$\begin{bmatrix}\frac{2}{3} & \frac{\sqrt{2}}{2} & \frac{1}{6}\sqrt{2}\\ \frac{2}{3} & \frac{-\sqrt{2}}{2} & a\\ -\frac{1}{3} & 0 & b\end{bmatrix}\begin{bmatrix}\frac{2}{3} & \frac{\sqrt{2}}{2} & \frac{1}{6}\sqrt{2}\\ \frac{2}{3} & \frac{-\sqrt{2}}{2} & a\\ -\frac{1}{3} & 0 & b\end{bmatrix}^T=\begin{bmatrix}1 & \frac{1}{6}\sqrt{2}a-\frac{1}{18} & \frac{1}{6}\sqrt{2}b-\frac{2}{9}\\ \frac{1}{6}\sqrt{2}a-\frac{1}{18} & a^2+\frac{17}{18} & ab-\frac{2}{9}\\ \frac{1}{6}\sqrt{2}b-\frac{2}{9} & ab-\frac{2}{9} & b^2+\frac{1}{9}\end{bmatrix}$$

This requires $a=\frac{1}{3\sqrt{2}},\ b=\frac{4}{3\sqrt{2}}$.

$$\begin{bmatrix}\frac{2}{3} & \frac{\sqrt{2}}{2} & \frac{1}{6}\sqrt{2}\\ \frac{2}{3} & \frac{-\sqrt{2}}{2} & \frac{1}{3\sqrt{2}}\\ -\frac{1}{3} & 0 & \frac{4}{3\sqrt{2}}\end{bmatrix}\begin{bmatrix}\frac{2}{3} & \frac{\sqrt{2}}{2} & \frac{1}{6}\sqrt{2}\\ \frac{2}{3} & \frac{-\sqrt{2}}{2} & \frac{1}{3\sqrt{2}}\\ -\frac{1}{3} & 0 & \frac{4}{3\sqrt{2}}\end{bmatrix}^T=\begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix}$$

Exercise $4.E.130$

Try

$$\begin{aligned}&\begin{bmatrix}\frac{1}{3} & -\frac{2}{\sqrt{5}} & c\\ \frac{2}{3} & 0 & d\\ \frac{2}{3} & \frac{1}{\sqrt{5}} & \frac{4}{15}\sqrt{5}\end{bmatrix}\begin{bmatrix}\frac{1}{3} & -\frac{2}{\sqrt{5}} & c\\ \frac{2}{3} & 0 & d\\ \frac{2}{3} & \frac{1}{\sqrt{5}} & \frac{4}{15}\sqrt{5}\end{bmatrix}^T\\ &=\begin{bmatrix}c^2+\frac{41}{45} & cd+\frac{2}{9} & \frac{4}{15}\sqrt{5}c-\frac{8}{45}\\ cd+\frac{2}{9} & d^2+\frac{4}{9} & \frac{4}{15}\sqrt{5}d+\frac{4}{9}\\ \frac{4}{15}\sqrt{5}c-\frac{8}{45} & \frac{4}{15}\sqrt{5}d+\frac{4}{9} & 1\end{bmatrix}\end{aligned} \tag{4.E.16}$$

This requires that $c=\frac{2}{3\sqrt{5}}, d=\frac{-5}{3\sqrt{5}}$.

$$\begin{bmatrix}\frac{1}{3} & -\frac{2}{\sqrt{5}} & \frac{2}{3\sqrt{5}}\\ \frac{2}{3} & 0 & \frac{-5}{3\sqrt{5}}\\ \frac{2}{3} & \frac{1}{\sqrt{5}} & \frac{4}{15}\sqrt{5}\end{bmatrix}\begin{bmatrix}\frac{1}{3} & -\frac{2}{\sqrt{5}} & \frac{2}{3\sqrt{5}}\\ \frac{2}{3} & 0 & \frac{-5}{3\sqrt{5}}\\ \frac{2}{3} & \frac{1}{\sqrt{5}} & \frac{4}{15}\sqrt{5}\end{bmatrix}^T=\begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix}$$

Exercise $4.E.131$

a. $\begin{bmatrix}\frac{3}{5}\\-\frac{4}{5}\\0\end{bmatrix}, \begin{bmatrix}\frac{4}{5}\\\frac{3}{5}\\0\end{bmatrix}, \begin{bmatrix}0\\0\\1\end{bmatrix}$

b. $\begin{bmatrix}\frac{3}{5}\\0\\-\frac{4}{5}\end{bmatrix}, \begin{bmatrix}\frac{4}{5}\\0\\\frac{3}{5}\end{bmatrix}, \begin{bmatrix}0\\1\\0\end{bmatrix}$

c. $\begin{bmatrix}\frac{3}{5}\\0\\-\frac{4}{5}\end{bmatrix}, \begin{bmatrix}\frac{4}{5}\\0\\\frac{3}{5}\end{bmatrix}, \begin{bmatrix}0\\1\\0\end{bmatrix}$

Exercise $4.E.132$

A solution is

$$\begin{bmatrix} \frac{1}{6}\sqrt{6} \\ \frac{1}{3}\sqrt{6} \\ \frac{1}{6}\sqrt{6} \end{bmatrix}, \begin{bmatrix} \frac{3}{10}\sqrt{2} \\ -\frac{2}{5}\sqrt{2} \\ \frac{1}{2}\sqrt{2} \end{bmatrix}, \begin{bmatrix} \frac{7}{15}\sqrt{3} \\ -\frac{1}{15}\sqrt{3} \\ -\frac{1}{3}\sqrt{3} \end{bmatrix}$$

Exercise $4.E.133$

Then a solution is

$$\begin{bmatrix} \frac{1}{6}\sqrt{6} \\ \frac{1}{3}\sqrt{6} \\ \frac{1}{6}\sqrt{6} \\ 0 \end{bmatrix}, \begin{bmatrix} \frac{1}{6}\sqrt{2}\sqrt{3} \\ -\frac{2}{9}\sqrt{2}\sqrt{3} \\ \frac{5}{18}\sqrt{2}\sqrt{3} \\ \frac{1}{9}\sqrt{2}\sqrt{3} \end{bmatrix}, \begin{bmatrix} \frac{5}{111}\sqrt{3}\sqrt{37} \\ \frac{1}{133}\sqrt{3}\sqrt{37} \\ -\frac{17}{333}\sqrt{3}\sqrt{37} \\ \frac{22}{333}\sqrt{3}\sqrt{37} \end{bmatrix}$$

Exercise $4.E.134$

The subspace is of the form

$$\begin{bmatrix} x \\ y \\ 2x+3y \end{bmatrix}$$

and a basis is $\begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 3 \end{bmatrix}$. Therefore, an orthonormal basis is

$$\begin{bmatrix} \frac{1}{5}\sqrt{5} \\ 0 \\ \frac{2}{5}\sqrt{5} \end{bmatrix}, \begin{bmatrix} -\frac{3}{35}\sqrt{5}\sqrt{14} \\ \frac{1}{14}\sqrt{5}\sqrt{14} \\ \frac{3}{70}\sqrt{5}\sqrt{14} \end{bmatrix}$$

Exercise $4.E.140$

$$\begin{aligned} \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 3 & 5 \end{bmatrix}^T \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 3 & 5 \end{bmatrix} &= \begin{bmatrix} 14 & 23 \\ 23 & 38 \end{bmatrix} \begin{bmatrix} 14 & 23 \\ 23 & 38 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \\ &= \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 3 & 5 \end{bmatrix}^T \begin{bmatrix} 1 \\ 2 \\ 4 \end{bmatrix} = \begin{bmatrix} 17 \\ 28 \end{bmatrix} \end{aligned} \tag{4.E.17}$$

$$\begin{aligned} \begin{bmatrix} 14 & 23 \\ 23 & 38 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} &= \begin{bmatrix} 17 \\ 28 \end{bmatrix} \\ \begin{bmatrix} 14 & 23 \\ 23 & 38 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} &= \begin{bmatrix} 17 \\ 28 \end{bmatrix}, \end{aligned} \tag{4.E.18}$$

Solution is: $\begin{bmatrix} \frac{2}{3} \\ \frac{1}{3} \end{bmatrix}$

Exercise $4.E.149$

The velocity is the sum of two vectors. $50\vec{i} + \frac{300}{\sqrt{2}}\left(\vec{i}+\vec{j}\right) = \left(50+\frac{300}{\sqrt{2}}\right)\vec{i} + \frac{300}{\sqrt{2}}\vec{j}$. The component in the direction of North is then $\frac{300}{\sqrt{2}} = 150\sqrt{2}$ and the velocity relative to the ground is

$$\left(50+\frac{300}{\sqrt{2}}\right)\vec{i} + \frac{300}{\sqrt{2}}\vec{j}$$

Exercise $4.E.152$

Velocity of plane for the first hour: $\begin{bmatrix} 0 & 150 \end{bmatrix} + \begin{bmatrix} 40 & 0 \end{bmatrix} = \begin{bmatrix} 40 & 150 \end{bmatrix}$. After one hour it is at $(40, 150)$. Next the velocity of the plane is $150\begin{bmatrix} \frac{1}{2} & \frac{\sqrt{3}}{2} \end{bmatrix} + \begin{bmatrix} 40 & 0 \end{bmatrix}$ in miles per hour. After two hours it is then at $(40,150) + 150\begin{bmatrix} \frac{1}{2} & \frac{\sqrt{3}}{2} \end{bmatrix} + \begin{bmatrix} 40 & 0 \end{bmatrix} = \begin{bmatrix} 155 & 75\sqrt{3}+150 \end{bmatrix} = \begin{bmatrix} 155.0 & 279.9 \end{bmatrix}$

Exercise $4.E.153$

Wind: $\begin{bmatrix} 0 & 50 \end{bmatrix}$. Direction it needs to travel: $(3,5)\frac{1}{\sqrt{34}}$. Then you need $250\begin{bmatrix} a & b \end{bmatrix} + \begin{bmatrix} 0 & 50 \end{bmatrix}$ to have this direction where $\begin{bmatrix} a & b \end{bmatrix}$ is an appropriate unit vector. Thus you need

$$\begin{aligned} a^2+b^2 &= 1 \\ \frac{250b+50}{250a} &= \frac{5}{3} \end{aligned} \tag{4.E.19}$$

Thus $a = \frac{3}{5}, b = \frac{4}{5}$. The velocity of the plane relative to the ground is $\begin{bmatrix} 150 & 250 \end{bmatrix}$. The speed of the plane relative to the ground is given by

$$\sqrt{(150)^2+(250)^2} = 291.55 \text{ miles per hour}$$

It has to go a distance of $\sqrt{(300)^2+(500)^2} = 583.\ 10$ miles. Therefore, it takes

$$\frac{583.1}{291.55} = 2 \text{ hours}$$

Exercise $4.E.154$

Water: $\begin{bmatrix} -2 & 0 \end{bmatrix}$ Swimmer: $\begin{bmatrix} 0 & 3 \end{bmatrix}$ Speed relative to earth: $\begin{bmatrix} -2 & 3 \end{bmatrix}$. It takes him $1/6$ of an hour to get across. Therefore, he ends up traveling $\frac{1}{6}\sqrt{4+9} = \frac{1}{6}\sqrt{13}$ miles. He ends up $1/3$ mile down stream.

Exercise $4.E.155$

Man: $3\begin{bmatrix} a & b \end{bmatrix}$ Water: $\begin{bmatrix} -2 & 0 \end{bmatrix}$ Then you need $3a = 2$ and so $a = 2/3$ and hence $b = \sqrt{5}/3$. The vector is then $\begin{bmatrix} \frac{2}{3} & \frac{\sqrt{5}}{3} \end{bmatrix}$.

In the second case, he could not do it. You would need to have a unit vector $\begin{bmatrix} a & b \end{bmatrix}$ such that $2a = 3$ which is not possible.

Exercise $4.E.159$

$\text{proj}_{\vec{D}}\left(\vec{F}\right) = \frac{\vec{F}\bullet\vec{D}}{\|\vec{D}\|}\frac{\vec{D}}{\|\vec{D}\|} = \left(\|\vec{F}\|\cos\theta\right)\frac{\vec{D}}{\|\vec{D}\|} = \left(\|\vec{F}\|\cos\theta\right)\vec{u}$

Exercise $4.E.160$

$40\cos\left(\frac{20}{180}\pi\right)100 = 3758.8$

Exercise $4.E.161$

$20\cos\left(\frac{\pi}{6}\right)200 = 3464.1$

Exercise $4.E.162$

$20\left(\cos\frac{\pi}{4}\right)300 = 4242.6$

Exercise $4.E.163$

$200\left(\cos\left(\frac{\pi}{6}\right)\right)20 = 3464.1$

Exercise $4.E.164$

$\begin{bmatrix} -4 \\ 3 \\ -4 \end{bmatrix} \bullet \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \times 10 = 30$ You can consider the resultant of the two forces because of the properties of the dot product.

Exercise $4.E.165$

$$\begin{aligned} \vec{F}_1 \bullet \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ 0 \end{bmatrix} 10 + \vec{F}_2 \bullet \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ 0 \end{bmatrix} 10 &= \left(\vec{F}_1 + \vec{F}_2\right) \bullet \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ 0 \end{bmatrix} 10 \\ &= \begin{bmatrix} 6 \\ 4 \\ -4 \end{bmatrix} \bullet \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ 0 \end{bmatrix} 10 \\ &= 50\sqrt{2} \end{aligned} \tag{4.E.20}$$

Exercise $4.E.166$

$\begin{bmatrix} 2 \\ 3 \\ -4 \end{bmatrix} \bullet \begin{bmatrix} 0 \\ \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix} 20 = -10\sqrt{2}$

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5.1: Algebraic Considerations

Outcomes

A. Develop the abstract concept of a vector space through axioms.
B. Deduce basic properties of vector spaces.
C. Use the vector space axioms to determine if a set and its operations constitute a vector space.

In this section we consider the idea of an abstract vector space. A vector space is something which has two operations satisfying the following vector space axioms.

Definition 5.1.1: Vector Space

A vector space V is a set of vectors with two operations defined, addition and scalar multiplication, which satisfy the axioms of addition and scalar multiplication.

In the following definition we define two operations; vector addition, denoted by $+$ and scalar multiplication denoted by placing the scalar next to the vector. A vector space need not have usual operations, and for this reason the operations will always be given in the definition of the vector space. The below axioms for addition (written +) and scalar multiplication must hold for however addition and scalar multiplication are defined for the vector space.

It is important to note that we have seen much of this content before, in terms of $\mathbb{R}^n$. We will prove in this section that $\mathbb{R}^n$ is an example of a vector space and therefore all discussions in this chapter will pertain to $\mathbb{R}^n$. While it may be useful to consider all concepts of this chapter in terms of $\mathbb{R}^n$, it is also important to understand that these concepts apply to *all* vector spaces.

In the following definition, we will choose scalars a, b to be real numbers and are thus dealing with *real* vector spaces. However, we could also choose scalars which are complex numbers. In this case, we would call the vector space V complex.

Definition 5.1.2: Axioms of Addition

Let $\vec{v}, \vec{w}, \vec{z}$ be vectors in a vector space V. Then they satisfy the following axioms of addition:

- Closed under Addition

$$\text{If } \vec{v}, \vec{w} \text{ are in } V, \text{ then } \vec{v} + \vec{w} \text{ is also in } V.$$

- The Commutative Law of Addition

$$\vec{v} + \vec{w} = \vec{w} + \vec{v}$$

- The Associative Law of Addition

$$\left(\vec{v} + \vec{w}\right) + \vec{z} = \vec{v} + \left(\vec{w} + \vec{z}\right)$$

- The Existence of an Additive Identity

$$\vec{v} + \vec{0} = \vec{v}$$

- The Existence of an Additive Inverse

$$\vec{v} + \left(-\vec{v}\right) = \vec{0}$$

vectorspaceaxiomsaddition

Definition 5.1.3: Axioms of Scalar Multiplication

Let $a, b \in \mathbb{R}$ and let $\vec{v}, \vec{w}, \vec{z}$ be vectors in a vector space V. Then they satisfy the following axioms of scalar multiplication:

- Closed under Scalar Multiplication

$$\text{If } a \text{ is a real number, and } \vec{v} \text{ is in } V, \text{ then } a\vec{v} \text{ is in } V.$$

- $$a\left(\vec{v}+\vec{w}\right) = a\vec{v} + a\vec{w}$$
- $$\left(a+b\right)\vec{v} = a\vec{v} + b\vec{v}$$
- $$a\left(b\vec{v}\right) = (ab)\vec{v}$$
- $$1\vec{v} = \vec{v}$$

Consider the following example, in which we prove that $\mathbb{R}^n$ is in fact a vector space.

Example 5.1.1: $\mathbb{R}^n$

$\mathbb{R}^n$, under the usual operations of vector addition and scalar multiplication, is a vector space.

Solution

To show that $\mathbb{R}^n$ is a vector space, we need to show that the above axioms hold. Let $\vec{x}, \vec{y}, \vec{z}$ be vectors in $\mathbb{R}^n$. We first prove the axioms for vector addition.

- To show that $\mathbb{R}^n$ is closed under addition, we must show that for two vectors in $\mathbb{R}^n$ their sum is also in $\mathbb{R}^n$. The sum $\vec{x}+\vec{y}$ is given by:

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} x_1 + y_1 \\ x_2 + y_2 \\ \vdots \\ x_n + y_n \end{bmatrix}$$

  The sum is a vector with n entries, showing that it is in $\mathbb{R}^n$. Hence $\mathbb{R}^n$ is closed under vector addition.
- To show that addition is commutative, consider the following:

$$\begin{aligned} \vec{x}+\vec{y} &= \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \\ &= \begin{bmatrix} x_1 + y_1 \\ x_2 + y_2 \\ \vdots \\ x_n + y_n \end{bmatrix} \\ &= \begin{bmatrix} y_1 + x_1 \\ y_2 + x_2 \\ \vdots \\ y_n + x_n \end{bmatrix} \\ &= \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} + \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \\ &= \vec{y}+\vec{x} \end{aligned} \tag{5.1.1}$$

  Hence addition of vectors in $\mathbb{R}^n$ is commutative.
- We will show that addition of vectors in $\mathbb{R}^n$ is associative in a similar way.

$$
\begin{aligned}
(\vec{x}+\vec{y})+\vec{z} &= \left(\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}\right) + \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix} \\
&= \begin{bmatrix} x_1+y_1 \\ x_2+y_2 \\ \vdots \\ x_n+y_n \end{bmatrix} + \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix} \\
&= \begin{bmatrix} (x_1+y_1)+z_1 \\ (x_2+y_2)+z_2 \\ \vdots \\ (x_n+y_n)+z_n \end{bmatrix} \\
&= \begin{bmatrix} x_1+(y_1+z_1) \\ x_2+(y_2+z_2) \\ \vdots \\ x_n+(y_n+z_n) \end{bmatrix} \\
&= \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} y_1+z_1 \\ y_2+z_2 \\ \vdots \\ y_n+z_n \end{bmatrix} \\
&= \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \left(\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} + \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix}\right) \\
&= \vec{x}+(\vec{y}+\vec{z})
\end{aligned}
\tag{5.1.2}
$$

Hence addition of vectors is associative.

- Next, we show the existence of an additive identity. Let $\vec{0} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$.

$$
\begin{aligned}
\vec{x}+\vec{0} &= \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \\
&= \begin{bmatrix} x_1+0 \\ x_2+0 \\ \vdots \\ x_n+0 \end{bmatrix} \\
&= \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \\
&= \vec{x}
\end{aligned}
\tag{5.1.3}
$$

Hence the zero vector $\vec{0}$ is an additive identity.

- Next, we prove the existence of an additive inverse. Let $-\vec{x} = \begin{pmatrix} -x_1 \\ -x_2 \\ \vdots \\ -x_n \end{pmatrix}$.

$$\begin{aligned}\vec{x}+(-\vec{x}) &= \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} -x_1 \\ -x_2 \\ \vdots \\ -x_n \end{bmatrix} \\ &= \begin{bmatrix} x_1 - x_1 \\ x_2 - x_2 \\ \vdots \\ x_n - x_n \end{bmatrix} \\ &= \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \\ &= \vec{0}\end{aligned} \tag{5.1.4}$$

Hence $-\vec{x}$ is an additive inverse.

We now need to prove the axioms related to scalar multiplication. Let a, b be real numbers and let $\vec{x}, \vec{y}$ be vectors in $\mathbb{R}^n$.

- We first show that $\mathbb{R}^n$ is closed under scalar multiplication. To do so, we show that $a\vec{x}$ is also a vector with n entries.

$$a\vec{x} = a \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} ax_1 \\ ax_2 \\ \vdots \\ ax_n \end{bmatrix}$$

  The vector $a\vec{x}$ is again a vector with n entries, showing that $\mathbb{R}^n$ is closed under scalar multiplication.
- We wish to show that $a(\vec{x}+\vec{y}) = a\vec{x} + a\vec{y}$.

$$\begin{aligned}a(\vec{x}+\vec{y}) &= a\left(\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} x_1 \\ x_2 \\ \vdots x_n \end{bmatrix} \right) \\ &= a \begin{bmatrix} x_1 + y_1 \\ x_2 + y_2 \\ \vdots \\ x_n + y_n \end{bmatrix} \\ &= \begin{bmatrix} a(x_1 + y_1) \\ a(x_2 + y_2) \\ \vdots \\ a(x_n + y_n) \end{bmatrix} \\ &= \begin{bmatrix} ax_1 + ay_1 \\ ax_2 + ay_2 \\ \vdots \\ ax_n + ay_n \end{bmatrix} \\ &= \begin{bmatrix} ax_1 \\ ax_2 \\ \vdots \\ ax_n \end{bmatrix} + \begin{bmatrix} ay_1 \\ ay_2 \\ \vdots \\ ay_n \end{bmatrix} \\ &= a\vec{x} + a\vec{y}\end{aligned} \tag{5.1.5}$$

- Next, we wish to show that $(a+b)\vec{x} = a\vec{x} + b\vec{x}$.

Illegal pream-token (x)

- We wish to show that $a(b\vec{x}) = (ab)\vec{x}$.

$$\begin{aligned} a(b\vec{x}) &= a\left(b\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}\right) \\ &= a\left(\begin{bmatrix} bx_1 \\ bx_2 \\ \vdots \\ bx_n \end{bmatrix}\right) \\ &= \begin{bmatrix} a(bx_1) \\ a(bx_2) \\ \vdots \\ a(bx_n) \end{bmatrix} \\ &= \begin{bmatrix} (ab)x_1 \\ (ab)x_2 \\ \vdots \\ (ab)x_n \end{bmatrix} \\ &= (ab)\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \\ &= (ab)\vec{x} \end{aligned} \tag{5.1.6}$$

- Finally, we need to show that $1\vec{x} = \vec{x}$.

$$\begin{aligned} 1\vec{x} &= 1\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \\ &= \begin{bmatrix} 1x_1 \\ 1x_2 \\ \vdots \\ 1x_n \end{bmatrix} \\ &= \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \\ &= \vec{x} \end{aligned} \tag{5.1.7}$$

By the above proofs, it is clear that $\mathbb{R}^n$ satisfies the vector space axioms. Hence, $\mathbb{R}^n$ is a vector space under the usual operations of vector addition and scalar multiplication.

We now consider some examples of vector spaces.

Example 5.1.2: Vector Space of Polynomials

Let $\mathbb{P}_2$ be the set of all polynomials of at most degree 2 as well as the zero polynomial. Define addition to be the standard addition of polynomials, and scalar multiplication the usual multiplication of a polynomial by a number. Then $\mathbb{P}_2$ is a vector space.

Solution

We can write $\mathbb{P}_2$ explicitly as

$$\mathbb{P}_2 = \left\{a_2x^2 + a_1x + a_0 | a_i \in \mathbb{R} \text{ for all } i\right\}$$

To show that $\mathbb{P}_2$ is a vector space, we verify the axioms. Let $p(x), q(x), r(x)$ be polynomials in $\mathbb{P}_2$ and let a, b, c be real numbers. Write $p(x) = p_2x^2 + p_1x + p_0$, $q(x) = q_2x^2 + q_1x + q_0$, and $r(x) = r_2x^2 + r_1x + r_0$.

- We first prove that addition of polynomials in $\mathbb{P}_2$ is closed. For two polynomials in $\mathbb{P}_2$ we need to show that their sum is also a polynomial in $\mathbb{P}_2$. From the definition of $\mathbb{P}_2$, a polynomial is contained in $\mathbb{P}_2$ if it is of degree at most 2 or the zero polynomial.

$$\begin{aligned} p(x) + q(x) &= p_2x^2 + p_1x + p_0 + q_2x^2 + q_1x + q_0 \\ &= (p_2 + q_2)x^2 + (p_1 + q_1)x + (p_0 + q_0) \end{aligned} \tag{5.1.8}$$

  The sum is a polynomial of degree 2 and therefore is in $\mathbb{P}_2$. It follows that $\mathbb{P}_2$ is closed under addition.
- We need to show that addition is commutative, that is $p(x) + q(x) = q(x) + p(x)$.

$$\begin{aligned} p(x) + q(x) &= p_2x^2 + p_1x + p_0 + q_2x^2 + q_1x + q_0 \\ &= (p_2 + q_2)x^2 + (p_1 + q_1)x + (p_0 + q_0) \\ &= (q_2 + p_2)x^2 + (q_1 + p_1)x + (q_0 + p_0) \\ &= q_2x^2 + q_1x + q_0 + p_2x^2 + p_1x + p_0 \\ &= q(x) + p(x) \end{aligned} \tag{5.1.9}$$

- Next, we need to show that addition is associative. That is, that $(p(x) + q(x)) + r(x) = p(x) + (q(x) + r(x))$.

$$\begin{aligned} (p(x) + q(x)) + r(x) &= \left(p_2x^2 + p_1x + p_0 + q_2x^2 + q_1x + q_0\right) + r_2x^2 + r_1x + r_0 \\ &= (p_2 + q_2)x^2 + (p_1 + q_1)x + (p_0 + q_0) + r_2x^2 + r_1x + r_0 \\ &= (p_2 + q_2 + r_2)x^2 + (p_1 + q_1 + r_1)x + (p_0 + q_0 + r_0) \\ &= p_2x^2 + p_1x + p_0 + (q_2 + r_2)x^2 + (q_1 + r_1)x + (q_0 + r_0) \\ &= p_2x^2 + p_1x + p_0 + \left(q_2x^2 + q_1x + q_0 + r_2x^2 + r_1x + r_0\right) \\ &= p(x) + (q(x) + r(x)) \end{aligned} \tag{5.1.10}$$

- Next, we must prove that there exists an additive identity. Let $0(x) = 0x^2 + 0x + 0$.

$$\begin{aligned} p(x) + 0(x) &= p_2x^2 + p_1x + p_0 + 0x^2 + 0x + 0 \\ &= (p_2 + 0)x^2 + (p_1 + 0)x + (p_0 + 0) \\ &= p_2x^2 + p_1x + p_0 \\ &= p(x) \end{aligned} \tag{5.1.11}$$

  Hence an additive identity exists, specifically the zero polynomial.
- Next we must prove that there exists an additive inverse. Let $-p(x) = -p_2x^2 - p_1x - p_0$ and consider the following:

$$\begin{aligned} p(x) + (-p(x)) &= p_2x^2 + p_1x + p_0 + \left(-p_2x^2 - p_1x - p_0\right) \\ &= (p_2 - p_2)x^2 + (p_1 - p_1)x + (p_0 - p_0) \\ &= 0x^2 + 0x + 0 \\ &= 0(x) \end{aligned} \tag{5.1.12}$$

  Hence an additive inverse $-p(x)$ exists such that $p(x) + (-p(x)) = 0(x)$.

We now need to verify the axioms related to scalar multiplication.

- First we prove that $\mathbb{P}_2$ is closed under scalar multiplication. That is, we show that $ap(x)$ is also a polynomial of degree at most 2.

$$ap(x) = a\left(p_2x^2 + p_1x + p_0\right) = ap_2x^2 + ap_1x + ap_0$$

  Therefore $\mathbb{P}_2$ is closed under scalar multiplication.
- We need to show that $a(p(x) + q(x)) = ap(x) + aq(x)$.

$$\begin{aligned} a(p(x) + q(x)) &= a\left(p_2x^2 + p_1x + p_0 + q_2x^2 + q_1x + q_0\right) \\ &= a\left((p_2 + q_2)x^2 + (p_1 + q_1)x + (p_0 + q_0)\right) \\ &= a(p_2 + q_2)x^2 + a(p_1 + q_1)x + a(p_0 + q_0) \\ &= (ap_2 + aq_2)x^2 + (ap_1 + aq_1)x + (ap_0 + aq_0) \\ &= ap_2x^2 + ap_1x + ap_0 + aq_2x^2 + aq_1x + aq_0 \\ &= ap(x) + aq(x) \end{aligned} \tag{5.1.13}$$

- Next we show that $(a + b)p(x) = ap(x) + bp(x)$.

$$\begin{aligned}(a+b)p(x) &= (a+b)(p_2x^2+p_1x+p_0)\\ &= (a+b)p_2x^2+(a+b)p_1x+(a+b)p_0\\ &= ap_2x^2+ap_1x+ap_0+bp_2x^2+bp_1x+bp_0\\ &= ap(x)+bp(x)\end{aligned} \tag{5.1.14}$$

- The next axiom which needs to be verified is $a(bp(x)) = (ab)p(x)$.

$$\begin{aligned}a(bp(x)) &= a\left(b\left(p_2x^2+p_1x+p_0\right)\right)\\ &= a\left(bp_2x^2+bp_1x+bp_0\right)\\ &= abp_2x^2+abp_1x+abp_0\\ &= (ab)(p_2x^2+p_1x+p_0)\\ &= (ab)p(x)\end{aligned} \tag{5.1.15}$$

- Finally, we show that $1p(x) = p(x)$.

$$\begin{aligned}1p(x) &= 1\left(p_2x^2+p_1x+p_0\right)\\ &= 1p_2x^2+1p_1x+1p_0\\ &= p_2x^2+p_1x+p_0\\ &= p(x)\end{aligned} \tag{5.1.16}$$

Since the above axioms hold, we know that $\mathbb{P}_2$ as described above is a vector space.

Another important example of a vector space is the set of all matrices of the same size.

Example 5.1.3: Vector Space of Matrices

Let $\mathbb{M}_{2,3}$ be the set of all 2×3 matrices. Using the usual operations of matrix addition and scalar multiplication, show that $\mathbb{M}_{2,3}$ is a vector space.

Solution

Let A, B be 2×3 matrices in $\mathbb{M}_{2,3}$. We first prove the axioms for addition.

- In order to prove that $\mathbb{M}_{2,3}$ is closed under matrix addition, we show that the sum $A+B$ is in $\mathbb{M}_{2,3}$. This means showing that $A+B$ is a 2×3 matrix.

$$\begin{aligned}A+B &= \begin{bmatrix}a_{11} & a_{12} & a_{13}\\ a_{21} & a_{22} & a_{23}\end{bmatrix}+\begin{bmatrix}b_{11} & b_{12} & b_{13}\\ b_{21} & b_{22} & b_{23}\end{bmatrix}\\ &= \begin{bmatrix}a_{11}+b_{11} & a_{12}+b_{12} & a_{13}+b_{13}\\ a_{21}+b_{21} & a_{22}+b_{22} & a_{23}+b_{23}\end{bmatrix}\end{aligned} \tag{5.1.17}$$

  You can see that the sum is a 2×3 matrix, so it is in $\mathbb{M}_{2,3}$. It follows that $\mathbb{M}_{2,3}$ is closed under matrix addition.
- The remaining axioms regarding matrix addition follow from properties of matrix addition. Therefore $\mathbb{M}_{2,3}$ satisfies the axioms of matrix addition.

We now turn our attention to the axioms regarding scalar multiplication. Let A, B be matrices in $\mathbb{M}_{2,3}$ and let c be a real number.

- We first show that $\mathbb{M}_{2,3}$ is closed under scalar multiplication. That is, we show that cA a 2×3 matrix.

$$\begin{aligned}cA &= c\begin{bmatrix}a_{11} & a_{12} & a_{13}\\ a_{21} & a_{22} & a_{23}\end{bmatrix}\\ &= \begin{bmatrix}ca_{11} & ca_{12} & ca_{13}\\ ca_{21} & ca_{22} & ca_{23}\end{bmatrix}\end{aligned} \tag{5.1.18}$$

  This is a 2×3 matrix in $\mathbb{M}_{2,3}$ which proves that the set is closed under scalar multiplication.
- The remaining axioms of scalar multiplication follow from properties of scalar multiplication of matrices. Therefore $\mathbb{M}_{2,3}$ satisfies the axioms of scalar multiplication.

In conclusion, $\mathbb{M}_{2,3}$ satisfies the required axioms and is a vector space.

While here we proved that the set of all 2×3 matrices is a vector space, there is nothing special about this choice of matrix size. In fact if we instead consider $\mathbb{M}_{m,n}$, the set of all $m \times n$ matrices, then $\mathbb{M}_{m,n}$ is a vector space under the operations of matrix addition and scalar multiplication.

We now examine an example of a set that does not satisfy all of the above axioms, and is therefore *not* a vector space.

Example 5.1.4: Not a Vector Space

Let V denote the set of 2×3 matrices. Let addition in V be defined by $A + B = A$ for matrices A, B in V. Let scalar multiplication in V be the usual scalar multiplication of matrices. Show that V is not a vector space.

Solution

In order to show that V is not a vector space, it suffices to find only one axiom which is not satisfied. We will begin by examining the axioms for addition until one is found which does not hold. Let A, B be matrices in V.

- We first want to check if addition is closed. Consider $A + B$. By the definition of addition in the example, we have that $A + B = A$. Since A is a 2×3 matrix, it follows that the sum $A + B$ is in V, and V is closed under addition.
- We now wish to check if addition is commutative. That is, we want to check if $A + B = B + A$ **for all** choices of A and B in V. From the definition of addition, we have that $A + B = A$ and $B + A = B$. Therefore, we can find A, B in V such that these sums are not equal. One example is

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}$$

Using the operation defined by $A + B = A$, we have

$$\begin{aligned} A + B &= A \\ &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \\ B + A &= B \\ &= \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} \end{aligned} \tag{5.1.19}$$

It follows that $A + B \neq B + A$. Therefore addition as defined for V is not commutative and V fails this axiom. Hence V is not a vector space.

Consider another example of a vector space.

Example 5.1.5: Vector Space of Functions

Let S be a nonempty set and define $\mathbb{F}_S$ to be the set of *real* functions defined on S. In other words, we write $\mathbb{F}_S : S \mapsto \mathbb{R}$. Letting a, b, c be scalars and f, g, h functions, the vector operations are defined as

$$\begin{aligned} (f + g)(x) &= f(x) + g(x) \\ (af)(x) &= a(f(x)) \end{aligned} \tag{5.1.20}$$

Show that $\mathbb{F}_S$ is a vector space.

Solution

To verify that $\mathbb{F}_S$ is a vector space, we must prove the axioms beginning with those for addition. Let f, g, h be functions in $\mathbb{F}_S$.

- First we check that addition is closed. For functions f, g defined on the set S, their sum given by

$$(f + g)(x) = f(x) + g(x)$$

is again a function defined on S. Hence this sum is in $\mathbb{F}_S$ and $\mathbb{F}_S$ is closed under addition.
- Secondly, we check the commutative law of addition:

$$(f + g)(x) = f(x) + g(x) = g(x) + f(x) = (g + f)(x)$$

Since x is arbitrary, $f+g=g+f$.

- Next we check the associative law of addition:

$$((f+g)+h)(x)=(f+g)(x)+h(x)=(f(x)+g(x))+h(x)$$
$$=f(x)+(g(x)+h(x))=(f(x)+(g+h)(x))=(f+(g+h))(x)$$

and so $(f+g)+h=f+(g+h)$.

- Next we check for an additive identity. Let 0 denote the function which is given by $0(x)=0$. Then this is an additive identity because

$$(f+0)(x)=f(x)+0(x)=f(x)$$

and so $f+0=f$.

- Finally, check for an additive inverse. Let $-f$ be the function which satisfies $(-f)(x)=-f(x)$. Then

$$(f+(-f))(x)=f(x)+(-f)(x)=f(x)+-f(x)=0$$

Hence $f+(-f)=0$.

Now, check the axioms for scalar multiplication.

- We first need to check that $\mathbb{F}_S$ is closed under scalar multiplication. For a function $f(x)$ in $\mathbb{F}_S$ and real number a, the function $(af)(x)=a(f(x))$ is again a function defined on the set S. Hence $a(f(x))$ is in $\mathbb{F}_S$ and $\mathbb{F}_S$ is closed under scalar multiplication.
- $$((a+b)f)(x)=(a+b)f(x)=af(x)+bf(x)=(af+bf)(x)$$

and so $(a+b)f=af+bf$.

- $$(a(f+g))(x)=a(f+g)(x)=a(f(x)+g(x))$$
$$=af(x)+bg(x)=(af+bg)(x)$$

and so $a(f+g)=af+bg$.

- $$((ab)f)(x)=(ab)f(x)=a(bf(x))=(a(bf))(x)$$

so $(abf)=a(bf)$.

- Finally $(1f)(x)=1f(x)=f(x)$ so $1f=f$.

It follows that V satisfies all the required axioms and is a vector space.

Consider the following important theorem.

Theorem 5.1.1: Uniqueness

In any vector space, the following are true:

1. $\vec{0}$, the additive identity, is unique
2. $-\vec{x}$, the additive inverse, is unique
3. $0\vec{x}=\vec{0}$ for all vectors $\vec{x}$
4. $(-1)\vec{x}=-\vec{x}$ for all vectors $\vec{x}$

Proof available at the end of this section.

An important use of the additive inverse is the following theorem.

Theorem 5.1.2

Let V be a vector space. Then $\vec{v}+\vec{w}=\vec{v}+\vec{z}$ implies that $\vec{w}=\vec{z}$ for all $\vec{v},\vec{w},\vec{z}\in V$

Proof available at the end of this section.

Answers

Theorem $5.1.1$**: Uniqueness**

1. When we say that the additive identity, $\vec{0}$, is unique, we mean that if a vector acts like the additive identity, then it **is** the additive identity. To prove this uniqueness, we want to show that another vector which acts like the additive identity is actually equal to $\vec{0}$. Suppose $\vec{0}'$ is also an additive identity. Then,

$$\vec{0} + \vec{0}' = \vec{0}$$

Now, for $\vec{0}$ the additive identity given above in the axioms, we have that

$$\vec{0}' + \vec{0} = \vec{0}'$$

So by the commutative property:

$$0 = 0 + 0' = 0' + 0 = 0'$$

This says that if a vector acts like an additive identity (such as $\vec{0}'$), it in fact equals $\vec{0}$. This proves the uniqueness of $\vec{0}$.

2. When we say that the additive inverse, $-\vec{x}$, is unique, we mean that if a vector acts like the additive inverse, then it **is** the additive inverse. Suppose that $\vec{y}$ acts like an additive inverse:

$$\vec{x} + \vec{y} = \vec{0}$$

Then the following holds:

$$\vec{y} = \vec{0} + \vec{y} = (-\vec{x} + \vec{x}) + \vec{y} = -\vec{x} + (\vec{x} + \vec{y}) = -\vec{x} + \vec{0} = -\vec{x}$$

Thus if $\vec{y}$ acts like the additive inverse, it is equal to the additive inverse $-\vec{x}$. This proves the uniqueness of $-\vec{x}$.

3. This statement claims that for all vectors $\vec{x}$, scalar multiplication by 0 equals the zero vector $\vec{0}$. Consider the following, using the fact that we can write $0 = 0 + 0$:

$$0\vec{x} = (0 + 0)\,\vec{x} = 0\vec{x} + 0\vec{x}$$

We use a small trick here: add $-0\vec{x}$ to both sides. This gives

$$\begin{aligned} 0\vec{x} + (-0\vec{x}) &= 0\vec{x} + 0\vec{x} + (-\vec{x}) \\ \vec{0} + 0 &= 0\vec{x} + 0 \\ \vec{0} &= 0\vec{x} \end{aligned} \tag{5.1.21}$$

This proves that scalar multiplication of any vector by 0 results in the zero vector $\vec{0}$.

4. Finally, we wish to show that scalar multiplication of -1 and any vector $\vec{x}$ results in the additive inverse of that vector, $-\vec{x}$. Recall from $2.$ above that the additive inverse is unique. Consider the following:

$$\begin{aligned} (-1)\,\vec{x} + \vec{x} &= (-1)\,\vec{x} + 1\vec{x} \\ &= (-1 + 1)\,\vec{x} \\ &= 0\vec{x} \\ &= \vec{0} \end{aligned} \tag{5.1.22}$$

By the uniqueness of the additive inverse shown earlier, any vector which acts like the additive inverse must be equal to the additive inverse. It follows that $(-1)\,\vec{x} = -\vec{x}$.

Theorem $5.1.2$

The proof follows from the vector space axioms, in particular the existence of an additive inverse $(-\vec{u})$. The proof is left as an exercise to the reader.

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5.2: SPANNING SETS

Outcomes

A. Determine if a vector is within a given span.

In this section we will examine the concept of spanning introduced earlier in terms of $\mathbb{R}^n$. Here, we will discuss these concepts in terms of abstract vector spaces.

Consider the following definition.

Definition 5.2.1: Subset

Let X and Y be two sets. If all elements of X are also elements of Y then we say that X is a **subset** of Y and we write

$$X \subseteq Y$$

In particular, we often speak of subsets of a vector space, such as $X \subseteq V$. By this we mean that every element in the set X is contained in the vector space V.

Definition 5.2.2: Linear Combination

Let V be a vector space and let $\vec{v}_1, \vec{v}_2, \cdots, \vec{v}_n \subseteq V$. A vector $\vec{v} \in V$ is called a linear combination of the $\vec{v}_i$ if there exist scalars $c_i \in \mathbb{R}$ such that

$$\vec{v} = c_1\vec{v}_1 + c_2\vec{v}_2 + \cdots + c_n\vec{v}_n$$

This definition leads to our next concept of span.

Definition 5.2.3: Span of Vectors

Let $\{\vec{v}_1, \cdots, \vec{v}_n\} \subseteq V$. Then

$$\text{span}\left\{\vec{v}_1, \cdots, \vec{v}_n\right\} = \left\{\sum_{i=1}^{n} c_i\vec{v}_i : c_i \in \mathbb{R}\right\}$$

When we say that a vector $\vec{w}$ is in $\text{span}\left\{\vec{v}_1, \cdots, \vec{v}_n\right\}$ we mean that $\vec{w}$ can be written as a linear combination of the $\vec{v}_1$. We say that a collection of vectors $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a **spanning set** for V if $V = \text{span}\{\vec{v}_1, \cdots, \vec{v}_n\}$.

Consider the following example.

Example 5.2.1: Matrix Span

Let $A = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$, $B = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$. Determine if A and B are in

$$\text{span}\left\{M_1, M_2\right\} = \text{span}\left\{\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}\right\}$$

Solution

First consider A. We want to see if scalars s, t can be found such that $A = sM_1 + tM_2$.

$$\begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} = s \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + t \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

The solution to this equation is given by

$$\begin{aligned} 1 &= s \\ 2 &= t \end{aligned} \tag{5.2.1}$$

and it follows that A is in $\text{span}\{M_1, M_2\}$.

Now consider B. Again we write $B = sM_1 + tM_2$ and see if a solution can be found for s, t.

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = s \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + t \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

Clearly no values of s and t can be found such that this equation holds. Therefore B is not in $\text{span}\{M_1, M_2\}$.

Consider another example.

Example 5.2.2: Polynomial Span

Show that $p(x) = 7x^2 + 4x - 3$ is in $\text{span}\{4x^2 + x, x^2 - 2x + 3\}$.

Solution

To show that $p(x)$ is in the given span, we need to show that it can be written as a linear combination of polynomials in the span. Suppose scalars a, b existed such that

$$7x^2 + 4x - 3 = a(4x^2 + x) + b(x^2 - 2x + 3)$$

If this linear combination were to hold, the following would be true:

$$\begin{aligned} 4a + b &= 7 \\ a - 2b &= 4 \\ 3b &= -3 \end{aligned} \tag{5.2.2}$$

You can verify that $a = 2, b = -1$ satisfies this system of equations. This means that we can write $p(x)$ as follows:

$$7x^2 + 4x - 3 = 2(4x^2 + x) - (x^2 - 2x + 3)$$

Hence $p(x)$ is in the given span.

Consider the following example.

Example 5.2.3: Spanning Set

Let $S = \{x^2 + 1, x - 2, 2x^2 - x\}$. Show that S is a spanning set for $\mathbb{P}_2$, the set of all polynomials of degree at most 2.

Solution

Let $p(x) = ax^2 + bx + c$ be an arbitrary polynomial in $\mathbb{P}_2$. To show that S is a spanning set, it suffices to show that $p(x)$ can be written as a linear combination of the elements of S. In other words, can we find r, s, t such that:

$$p(x) = ax^2 + bx + c = r(x^2 + 1) + s(x - 2) + t(2x^2 - x)$$

If a solution r, s, t can be found, then this shows that for any such polynomial $p(x)$, it can be written as a linear combination of the above polynomials and S is a spanning set.

$$\begin{aligned} ax^2+bx+c &= r(x^2+1)+s(x-2)+t(2x^2-x) \\ &= rx^2+r+sx-2s+2tx^2-tx \\ &= (r+2t)x^2+(s-t)x+(r-2s) \end{aligned} \tag{5.2.3}$$

For this to be true, the following must hold:

$$\begin{aligned} a &= r+2t \\ b &= s-t \\ c &= r-2s \end{aligned} \tag{5.2.4}$$

To check that a solution exists, set up the augmented matrix and row reduce:

$$\begin{bmatrix} 1 & 0 & 2 & a \\ 0 & 1 & -1 & b \\ 1 & -2 & 0 & c \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & 0 & \frac{1}{2}a+2b+\frac{1}{2}c \\ 0 & 1 & 0 & \frac{1}{4}a-\frac{1}{4}c \\ 0 & 0 & 1 & \frac{1}{4}a-b-\frac{1}{4}c \end{bmatrix}$$

Clearly a solution exists for any choice of a, b, c. Hence S is a spanning set for $\mathbb{P}_2$.

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5.3: Linear Independence

Outcomes

A. Determine if a set is linearly independent.

In this section, we will again explore concepts introduced earlier in terms of $\mathbb{R}^n$ and extend them to apply to abstract vector spaces.

Definition 5.3.1: Linear Independence

Let V be a vector space. If $\{\vec{v}_1, \cdots, \vec{v}_n\} \subseteq V$, then it is linearly independent if

$$\sum_{i=1}^{n} a_i \vec{v}_i = \vec{0} \text{ implies } a_1 = \cdots = a_n = 0$$

where the a_i are real numbers.

The set of vectors is called linearly dependent if it is not linearly independent.

Example 5.3.1: Linear Independence

Let $S \subseteq \mathbb{P}_2$ be a set of polynomials given by

$$S = \left\{x^2 + 2x - 1, 2x^2 - x + 3\right\}$$

Determine if S is linearly independent.

Solution

To determine if this set S is linearly independent, we write

$$a(x^2 + 2x - 1) + b(2x^2 - x + 3) = 0x^2 + 0x + 0$$

If it is linearly independent, then $a = b = 0$ will be the only solution. We proceed as follows.

$$\begin{aligned} a(x^2 + 2x - 1) + b(2x^2 - x + 3) &= 0x^2 + 0x + 0 \\ ax^2 + 2ax - a + 2bx^2 - bx + 3b &= 0x^2 + 0x + 0 \\ (a + 2b)x^2 + (2a - b)x - a + 3b &= 0x^2 + 0x + 0 \end{aligned} \tag{5.3.1}$$

It follows that

$$\begin{aligned} a + 2b &= 0 \\ 2a - b &= 0 \\ -a + 3b &= 0 \end{aligned} \tag{5.3.2}$$

The augmented matrix and resulting reduced row-echelon form are given by

$$\begin{bmatrix} 1 & 2 & 0 \\ 2 & -1 & 0 \\ -1 & 3 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Hence the solution is $a = b = 0$ and the set is linearly independent.

The next example shows us what it means for a set to be dependent.

Example 5.3.2: Dependent Set

Determine if the set S given below is independent.

$$S = \left\{ \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 3 \\ 5 \end{bmatrix} \right\}$$

Solution

To determine if S is linearly independent, we look for solutions to

$$a \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} + b \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} + c \begin{bmatrix} 1 \\ 3 \\ 5 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Notice that this equation has nontrivial solutions, for example $a = 2$, $b = 3$ and $c = -1$. Therefore S is dependent.

The following is an important result regarding dependent sets.

Lemma 5.3.1: Dependent Sets

Let V be a vector space and suppose $W = \{\vec{v}_1, \vec{v}_2, \cdots, \vec{v}_k\}$ is a subset of V. Then W is dependent if and only if $\vec{v}_i$ can be written as a linear combination of $\{\vec{v}_1, \vec{v}_2, \cdots, \vec{v}_{i-1}, \vec{v}_{i+1}, \cdots, \vec{v}_k\}$ for some $i \leq k$.

Revisit Example 5.3.2 with this in mind. Notice that we can write one of the three vectors as a combination of the others.

$$\begin{bmatrix} 1 \\ 3 \\ 5 \end{bmatrix} = 2 \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} + 3 \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

By Lemma 5.3.1 this set is dependent.

If we know that one particular set is linearly independent, we can use this information to determine if a related set is linearly independent. Consider the following example.

Example 5.3.3: Related Independent Sets

Let V be a vector space and suppose $S \subseteq V$ is a set of linearly independent vectors given by $S = \{\vec{u}, \vec{v}, \vec{w}\}$. Let $R \subseteq V$ be given by $R = \left\{2\vec{u} - \vec{w}, \vec{w} + \vec{v}, 3\vec{v} + \frac{1}{2}\vec{u}\right\}$. Show that R is also linearly independent.

Solution

To determine if R is linearly independent, we write

$$a(2\vec{u} - \vec{w}) + b(\vec{w} + \vec{v}) + c(3\vec{v} + \frac{1}{2}\vec{u}) = \vec{0}$$

If the set is linearly independent, the only solution will be $a = b = c = 0$. We proceed as follows.

$$\begin{aligned} a(2\vec{u} - \vec{w}) + b(\vec{w} + \vec{v}) + c(3\vec{v} + \frac{1}{2}\vec{u}) &= \vec{0} \\ 2a\vec{u} - a\vec{w} + b\vec{w} + b\vec{v} + 3c\vec{v} + \frac{1}{2}c\vec{u} &= \vec{0} \\ (2a + \frac{1}{2}c)\vec{u} + (b + 3c)\vec{v} + (-a + b)\vec{w} &= \vec{0} \end{aligned} \tag{5.3.3}$$

We know that the set $S = \{\vec{u}, \vec{v}, \vec{w}\}$ is linearly independent, which implies that the coefficients in the last line of this equation must all equal 0. In other words:

$$\begin{aligned} 2a + \frac{1}{2}c &= 0 \\ b + 3c &= 0 \\ -a + b &= 0 \end{aligned} \tag{5.3.4}$$

The augmented matrix and resulting reduced row-echelon form are given by:

$$\begin{bmatrix} 2 & 0 & \frac{1}{2} & 0 \\ 0 & 1 & 3 & 0 \\ -1 & 1 & 0 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

Hence the solution is $a = b = c = 0$ and the set is linearly independent.

The following theorem was discussed in terms in $\mathbb{R}^n$. We consider it here in the general case.

Theorem 5.3.1: Unique Representation

Let V be a vector space and let $U = \{\vec{v}_1, \cdots, \vec{v}_k\} \subseteq V$ be an independent set. If $\vec{v} \in \text{span } U$, then $\vec{v}$ can be written uniquely as a linear combination of the vectors in U.

Consider the span of a linearly independent set of vectors. Suppose we take a vector which is not in this span and add it to the set. The following lemma claims that the resulting set is still linearly independent.

Lemma 5.3.2: Adding to a Linearly Independent Set

Suppose $\vec{v} \notin \text{span}\{\vec{u}_1, \cdots, \vec{u}_k\}$ and $\{\vec{u}_1, \cdots, \vec{u}_k\}$ is linearly independent. Then the set

$$\{\vec{u}_1, \cdots, \vec{u}_k, \vec{v}\}$$

is also linearly independent.

Proof available at the end of this section.

Consider the following example.

Example 5.3.4: Adding to a Linearly Independent Set

Let $S \subseteq M_{22}$ be a linearly independent set given by

$$S = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \right\}$$

Show that the set $R \subseteq M_{22}$ given by

$$R = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \right\}$$

is also linearly independent.

Solution

Instead of writing a linear combination of the matrices which equals 0 and showing that the coefficients must equal 0, we can instead use Lemma 5.3.2.

To do so, we show that

$$\begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \notin \text{span} \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \right\}$$

Write

$$\begin{aligned}\begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} &= a\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + b\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \\ &= \begin{bmatrix} a & 0 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & b \\ 0 & 0 \end{bmatrix} \\ &= \begin{bmatrix} a & b \\ 0 & 0 \end{bmatrix}\end{aligned} \tag{5.3.5}$$

Clearly there are no possible a, b to make this equation true. Hence the new matrix does not lie in the span of the matrices in S. By Lemma 5.3.2, R is also linearly independent.

Answers

Lemma 5.3.2: Adding to a Linearly Independent Set

Suppose $\sum_{i=1}^{k} c_i \vec{u}_i + d\vec{v} = \vec{0}$. It is required to verify that each $c_i = 0$ and that $d = 0$. But if $d \neq 0$, then you can solve for $\vec{v}$ as a linear combination of the vectors, $\{\vec{u}_1, \cdots, \vec{u}_k\}$,

$$\vec{v} = -\sum_{i=1}^{k} \left(\frac{c_i}{d}\right) \vec{u}_i$$

contrary to the assumption that $\vec{v}$ is not in the span of the $\vec{u}_i$. Therefore, $d = 0$. But then $\sum_{i=1}^{k} c_i \vec{u}_i = \vec{0}$ and the linear independence of $\{\vec{u}_1, \cdots, \vec{u}_k\}$ implies each $c_i = 0$ also.

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5.4: Subspaces and Basis

Outcomes

A. Utilize the subspace test to determine if a set is a subspace of a given vector space.
B. Extend a linearly independent set and shrink a spanning set to a basis of a given vector space.

In this section we will examine the concept of subspaces introduced earlier in terms of $\mathbb{R}^n$. Here, we will discuss these concepts in terms of abstract vector spaces.

Consider the definition of a subspace.

Definition 5.4.1: Subspace

Let V be a vector space. A subset $W \subseteq V$ is said to be a **subspace** of V if $a\vec{x} + b\vec{y} \in W$ whenever $a, b \in \mathbb{R}$ and $\vec{x}, \vec{y} \in W$.

The span of a set of vectors as described in Definition 9.2.3 is an example of a subspace. The following fundamental result says that subspaces are subsets of a vector space which are themselves vector spaces.

Theorem 5.4.1: Subspaces are Vector Spaces

Let W be a nonempty collection of vectors in a vector space V. Then W is a subspace if and only if W satisfies the vector space axioms, using the same operations as those defined on V.

Proof available at the end of this section.

Consider the following useful Corollary.

Corollary 5.4.1: Span is a Subspace

Let V be a vector space with $W \subseteq V$. If $W = \text{span}\{\vec{v}_1, \cdots, \vec{v}_n\}$ then W is a subspace of V.

When determining spanning sets the following theorem proves useful.

Theorem 5.4.2: Spanning Set

Let $W \subseteq V$ for a vector space V and suppose $W = \text{span}\{\vec{v}_1, \vec{v}_2, \cdots, \vec{v}_n\}$.

Let $U \subseteq V$ be a subspace such that $\vec{v}_1, \vec{v}_2, \cdots, \vec{v}_n \in U$. Then it follows that $W \subseteq U$.

In other words, this theorem claims that any subspace that contains a set of vectors must also contain the span of these vectors.

The following example will show that two spans, described differently, can in fact be equal.

Example 5.4.1: Equal Span

Let $p(x), q(x)$ be polynomials and suppose $U = \text{span}\{2p(x) - q(x), p(x) + 3q(x)\}$ and $W = \text{span}\{p(x), q(x)\}$. Show that $U = W$.

Solution

We will use Theorem 5.4.2 to show that $U \subseteq W$ and $W \subseteq U$. It will then follow that $U = W$.

1. $U \subseteq W$ Notice that $2p(x) - q(x)$ and $p(x) + 3q(x)$ are both in $W = span\{p(x), q(x)\}$. Then by Theorem 5.4.2 W must contain the span of these polynomials and so $U \subseteq W$.
2. $W \subseteq U$ Notice that

$$\begin{aligned} p(x) &= \frac{3}{7}(2p(x) - q(x)) + \frac{2}{7}(p(x) + 3q(x)) \\ q(x) &= -\frac{1}{7}(2p(x) - q(x)) + \frac{2}{7}(p(x) + 3q(x)) \end{aligned} \tag{5.4.1}$$

Hence $p(x),\ q(x)$ are in $span\{2p(x) - q(x),\ p(x) + 3q(x)\}$. By Theorem 5.4.2 U must contain the span of these polynomials and so $W \subseteq U$.

To prove that a set is a vector space, one must verify each of the axioms given in Definition 9.1.2 and 9.1.3. This is a cumbersome task, and therefore a shorter procedure is used to verify a subspace.

Procedure 5.4.1: Subspace Test

Suppose W is a subset of a vector space V. To determine if W is a subspace of V, it is sufficient to determine if the following three conditions hold, using the operations of V:

1. The additive identity $\vec{0}$ of V is contained in W.
2. For any vectors $\vec{w}_1, \vec{w}_2$ in W, $\vec{w}_1 + \vec{w}_2$ is also in W.
3. For any vector $\vec{w}_1$ in W and scalar a, the product $a\vec{w}_1$ is also in W.

Therefore it suffices to prove these three steps to show that a set is a subspace.

Consider the following example.

Example 5.4.2: Improper Subspaces

Let V be an arbitrary vector space. Then V is a subspace of itself. Similarly, the set $\left\{\vec{0}\right\}$ containing only the zero vector is also a subspace.

Solution

Using the subspace test in Procedure 5.4.1 we can show that V and $\left\{\vec{0}\right\}$ are subspaces of V.

Since V satisfies the vector space axioms it also satisfies the three steps of the subspace test. Therefore V is a subspace.

Let's consider the set $\left\{\vec{0}\right\}$.

1. The vector $\vec{0}$ is clearly contained in $\left\{\vec{0}\right\}$, so the first condition is satisfied.
2. Let $\vec{w}_1, \vec{w}_2$ be in $\left\{\vec{0}\right\}$. Then $\vec{w}_1 = \vec{0}$ and $\vec{w}_2 = \vec{0}$ and so

$$\vec{w}_1 + \vec{w}_2 = \vec{0} + \vec{0} = \vec{0}$$

It follows that the sum is contained in $\left\{\vec{0}\right\}$ and the second condition is satisfied.
3. Let $\vec{w}_1$ be in $\left\{\vec{0}\right\}$ and let a be an arbitrary scalar. Then

$$a\vec{w}_1 = a\vec{0} = \vec{0}$$

Hence the product is contained in $\left\{\vec{0}\right\}$ and the third condition is satisfied.

It follows that $\left\{\vec{0}\right\}$ is a subspace of V.

The two subspaces described above are called **improper subspaces**. Any subspace of a vector space V which is not equal to V or $\left\{\vec{0}\right\}$ is called a **proper subspace**.

Consider another example.

Example 5.4.3: Subspace of Polynomials

Let $\mathbb{P}_2$ be the vector space of polynomials of degree two or less. Let $W \subseteq \mathbb{P}_2$ be all polynomials of degree two or less which have 1 as a root. Show that W is a subspace of $\mathbb{P}_2$.

Solution

First, express W as follows:

$$W = \left\{p(x) = ax^2 + bx + c, a, b, c, \in \mathbb{R} | p(1) = 0\right\}$$

We need to show that W satisfies the three conditions of Procedure 5.4.1.

1. The zero polynomial of $\mathbb{P}_2$ is given by $0(x) = 0x^2 + 0x + 0 = 0$. Clearly $0(1) = 0$ so $0(x)$ is contained in W.
2. Let $p(x), q(x)$ be polynomials in W. It follows that $p(1) = 0$ and $q(1) = 0$. Now consider $p(x) + q(x)$. Let $r(x)$ represent this sum.

$$\begin{aligned} r(1) &= p(1) + q(1) \\ &= 0 + 0 \\ &= 0 \end{aligned} \tag{5.4.2}$$

   Therefore the sum is also in W and the second condition is satisfied.
3. Let $p(x)$ be a polynomial in W and let a be a scalar. It follows that $p(1) = 0$. Consider the product $ap(x)$.

$$\begin{aligned} ap(1) &= a(0) \\ &= 0 \end{aligned} \tag{5.4.3}$$

   Therefore the product is in W and the third condition is satisfied.

It follows that W is a subspace of $\mathbb{P}_2$.

Recall the definition of basis, considered now in the context of vector spaces.

Definition 5.4.2: Basis

Let V be a vector space. Then $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is called a basis for V if the following conditions hold.

1. $\text{span}\left\{\vec{v}_1, \cdots, \vec{v}_n\right\} = V$
2. $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is linearly independent

Consider the following example.

Example 5.4.4: Polynomials of Degree Two

Let $\mathbb{P}_2$ be the set polynomials of degree no more than 2. We can write $\mathbb{P}_2 = \text{span}\left\{x^2, x, 1\right\}$. Is $\left\{x^2, x, 1\right\}$ a basis for $\mathbb{P}_2$?

Solution

It can be verified that $\mathbb{P}_2$ is a vector space defined under the usual addition and scalar multiplication of polynomials.

Now, since $\mathbb{P}_2 = \text{span}\{x^2, x, 1\}$, the set $\{x^2, x, 1\}$ is a basis if it is linearly independent. Suppose then that

$$ax^2 + bx + c = 0x^2 + 0x + 0$$

where a, b, c are real numbers. It is clear that this can only occur if $a = b = c = 0$. Hence the set is linearly independent and forms a basis of $\mathbb{P}_2$.

The next theorem is an essential result in linear algebra and is called the exchange theorem.

Theorem 5.4.3: Exchange Theorem

Let $\{\vec{x}_1, \cdots, \vec{x}_r\}$ be a linearly independent set of vectors such that each $\vec{x}_i$ is contained in span$\{\vec{y}_1, \cdots, \vec{y}_s\}$. Then $r \leq s$.

Proof available at the end of this section.

The following corollary follows from the exchange theorem.

Corollary 5.4.2: Two Bases of the Same Length

Let B_1, B_2 be two bases of a vector space V. Suppose B_1 contains m vectors and B_2 contains n vectors. Then $m = n$.

Proof available at the end of this section.

Given the result of the previous corollary, the following definition follows.

Definition 5.4.3: Dimension

A vector space V is of dimension n if it has a basis consisting of n vectors.

Notice that the dimension is well defined by Corollary 5.4.2. It is assumed here that $n < \infty$ and therefore such a vector space is said to be **finite dimensional**.

Example 5.4.5: Dimension of a Vector Space

Let $\mathbb{P}_2$ be the set of all polynomials of degree at most 2. Find the dimension of $\mathbb{P}_2$.

Solution

If we can find a basis of $\mathbb{P}_2$ then the number of vectors in the basis will give the dimension. Recall from Example 5.4.4 that a basis of $\mathbb{P}_2$ is given by

$$S = \{x^2, x, 1\}$$

There are three polynomials in S and hence the dimension of $\mathbb{P}_2$ is three.

It is important to note that a basis for a vector space is not unique. A vector space can have many bases. Consider the following example.

Example 5.4.6: A Different Basis for Polynomials of Degree Two

Let $\mathbb{P}_2$ be the polynomials of degree no more than 2. Is $\{x^2 + x + 1, 2x + 1, 3x^2 + 1\}$ a basis for $\mathbb{P}_2$?

Solution

Suppose these vectors are linearly independent but do not form a spanning set for $\mathbb{P}_2$. Then by Lemma 9.3.2, we could find a fourth polynomial in $\mathbb{P}_2$ to create a new linearly independent set containing four polynomials. However this would imply that we could find a basis of $\mathbb{P}_2$ of more than three polynomials. This contradicts the result of Example 5.4.5 in which we determined the dimension of $\mathbb{P}_2$ is three. Therefore if these vectors are linearly independent they must also form a spanning set and thus a basis for $\mathbb{P}_2$.

Suppose then that

$$\begin{aligned} a\left(x^2+x+1\right)+b\left(2x+1\right)+c\left(3x^2+1\right)&=0 \\ \left(a+3c\right)x^2+\left(a+2b\right)x+\left(a+b+c\right)&=0 \end{aligned} \tag{5.4.4}$$

We know that $\{x^2, x, 1\}$ is linearly independent, and so it follows that

$$\begin{aligned} a+3c&=0 \\ a+2b&=0 \\ a+b+c&=0 \end{aligned} \tag{5.4.5}$$

and there is only one solution to this system of equations, $a=b=c=0$. Therefore, these are linearly independent and form a basis for $\mathbb{P}_2$.

Consider the following theorem.

Theorem 5.4.4: Every Subspace has a Basis

Let W be a nonzero subspace of a finite dimensional vector space V. Suppose V has dimension n. Then W has a basis with no more than n vectors.

Proof available at the end of this section.

If in fact W has n vectors, then it follows that $W=V$.

Theorem 5.4.5: Subspace of Same Dimension

Let V be a vector space of dimension n and let W be a subspace. Then $W=V$ if and only if the dimension of W is also n.

Proof available at the end of this section.

Consider the following example.

Example 5.4.7: Basis of a Subspace

Let $U=\left\{A\in\mathbb{M}_{22} \;\middle|\; A\begin{bmatrix}1&0\\1&-1\end{bmatrix}=\begin{bmatrix}1&1\\0&-1\end{bmatrix}A\right\}$. Then U is a subspace of $\mathbb{M}_{22}$ Find a basis of U, and hence $\dim(U)$.

Solution

Let $A=\begin{bmatrix}a&b\\c&d\end{bmatrix}\in\mathbb{M}_{22}$. Then

$$A\begin{bmatrix}1&0\\1&-1\end{bmatrix}=\begin{bmatrix}a&b\\c&d\end{bmatrix}\begin{bmatrix}1&0\\1&-1\end{bmatrix}=\begin{bmatrix}a+b&-b\\c+d&-d\end{bmatrix}$$

and

$$\begin{bmatrix}1&1\\0&-1\end{bmatrix}A=\begin{bmatrix}1&1\\0&-1\end{bmatrix}\begin{bmatrix}a&b\\c&d\end{bmatrix}=\begin{bmatrix}a+c&b+d\\-c&-d\end{bmatrix}.$$

If $A \in U$, then $\begin{bmatrix} a+b & -b \\ c+d & -d \end{bmatrix} = \begin{bmatrix} a+c & b+d \\ -c & -d \end{bmatrix}$.

Equating entries leads to a system of four equations in the four variables a, b, c and d.

$$\begin{aligned} a+b &= a+c \\ -b &= b+d \\ c+d &= -c \\ -d &= -d \end{aligned}$$

or

$$\begin{aligned} b-c &= 0 \\ -2b-d &= 0 \\ 2c+d &= 0 \end{aligned}.$$

The solution to this system is $a = s$, $b = -\frac{1}{2}t$, $c = -\frac{1}{2}t$, $d = t$ for any $s, t \in \mathbb{R}$, and thus

$$A = \begin{bmatrix} s & \frac{t}{2} \\ -\frac{t}{2} & t \end{bmatrix} = s\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + t\begin{bmatrix} 0 & -\frac{1}{2} \\ -\frac{1}{2} & 1 \end{bmatrix}.$$

Let

$$B = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & -\frac{1}{2} \\ -\frac{1}{2} & 1 \end{bmatrix} \right\}.$$

Then $\text{span}(B) = U$, and it is routine to verify that B is an independent subset of $\mathbb{M}_{22}$. Therefore B is a basis of U, and $\dim(U) = 2$.

The following theorem claims that a spanning set of a vector space V can be shrunk down to a basis of V. Similarly, a linearly independent set within V can be enlarged to create a basis of V.

Theorem 5.4.6: Basis of V

If $V = \text{span}\{\vec{u}_1, \cdots, \vec{u}_n\}$ is a vector space, then some subset of $\{\vec{u}_1, \cdots, \vec{u}_n\}$ is a basis for V. Also, if $\{\vec{u}_1, \cdots, \vec{u}_k\} \subseteq V$ is linearly independent and the vector space is finite dimensional, then the set $\{\vec{u}_1, \cdots, \vec{u}_k\}$, can be enlarged to obtain a basis of V.

Proof available at the end of this section.

Recall Example 9.3.4 in which we added a matrix to a linearly independent set to create a larger linearly independent set. By Theorem 5.4.6 we can extend a linearly independent set to a basis.

Example 5.4.8: Adding to a Linearly Independent Set

Let $S \subseteq M_{22}$ be a linearly independent set given by

$$S = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \right\}$$

Enlarge S to a basis of M_{22}.

Solution

Recall from the solution of Example 9.3.4 that the set $R \subseteq M_{22}$ given by

$$R = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \right\}$$

is also linearly independent. However this set is still not a basis for M_{22} as it is not a spanning set. In particular, $\begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$ is not in $\mathrm{span}R$. Therefore, this matrix can be added to the set by Lemma 9.3.2 to obtain a new linearly independent set given by

$$T = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}$$

This set is linearly independent and now spans M_{22}. Hence T is a basis.

Next we consider the case where you have a spanning set and you want a subset which is a basis. The above discussion involved adding vectors to a set. The next theorem involves removing vectors.

Theorem 5.4.7: Basis from a Spanning Set

Let V be a vector space and let W be a subspace. Also suppose that $W = \mathrm{span}\left\{\vec{w}_1, \cdots, \vec{w}_m\right\}$. Then there exists a subset of $\left\{\vec{w}_1, \cdots, \vec{w}_m\right\}$ which is a basis for W.

Proof available at the end of this section.

Consider the following example of this concept.

Example 5.4.9: Basis from a Spanning Set

Let V be the vector space of polynomials of degree no more than 3, denoted earlier as $\mathbb{P}_3$. Consider the following vectors in V.

$$\begin{aligned} &2x^2 + x + 1, x^3 + 4x^2 + 2x + 2, 2x^3 + 2x^2 + 2x + 1, \\ &x^3 + 4x^2 - 3x + 2, x^3 + 3x^2 + 2x + 1 \end{aligned} \tag{5.4.6}$$

Then, as mentioned above, V has dimension 4 and so clearly these vectors are not linearly independent. A basis for V is $\left\{1, x, x^2, x^3\right\}$. Determine a linearly independent subset of these which has the same span. Determine whether this subset is a basis for V.

Solution

Consider an isomorphism which maps $\mathbb{R}^4$ to V in the obvious way. Thus

$$\begin{bmatrix} 1 \\ 1 \\ 2 \\ 0 \end{bmatrix}$$

corresponds to $2x^2 + x + 1$ through the use of this isomorphism. Then corresponding to the above vectors in V we would have the following vectors in $\mathbb{R}^4$.

$$\begin{bmatrix} 1 \\ 1 \\ 2 \\ 0 \end{bmatrix}, \begin{bmatrix} 2 \\ 2 \\ 4 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 2 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ -3 \\ 4 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 3 \\ 1 \end{bmatrix}$$

Now if we obtain a subset of these which has the same span but which is linearly independent, then the corresponding vectors from V will also be linearly independent. If there are four in the list, then the resulting vectors from V must be a basis for V. The reduced row-echelon form for the matrix which has the above vectors as columns is

$$\begin{bmatrix} 1 & 0 & 0 & -15 & 0 \\ 0 & 1 & 0 & 11 & 0 \\ 0 & 0 & 1 & -5 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Therefore, a basis for V consists of the vectors

$$\begin{aligned} &2x^2+x+1, x^3+4x^2+2x+2, 2x^3+2x^2+2x+1, \\ &x^3+3x^2+2x+1. \end{aligned} \tag{5.4.7}$$

Note how this is a subset of the original set of vectors. If there had been only three pivot columns in this matrix, then we would not have had a basis for V but we would at least have obtained a linearly independent subset of the original set of vectors in this way.

Note also that, since all linear relations are preserved by an isomorphism,

$$\begin{aligned} &-15\left(2x^2+x+1\right)+11\left(x^3+4x^2+2x+2\right)+(-5)\left(2x^3+2x^2+2x+1\right) \\ =&x^3+4x^2-3x+2 \end{aligned} \tag{5.4.8}$$

Consider the following example.

Example 5.4.10: Shrinking a Spanning Set

Consider the set $S \subseteq \mathbb{P}_2$ given by

$$S = \left\{1, x, x^2, x^2+1\right\}$$

Show that S spans $\mathbb{P}_2$, then remove vectors from S until it creates a basis.

Solution

First we need to show that S spans $\mathbb{P}_2$. Let ax^2+bx+c be an arbitrary polynomial in $\mathbb{P}_2$. Write

$$ax^2+bx+c = r(1)+s(x)+t(x^2)+u(x^2+1)$$

Then,

$$\begin{aligned} ax^2+bx+c &= r(1)+s(x)+t(x^2)+u(x^2+1) \\ &= (t+u)x^2+s(x)+(r+u) \end{aligned} \tag{5.4.9}$$

It follows that

$$\begin{aligned} a &= t+u \\ b &= s \\ c &= r+u \end{aligned} \tag{5.4.10}$$

Clearly a solution exists for all a, b, c and so S is a spanning set for $\mathbb{P}_2$. By Theorem 5.4.6, some subset of S is a basis for $\mathbb{P}_2$.

Recall that a basis must be both a spanning set and a linearly independent set. Therefore we must remove a vector from S keeping this in mind. Suppose we remove x from S. The resulting set would be $\left\{1, x^2, x^2+1\right\}$. This set is clearly linearly dependent (and also does not span $\mathbb{P}_2$) and so is not a basis.

Suppose we remove x^2+1 from S. The resulting set is $\left\{1, x, x^2\right\}$ which is both linearly independent and spans $\mathbb{P}_2$. Hence this is a basis for $\mathbb{P}_2$. Note that removing any one of $1, x^2$, or x^2+1 will result in a basis.

Now the following is a fundamental result about subspaces.

Theorem 5.4.8: Basis of a Vector Space

Let V be a finite dimensional vector space and let W be a non-zero subspace. Then W has a basis. That is, there exists a linearly independent set of vectors $\{\vec{w}_1, \cdots, \vec{w}_r\}$ such that

$$\{\vec{w}_1, \cdots, \vec{w}_r\} = W$$

Also if $\{\vec{w}_1, \cdots, \vec{w}_s\}$ is a linearly independent set of vectors, then W has a basis of the form $\{\vec{w}_1, \cdots, \vec{w}_s, \cdots, \vec{w}_r\}$ for $r \geq s$.

Proof available at the end of this section.

This also proves the following corollary. Let V play the role of W in the above theorem and begin with a basis for W, enlarging it to form a basis for V as discussed above.

Corollary 5.4.3: Basis Extension

Let W be any non-zero subspace of a vector space V. Then every basis of W can be extended to a basis for V.

Consider the following example.

Example 5.4.11: Basis Extension

Let $V = \mathbb{R}^4$ and let

$$W = \text{span}\left\{\begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}\right\}$$

Extend this basis of W to a basis of V.

Solution

An easy way to do this is to take the reduced row-echelon form of the matrix

$$\begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{5.4.11}$$

Note how the given vectors were placed as the first two and then the matrix was extended in such a way that it is clear that the span of the columns of this matrix yield all of $\mathbb{R}^4$. Now determine the pivot columns. The reduced row-echelon form is

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & -1 & 1 \\ 0 & 0 & 1 & 0 & -1 & 0 \\ 0 & 0 & 0 & 1 & 1 & -1 \end{bmatrix} \tag{5.4.12}$$

These are

$$\begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

and now this is an extension of the given basis for W to a basis for $\mathbb{R}^4$.

Why does this work? The columns of (5.4.11) obviously span $\mathbb{R}^4$ the span of the first four is the same as the span of all six.

Answers

Theorem 5.4.1**: Subspaces are Vector Spaces**

Suppose first that W is a subspace. It is obvious that all the algebraic laws hold on W because it is a subset of V and they hold on V. Thus $\vec{u}+\vec{v}=\vec{v}+\vec{u}$ along with the other axioms. Does W contain $\vec{0}$? Yes because it contains $0\vec{u}=\vec{0}$. See Theorem 9.1.1.

Are the operations of V defined on W? That is, when you add vectors of W do you get a vector in W? When you multiply a vector in W by a scalar, do you get a vector in W? Yes. This is contained in the definition. Does every vector in W have an additive inverse? Yes by Theorem 9.1.1 because $-\vec{v}=(-1)\,\vec{v}$ which is given to be in W provided $\vec{v}\in W$.

Next suppose W is a vector space. Then by definition, it is closed with respect to linear combinations. Hence it is a subspace.

Theorem 5.4.3**: Exchange Theorem**

The proof will proceed as follows. First, we set up the necessary steps for the proof. Next, we will assume that $r>s$ and show that this leads to a contradiction, thus requiring that $r\leq s$.

Define $\text{span}\{\vec{y}_1,\cdots,\vec{y}_s\}=V$. Since each $\vec{x}_i$ is in $\text{span}\{\vec{y}_1,\cdots,\vec{y}_s\}$, it follows there exist scalars $c_1,\cdots,c_s$ such that

$$\vec{x}_1=\sum_{i=1}^{s}c_i\vec{y}_i \tag{5.4.13}$$

Note that not all of these scalars c_i can equal zero. Suppose that all the $c_i=0$. Then it would follow that $\vec{x}_1=\vec{0}$ and so $\{\vec{x}_1,\cdots,\vec{x}_r\}$ would not be linearly independent. Indeed, if $\vec{x}_1=\vec{0}$, $1\vec{x}_1+\sum_{i=2}^{r}0\vec{x}_i=\vec{x}_1=\vec{0}$ and so there would exist a nontrivial linear combination of the vectors $\{\vec{x}_1,\cdots,\vec{x}_r\}$ which equals zero. Therefore at least one c_i is nonzero.

Say $c_k\neq 0$. Then solve (5.4.13) for $\vec{y}_k$ and obtain

$$\vec{y}_k\in\text{span}\left\{\vec{x}_1,\overbrace{\vec{y}_1,\cdots,\vec{y}_{k-1},\vec{y}_{k+1},\cdots,\vec{y}_s}^{\text{s-1 vectors here}}\right\}.$$

Define $\{\vec{z}_1,\cdots,\vec{z}_{s-1}\}$ to be

$$\{\vec{z}_1,\cdots,\vec{z}_{s-1}\}=\{\vec{y}_1,\cdots,\vec{y}_{k-1},\vec{y}_{k+1},\cdots,\vec{y}_s\}$$

Now we can write

$$\vec{y}_k\in\text{span}\{\vec{x}_1,\vec{z}_1,\cdots,\vec{z}_{s-1}\}$$

Therefore, $\text{span}\{\vec{x}_1,\vec{z}_1,\cdots,\vec{z}_{s-1}\}=V$. To see this, suppose $\vec{v}\in V$. Then there exist constants $c_1,\cdots,c_s$ such that

$$\vec{v}=\sum_{i=1}^{s-1}c_i\vec{z}_i+c_s\vec{y}_k.$$

Replace this $\vec{y}_k$ with a linear combination of the vectors $\{\vec{x}_1,\vec{z}_1,\cdots,\vec{z}_{s-1}\}$ to obtain $\vec{v}\in\text{span}\{\vec{x}_1,\vec{z}_1,\cdots,\vec{z}_{s-1}\}$. The vector $\vec{y}_k$, in the list $\{\vec{y}_1,\cdots,\vec{y}_s\}$, has now been replaced with the vector $\vec{x}_1$ and the resulting modified list of vectors has the same span as the original list of vectors, $\{\vec{y}_1,\cdots,\vec{y}_s\}$.

We are now ready to move on to the proof. Suppose that $r>s$ and that

$$\text{span}\{\vec{x}_1,\cdots,\vec{x}_l,\vec{z}_1,\cdots,\vec{z}_p\}=V$$

where the process established above has continued. In other words, the vectors $\vec{z}_1,\cdots,\vec{z}_p$ are each taken from the set $\{\vec{y}_1,\cdots,\vec{y}_s\}$ and $l+p=s$. This was done for $l=1$ above. Then since $r>s$, it follows that $l\leq s<r$ and so $l+1\leq r$. Therefore, $\vec{x}_{l+1}$ is a vector not in the list, $\{\vec{x}_1,\cdots,\vec{x}_l\}$ and since

$$\text{span}\{\vec{x}_1,\cdots,\vec{x}_l,\vec{z}_1,\cdots,\vec{z}_p\}=V$$

there exist scalars, c_i and d_j such that

$$\vec{x}_{l+1}=\sum_{i=1}^{l}c_i\vec{x}_i+\sum_{j=1}^{p}d_j\vec{z}_j. \tag{5.4.14}$$

Not all the d_j can equal zero because if this were so, it would follow that $\{\vec{x}_1,\cdots,\vec{x}_r\}$ would be a linearly dependent set because one of the vectors would equal a linear combination of the others. Therefore, (5.4.14) can be solved for one of the $\vec{z}_i$, say $\vec{z}_k$, in terms of $\vec{x}_{l+1}$ and the other $\vec{z}_i$ and just as in the above argument, replace that $\vec{z}_i$ with $\vec{x}_{l+1}$ to obtain

$$\text{span}\left\{\vec{x}_1,\cdots\vec{x}_l,\vec{x}_{l+1},\overbrace{\vec{z}_1,\cdots\vec{z}_{k-1},\vec{z}_{k+1},\cdots,\vec{z}_p}^{\text{p-1 vectors here}}\right\}=V$$

Continue this way, eventually obtaining

$$\text{span}\{\vec{x}_1,\cdots,\vec{x}_s\}=V.$$

But then $\vec{x}_r\in\text{span}\{\vec{x}_1,\cdots,\vec{x}_s\}$ contrary to the assumption that $\{\vec{x}_1,\cdots,\vec{x}_r\}$ is linearly independent. Therefore, $r\leq s$ as claimed.

Corollary 5.4.2**: Two Bases of the Same Length**

By Theorem 5.4.3, $m\leq n$ and $n\leq m$. Therefore $m=n$.

This corollary is very important so we provide another proof independent of the exchange theorem above.

Suppose $n>m$. Then since the vectors $\{\vec{u}_1,\cdots,\vec{u}_m\}$ span V, there exist scalars c_{ij} such that

$$\sum_{i=1}^{m}c_{ij}\vec{u}_i=\vec{v}_j.$$

Therefore,

$$\sum_{j=1}^{n}d_j\vec{v}_j=\vec{0}\text{ if and only if }\sum_{j=1}^{n}\sum_{i=1}^{m}c_{ij}d_j\vec{u}_i=\vec{0}$$

if and only if

$$\sum_{i=1}^{m}\left(\sum_{j=1}^{n}c_{ij}d_j\right)\vec{u}_i=\vec{0}$$

Now since $\{\vec{u}_1,\cdots,\vec{u}_n\}$ is independent, this happens if and only if

$$\sum_{j=1}^{n}c_{ij}d_j=0,\ i=1,2,\cdots,m.$$

However, this is a system of m equations in n variables, $d_1,\cdots,d_n$ and $m<n$. Therefore, there exists a solution to this system of equations in which not all the d_j are equal to zero. Recall why this is so. The augmented matrix for the system is of the form $\begin{bmatrix} C & \vec{0}\end{bmatrix}$ where C is a matrix which has more columns than rows. Therefore, there are free variables and hence nonzero solutions to the system of equations. However, this contradicts the linear independence of $\{\vec{u}_1,\cdots,\vec{u}_m\}$. Similarly it cannot happen that $m>n$.

Theorem 5.4.4**: Every Subspace has a Basis**

Let $\vec{v}_1\in V$ where $\vec{v}_1\neq 0$. If $\operatorname{span}\{\vec{v}_1\}=V$, then it follows that $\{\vec{v}_1\}$ is a basis for V. Otherwise, there exists $\vec{v}_2\in V$ which is not in $\operatorname{span}\{\vec{v}_1\}$. By Lemma 9.3.2 $\{\vec{v}_1,\vec{v}_2\}$ is a linearly independent set of vectors. Then $\{\vec{v}_1,\vec{v}_2\}$ is a basis for V and we are done. If $\operatorname{span}\{\vec{v}_1,\vec{v}_2\}\neq V$, then there exists $\vec{v}_3\notin\operatorname{span}\{\vec{v}_1,\vec{v}_2\}$ and $\{\vec{v}_1,\vec{v}_2,\vec{v}_3\}$ is a larger linearly independent set of vectors. Continuing this way, the process must stop before $n+1$ steps because if not, it would be possible to obtain $n+1$ linearly independent vectors contrary to the exchange theorem, Theorem 5.4.3.

Theorem 5.4.5**: Subspace of Same Dimension**

First suppose $W=V$. Then obviously the dimension of $W=n$.

Now suppose that the dimension of W is n. Let a basis for W be $\{\vec{w}_1,\cdots,\vec{w}_n\}$. If W is not equal to V, then let $\vec{v}$ be a vector of V which is not contained in W. Thus $\vec{v}$ is not in $\operatorname{span}\{\vec{w}_1,\cdots,\vec{w}_n\}$ and by Lemma 9.7.2, $\{\vec{w}_1,\cdots,\vec{w}_n,\vec{v}\}$ is linearly independent which contradicts Theorem 5.4.3 because it would be an independent set of $n+1$ vectors even though each of these vectors is in a spanning set of n vectors, a basis of V.

Theorem 5.4.6**: Basis of** V

Let

$$S=\{E\subseteq\{\vec{u}_1,\cdots,\vec{u}_n\}\text{ such that }\operatorname{span}\{E\}=V\}.$$

For $E\in S$, let $|E|$ denote the number of elements of E. Let

$$m=\min\{|E|\text{ such that }E\in S\}.$$

Thus there exist vectors

$$\{\vec{v}_1,\cdots,\vec{v}_m\}\subseteq\{\vec{u}_1,\cdots,\vec{u}_n\}$$

such that

$$\operatorname{span}\{\vec{v}_1,\cdots,\vec{v}_m\}=V$$

and m is as small as possible for this to happen. If this set is linearly independent, it follows it is a basis for V and the theorem is proved. On the other hand, if the set is not linearly independent, then there exist scalars, $c_1,\cdots,c_m$ such that

$$\vec{0}=\sum_{i=1}^{m}c_i\vec{v}_i$$

and not all the c_i are equal to zero. Suppose $c_k\neq 0$. Then solve for the vector $\vec{v}_k$ in terms of the other vectors. Consequently,

$$V=\operatorname{span}\{\vec{v}_1,\cdots,\vec{v}_{k-1},\vec{v}_{k+1},\cdots,\vec{v}_m\}$$

contradicting the definition of m. This proves the first part of the theorem.

To obtain the second part, begin with $\{\vec{u}_1,\cdots,\vec{u}_k\}$ and suppose a basis for V is

$$\{\vec{v}_1,\cdots,\vec{v}_n\}$$

If

$$\operatorname{span}\{\vec{u}_1,\cdots,\vec{u}_k\}=V,$$

then $k=n$. If not, there exists a vector

$$\vec{u}_{k+1}\notin\operatorname{span}\{\vec{u}_1,\cdots,\vec{u}_k\}$$

Then from Lemma 9.3.2, $\{\vec{u}_1,\cdots,\vec{u}_k,\vec{u}_{k+1}\}$ is also linearly independent. Continue adding vectors in this way until n linearly independent vectors have been obtained. Then

$$\operatorname{span}\{\vec{u}_1,\cdots,\vec{u}_n\}=V$$

because if it did not do so, there would exist $\vec{u}_{n+1}$ as just described and $\{\vec{u}_1,\cdots,\vec{u}_{n+1}\}$ would be a linearly independent set of vectors having $n+1$ elements. This contradicts the fact that $\{\vec{v}_1,\cdots,\vec{v}_n\}$ is a basis. In turn this would contradict Theorem 5.4.3. Therefore, this list is a basis.

Theorem 5.4.7**: Basis from a Spanning Set**

Let S denote the set of positive integers such that for $k\in S$, there exists a subset of $\{\vec{w}_1,\cdots,\vec{w}_m\}$ consisting of exactly k vectors which is a spanning set for W. Thus $m\in S$. Pick the smallest positive integer in S. Call it k. Then there exists $\{\vec{u}_1,\cdots,\vec{u}_k\}\subseteq\{\vec{w}_1,\cdots,\vec{w}_m\}$ such that $span\{\vec{u}_1,\cdots,\vec{u}_k\}=W$. If

$$\sum_{i=1}^{k}c_i\vec{w}_i=\vec{0}$$

and not all of the $c_i=0$, then you could pick $c_j\neq 0$, divide by it and solve for $\vec{u}_j$ in terms of the others.

$$\vec{w}_j=\sum_{i\neq j}\left(-\frac{c_i}{c_j}\right)\vec{w}_i$$

Then you could delete $\vec{w}_j$ from the list and have the same span. In any linear combination involving $\vec{w}_j$, the linear combination would equal one in which $\vec{w}_j$ is replaced with the above sum, showing that it could have been obtained as a linear combination of $\vec{w}_i$ for $i\neq j$. Thus $k-1\in S$ contrary to the choice of k. Hence each $c_i=0$ and so $\{\vec{u}_1,\cdots,\vec{u}_k\}$ is a basis for W consisting of vectors of $\{\vec{w}_1,\cdots,\vec{w}_m\}$.

Theorem 5.4.8**: Basis of a Vector Space**

Let the dimension of V be n. Pick $\vec{w}_1 \in W$ where $\vec{w}_1 \neq \vec{0}$. If $\vec{w}_1, \cdots, \vec{w}_s$ have been chosen such that $\{\vec{w}_1, \cdots, \vec{w}_s\}$ is linearly independent, if $span\{\vec{w}_1, \cdots, \vec{w}_r\} = W$, stop. You have the desired basis. Otherwise, there exists $\vec{w}_{s+1} \notin span\{\vec{w}_1, \cdots, \vec{w}_s\}$ and $\{\vec{w}_1, \cdots, \vec{w}_s, \vec{w}_{s+1}\}$ is linearly independent. Continue this way until the process stops. It must stop since otherwise, you could obtain a linearly independent set of vectors having more than n vectors which is impossible.

The last claim is proved by following the above procedure starting with $\{\vec{w}_1, \cdots, \vec{w}_s\}$ as above.

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5.5: Sums and Intersections

Outcomes

A. Show that the sum of two subspaces is a subspace.
B. Show that the intersection of two subspaces is a subspace.

We begin this section with a definition.

Definition 5.5.1: Sum and Intersection

Let V be a vector space, and let U and W be subspaces of V. Then

1. $U+W=\{\vec{u}+\vec{w} \mid \vec{u} \in U \text{ and } \vec{w} \in W\}$ and is called the sum of U and W.
2. $U \cap W=\{\vec{v} \mid \vec{v} \in U \text{ and } \vec{v} \in W\}$ and is called the intersection of U and W.

Therefore the intersection of two subspaces is all the vectors shared by both. If there are no vectors shared by both subspaces, meaning that $U \cap W=\left\{\vec{0}\right\}$, the sum $U+W$ takes on a special name.

Definition 5.5.2: Direct Sum

Let V be a vector space and suppose U and W are subspaces of V such that $U \cap W=\left\{\vec{0}\right\}$. Then the sum of U and W is called the direct sum and is denoted $U \oplus W$.

An interesting result is that both the sum $U+W$ and the intersection $U \cap W$ are subspaces of V.

Example 5.5.1: Intersection is a Subspace

Let V be a vector space and suppose U and W are subspaces. Then the intersection $U \cap W$ is a subspace of V.

Solution

By the subspace test, we must show three things:

1. $\vec{0} \in U \cap W$
2. For vectors $\vec{v}_1, \vec{v}_2 \in U \cap W, \vec{v}_1+\vec{v}_2 \in U \cap W$
3. For scalar a and vector $\vec{v} \in U \cap W, a\vec{v} \in U \cap W$

We proceed to show each of these three conditions hold.

1. Since U and W are subspaces of V, they each contain $\vec{0}$. By definition of the intersection, $\vec{0} \in U \cap W$.
2. Let $\vec{v}_1, \vec{v}_2 \in U \cap W$,. Then in particular, $\vec{v}_1, \vec{v}_2 \in U$. Since U is a subspace, it follows that $\vec{v}_1+\vec{v}_2 \in U$. The same argument holds for W. Therefore $\vec{v}_1+\vec{v}_2$ is in both U and W and by definition is also in $U \cap W$.
3. Let a be a scalar and $\vec{v} \in U \cap W$. Then in particular, $\vec{v} \in U$. Since U is a subspace, it follows that $a\vec{v} \in U$. The same argument holds for W so $a\vec{v}$ is in both U and W. By definition, it is in $U \cap W$.

Therefore $U \cap W$ is a subspace of V.

It can also be shown that $U+W$ is a subspace of V.

We conclude this section with an important theorem on dimension.

Theorem 5.5.1: Dimension of Sum

Let V be a vector space with subspaces U and W. Suppose U and W each have finite dimension. Then $U+W$ also has finite dimension which is given by

$$\dim(U+W)=\dim(U)+\dim(W)-\dim(U\cap W)$$

Notice that when $U\cap W=\left\{\vec{0}\right\}$, the sum becomes the direct sum and the above equation becomes

$$\dim(U\oplus W)=\dim(U)+\dim(W)$$

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5.6: Linear Transformations

Outcomes

A. Understand the definition of a linear transformation in the context of vector spaces.

Recall that a function is simply a transformation of a vector to result in a new vector. Consider the following definition.

Definition 5.6.1: Linear Transformation

Let V and W be vector spaces. Suppose $T : V \mapsto W$ is a function, where for each $\vec{x} \in V, T(\vec{x}) \in W$. Then T is a **linear transformation** if whenever k, p are scalars and $\vec{v}_1$ and $\vec{v}_2$ are vectors in V

$$T(k\vec{v}_1 + p\vec{v}_2) = kT(\vec{v}_1) + pT(\vec{v}_2)$$

Several important examples of linear transformations include the zero transformation, the identity transformation, and the scalar transformation.

Example 5.6.1: Linear Transformations

Let V and W be vector spaces.

1. **The zero transformation**
   $0 : V \to W$ is defined by $0(\vec{v}) = \vec{0}$ for all $\vec{v} \in V$.
2. **The identity transformation**
   $1_V : V \to V$ is defined by $1_V(\vec{v}) = \vec{v}$ for all $\vec{v} \in V$.
3. **The scalar transformation** Let $a \in \mathbb{R}$.
   $s_a : V \to V$ is defined by $s_a(\vec{v}) = a\vec{v}$ for all $\vec{v} \in V$.

Solution

We will show that the scalar transformation s_a is linear, the rest are left as an exercise.

By Definition 5.6.1 we must show that for all scalars k, p and vectors $\vec{v}_1$ and $\vec{v}_2$ in V, $s_a(k\vec{v}_1 + p\vec{v}_2) = ks_a(\vec{v}_1) + ps_a(\vec{v}_2)$. Assume that a is also a scalar.

$$\begin{aligned} s_a(k\vec{v}_1 + p\vec{v}_2) &= a(k\vec{v}_1 + p\vec{v}_2) \\ &= ak\vec{v}_1 + ap\vec{v}_2 \\ &= k(a\vec{v}_1) + p(a\vec{v}_2) \\ &= ks_a(\vec{v}_1) + ps_a(\vec{v}_2) \end{aligned} \tag{5.6.1}$$

Therefore s_a is a linear transformation.

Consider the following important theorem.

Theorem 5.6.1: Properties of Linear Transformations

Let V and W be vector spaces, and $T : V \mapsto W$ a linear transformation. Then

1. T preserves the zero vector.

$$T(\vec{0}) = \vec{0}$$

2. T preserves additive inverses. For all $\vec{v} \in V$,
$$T(-\vec{v}) = -T(\vec{v})$$
3. T preserves linear combinations. For all $\vec{v}_1, \vec{v}_2, \ldots, \vec{v}_m \in V$ and all $k_1, k_2, \ldots, k_m \in \mathbb{R}$,
$$T(k_1\vec{v}_1 + k_2\vec{v}_2 + \cdots + k_m\vec{v}_m) = k_1T(\vec{v}_1) + k_2T(\vec{v}_2) + \cdots + k_mT(\vec{v}_m).$$

Proof available at the end of this section.

Consider the following example using the above theorem.

Example 5.6.2: Linear Combination

Let $T : \mathbb{P}_2 \to \mathbb{R}$ be a linear transformation such that
$$T(x^2 + x) = -1; T(x^2 - x) = 1; T(x^2 + 1) = 3.$$
Find $T(4x^2 + 5x - 3)$.

We provide two solutions to this problem.

Solution 1:

Suppose $a(x^2 + x) + b(x^2 - x) + c(x^2 + 1) = 4x^2 + 5x - 3$. Then
$$(a + b + c)x^2 + (a - b)x + c = 4x^2 + 5x - 3.$$
Solving for a, b, and c results in the unique solution $a = 6$, $b = 1$, $c = -3$. Thus
$$\begin{aligned} T(4x^2 + 5x - 3) &= T(6(x^2 + x) + (x^2 - x) - 3(x^2 + 1)) \\ &= 6T(x^2 + x) + T(x^2 - x) - 3T(x^2 + 1) \\ &= 6(-1) + 1 - 3(3) = -14. \end{aligned} \tag{5.6.2}$$

Solution 2:

Notice that $S = \{x^2 + x, x^2 - x, x^2 + 1\}$ is a basis of $\mathbb{P}_2$, and thus x^2, x, and 1 can each be written as a linear combination of elements of S.
$$\begin{aligned} x^2 &= \tfrac{1}{2}(x^2 + x) + \tfrac{1}{2}(x^2 - x) \\ x &= \tfrac{1}{2}(x^2 + x) - \tfrac{1}{2}(x^2 - x) \\ 1 &= (x^2 + 1) - \tfrac{1}{2}(x^2 + x) - \tfrac{1}{2}(x^2 - x). \end{aligned} \tag{5.6.3}$$
Then
$$\begin{aligned} T(x^2) &= T\left(\tfrac{1}{2}(x^2 + x) + \tfrac{1}{2}(x^2 - x)\right) = \tfrac{1}{2}T(x^2 + x) + \tfrac{1}{2}T(x^2 - x) \\ &= \tfrac{1}{2}(-1) + \tfrac{1}{2}(1) = 0. \\ T(x) &= T\left(\tfrac{1}{2}(x^2 + x) - \tfrac{1}{2}(x^2 - x)\right) = \tfrac{1}{2}T(x^2 + x) - \tfrac{1}{2}T(x^2 - x) \\ &= \tfrac{1}{2}(-1) - \tfrac{1}{2}(1) = -1. \\ T(1) &= T\left((x^2 + 1) - \tfrac{1}{2}(x^2 + x) - \tfrac{1}{2}(x^2 - x)\right) \\ &= T(x^2 + 1) - \tfrac{1}{2}T(x^2 + x) - \tfrac{1}{2}T(x^2 - x) \\ &= 3 - \tfrac{1}{2}(-1) - \tfrac{1}{2}(1) = 3. \end{aligned} \tag{5.6.4}$$
Therefore,
$$\begin{aligned} T(4x^2 + 5x - 3) &= 4T(x^2) + 5T(x) - 3T(1) \\ &= 4(0) + 5(-1) - 3(3) = -14. \end{aligned} \tag{5.6.5}$$
The advantage of **Solution 2** over **Solution 1** is that if you were now asked to find $T(-6x^2 - 13x + 9)$, it is easy to use $T(x^2) = 0$, $T(x) = -1$ and $T(1) = 3$:
$$\begin{aligned} T(-6x^2 - 13x + 9) &= -6T(x^2) - 13T(x) + 9T(1) \\ &= -6(0) - 13(-1) + 9(3) = 13 + 27 = 40. \end{aligned} \tag{5.6.6}$$

More generally,

$$\begin{aligned} T(ax^2+bx+c) &= aT(x^2)+bT(x)+cT(1) \\ &= a(0)+b(-1)+c(3) = -b+3c. \end{aligned} \tag{5.6.7}$$

Suppose two linear transformations act in the same way on $\vec{v}$ for all vectors. Then we say that these transformations are equal.

Definition 5.6.2: Equal Transformations

Let S and T be linear transformations from V to W. Then $S = T$ if and only if for every $\vec{v} \in V$,

$$S(\vec{v}) = T(\vec{v})$$

The definition above requires that two transformations have the same action on every vector in order for them to be equal. The next theorem argues that it is only necessary to check the action of the transformations on basis vectors.

Theorem 5.6.2: Transformation of a Spanning Set

Let V and W be vector spaces and suppose that S and T are linear transformations from V to W. Then in order for S and T to be equal, it suffices that $S(\vec{v}_i) = T(\vec{v}_i)$ where $V = span\{\vec{v}_1, \vec{v}_2, \ldots, \vec{v}_n\}$.

This theorem tells us that a linear transformation is completely determined by its actions on a spanning set. We can also examine the effect of a linear transformation on a basis.

Theorem 5.6.3: Transformation of a Basis

Suppose V and W are vector spaces and let $\{\vec{w}_1, \vec{w}_2, \ldots, \vec{w}_n\}$ be any given vectors in W that may not be distinct. Then there exists a basis $\{\vec{v}_1, \vec{v}_2, \ldots, \vec{v}_n\}$ of V and a unique linear transformation $T : V \mapsto W$ with $T(\vec{v}_i) = \vec{w}_i$.

Furthermore, if

$$\vec{v} = k_1\vec{v}_1 + k_2\vec{v}_2 + \cdots + k_n\vec{v}_n$$

is a vector of V, then

$$T(\vec{v}) = k_1\vec{w}_1 + k_2\vec{w}_2 + \cdots + k_n\vec{w}_n.$$

Answers

Theorem 5.6.1: Properties of Linear Transformations

1. Let $\vec{0}_V$ denote the zero vector of V and let $\vec{0}_W$ denote the zero vector of W. We want to prove that $T(\vec{0}_V) = \vec{0}_W$. Let $\vec{v} \in V$. Then $0\vec{v} = \vec{0}_V$ and
$$T(\vec{0}_V) = T(0\vec{v}) = 0T(\vec{v}) = \vec{0}_W.$$
2. Let $\vec{v} \in V$; then $-\vec{v} \in V$ is the additive inverse of $\vec{v}$, so $\vec{v} + (-\vec{v}) = \vec{0}_V$. Thus
$$\begin{aligned} T(\vec{v}+(-\vec{v})) &= T(\vec{0}_V) \\ T(\vec{v})+T(-\vec{v})) &= \vec{0}_W \\ T(-\vec{v}) &= \vec{0}_W - T(\vec{v}) = -T(\vec{v}). \end{aligned} \tag{5.6.8}$$
3. This result follows from preservation of addition and preservation of scalar multiplication. A formal proof would be by induction on m.

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5.7: Isomorphisms

Outcomes

A. Apply the concepts of one to one and onto to transformations of vector spaces.
B. Determine if a linear transformation of vector spaces is an isomorphism.
C. Determine if two vector spaces are isomorphic.

One to One and Onto Transformations

Recall the following definitions, given here in terms of vector spaces.

Definition 5.7.1: One to One Transformation

Let V, W be vector spaces with $\vec{v}_1, \vec{v}_2$ vectors in V. Then a linear transformation $T : V \mapsto W$ is called **one to one** if whenever $\vec{v}_1 \neq \vec{v}_2$ it follows that

$$T(\vec{v}_1) \neq T(\vec{v}_2)$$

Definition 5.7.2: Onto Transformation

Let V, W be vector spaces. Then a linear transformation $T : V \mapsto W$ is called **onto** if for all $\vec{w} \in \vec{W}$ there exists $\vec{v} \in V$ such that $T(\vec{v}) = \vec{w}$.

Recall that every linear transformation T has the property that $T(\vec{0}) = \vec{0}$. This will be necessary to prove the following useful lemma.

Lemma 5.7.1: One to One

The assertion that a linear transformation T is one to one is equivalent to saying that if $T(\vec{v}) = \vec{0}$, then $\vec{v} = 0$.

Proof available at the end of this section.

Consider the following example.

Example 5.7.1: One to One Transformation

Let $S : \mathbb{P}_2 \to \mathbb{M}_{22}$ be a linear transformation defined by

$$S(ax^2 + bx + c) = \begin{bmatrix} a+b & a+c \\ b-c & b+c \end{bmatrix}$$

for all $ax^2 + bx + c \in \mathbb{P}_2$.

Prove that S is one to one but not onto.

Solution

By definition,

$$\ker(S) = \{ax^2 + bx + c \in \mathbb{P}_2 \mid a + b = 0, a + c = 0, b - c = 0, b + c = 0\}.$$

Suppose $p(x) = ax^2 + bx + c \in \ker(S)$. This leads to a homogeneous system of four equations in three variables. Putting the augmented matrix in reduced row-echelon form:

$$\begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 1 & 1 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

The solution is $a = b = c = 0$. This tells us that if $S(p(x)) = 0$, then $p(x) = ax^2 + bx + c = 0x^2 + 0x + 0 = 0$. Therefore it is one to one.

To show that S is **not** onto, find a matrix $A \in \mathbb{M}_{22}$ such that for every $p(x) \in \mathbb{P}_2$, $S(p(x)) \neq A$. Let

$$A = \begin{bmatrix} 0 & 1 \\ 0 & 2 \end{bmatrix},$$

and suppose $p(x) = ax^2 + bx + c \in \mathbb{P}_2$ is such that $S(p(x)) = A$. Then

$$\begin{array}{ll} a + b = 0 & a + c = 1 \\ b - c = 0 & b + c = 2 \end{array}$$

Solving this system

$$\begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & -1 & 0 \\ 0 & 1 & 1 & 2 \end{bmatrix} \to \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & -1 & 1 & 1 \\ 0 & 1 & -1 & 0 \\ 0 & 1 & 1 & 2 \end{bmatrix}.$$

Since the system is inconsistent, there is no $p(x) \in \mathbb{P}_2$ so that $S(p(x)) = A$, and therefore S is not onto.

Example 5.7.2: An Onto Transformation

Let $T : \mathbb{M}_{22} \to \mathbb{R}^2$ be a linear transformation defined by

$$T \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} a + d \\ b + c \end{bmatrix} \text{ for all } \begin{bmatrix} a & b \\ c & d \end{bmatrix} \in \mathbb{M}_{22}.$$

Prove that T is onto but not one to one.

Solution

Let $\begin{bmatrix} x \\ y \end{bmatrix}$ be an arbitrary vector in $\mathbb{R}^2$. Since $T \begin{bmatrix} x & y \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix}$, T is onto.

By Lemma 5.7.1 T is one to one if and only if $T(A) = \vec{0}$ implies that $A = 0$ the zero matrix. Observe that

$$T\left(\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \right) = \begin{bmatrix} 1 + -1 \\ 0 + 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

There exists a nonzero matrix A such that $T(A) = \vec{0}$. It follows that T is not one to one.

The following example demonstrates that a one to one transformation preserves linear independence.

Example 5.7.3: One to One and Independence

Let V and W be vector spaces and $T : V \mapsto W$ a linear transformation. Prove that if T is one to one and $\{\vec{v}_1, \vec{v}_2, \ldots, \vec{v}_k\}$ is an independent subset of V, then $\{T(\vec{v}_1), T(\vec{v}_2), \ldots, T(\vec{v}_k)\}$ is an independent subset of W.

Solution

Let $\vec{0}_V$ and $\vec{0}_W$ denote the zero vectors of V and W, respectively. Suppose that

$$a_1T(\vec{v}_1) + a_2T(\vec{v}_2) + \cdots + a_kT(\vec{v}_k) = \vec{0}_W$$

for some $a_1, a_2, \ldots, a_k \in \mathbb{R}$. Since linear transformations preserve linear combinations (addition and scalar multiplication),

$$T(a_1\vec{v}_1 + a_2\vec{v}_2 + \cdots + a_k\vec{v}_k) = \vec{0}_W.$$

Now, since T is one to one, $\ker(T) = \{\vec{0}_V\}$, and thus

$$a_1\vec{v}_1 + a_2\vec{v}_2 + \cdots + a_k\vec{v}_k = \vec{0}_V.$$

However, $\{\vec{v}_1, \vec{v}_2, \ldots, \vec{v}_k\}$ is independent so $a_1 = a_2 = \cdots = a_k = 0$. Therefore, $\{T(\vec{v}_1), T(\vec{v}_2), \ldots, T(\vec{v}_k)\}$ is independent.

A similar claim can be made regarding onto transformations. In this case, an onto transformation preserves a spanning set.

Example 5.7.4: Onto and Spanning

Let V and W be vector spaces and $T : V \to W$ a linear transformation. Prove that if T is onto and $V = span\{\vec{v}_1, \vec{v}_2, \ldots, \vec{v}_k\}$, then

$$W = span\{T(\vec{v}_1), T(\vec{v}_2), \ldots, T(\vec{v}_k)\}.$$

Solution

Suppose that T is onto and let $\vec{w} \in W$. Then there exists $\vec{v} \in V$ such that $T(\vec{v}) = \vec{w}$. Since $V = span\{\vec{v}_1, \vec{v}_2, \ldots, \vec{v}_k\}$, there exist $a_1, a_2, \ldots a_k \in \mathbb{R}$ such that $\vec{v} = a_1\vec{v}_1 + a_2\vec{v}_2 + \cdots + a_k\vec{v}_k$. Using the fact that T is a linear transformation,

$$\begin{aligned} \vec{w} = T(\vec{v}) &= T(a_1\vec{v}_1 + a_2\vec{v}_2 + \cdots + a_k\vec{v}_k) \\ &= a_1T(\vec{v}_1) + a_2T(\vec{v}_2) + \cdots + a_kT(\vec{v}_k), \end{aligned} \tag{5.7.1}$$

i.e., $\vec{w} \in span\{T(\vec{v}_1), T(\vec{v}_2), \ldots, T(\vec{v}_k)\}$, and thus

$$W \subseteq span\{T(\vec{v}_1), T(\vec{v}_2), \ldots, T(\vec{v}_k)\}.$$

Since $T(\vec{v}_1), T(\vec{v}_2), \ldots, T(\vec{v}_k) \in W$, it follows from that $span\{T(\vec{v}_1), T(\vec{v}_2), \ldots, T(\vec{v}_k)\} \subseteq W$, and therefore $W = span\{T(\vec{v}_1), T(\vec{v}_2), \ldots, T(\vec{v}_k)\}$.

Isomorphisms

The focus of this section is on linear transformations which are both one to one and onto. When this is the case, we call the transformation an isomorphism.

Definition 5.7.3: Isomorphism

Let V and W be two vector spaces and let $T : V \mapsto W$ be a linear transformation. Then T is called an **isomorphism** if the following two conditions are satisfied.

- T is one to one.
- T is onto.

Definition 5.7.4: Isomorphic

Let V and W be two vector spaces and let $T : V \mapsto W$ be a linear transformation. Then if T is an isomorphism, we say that V and W are **isomorphic.**

Consider the following example of an isomorphism.

Example 5.7.5: Isomorphism

Let $T : \mathbb{M}_{22} \to \mathbb{R}^4$ be defined by

$$T\begin{pmatrix} a & b \\ c & d \end{pmatrix} = \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \text{ for all } \begin{bmatrix} a & b \\ c & d \end{bmatrix} \in \mathbb{M}_{22}.$$

Show that T is an isomorphism.

Solution

Notice that if we can prove T is an isomorphism, it will mean that $\mathbb{M}_{22}$ and $\mathbb{R}^4$ are isomorphic. It remains to prove that

1. T is a linear transformation;
2. T is one-to-one;
3. T is onto.

T is linear: Let k, p be scalars.

$$\begin{aligned} T\left(k\begin{bmatrix} a_1 & b_1 \\ c_1 & d_1 \end{bmatrix} + p\begin{bmatrix} a_2 & b_2 \\ c_2 & d_2 \end{bmatrix}\right) &= T\left(\begin{bmatrix} ka_1 & kb_1 \\ kc_1 & kd_1 \end{bmatrix} + \begin{bmatrix} pa_2 & pb_2 \\ pc_2 & pd_2 \end{bmatrix}\right) \\ &= T\left(\begin{bmatrix} ka_1 + pa_2 & kb_1 + pb_2 \\ kc_1 + pc_2 & kd_1 + pd_2 \end{bmatrix}\right) \\ &= \begin{bmatrix} ka_1 + pa_2 \\ kb_1 + pb_2 \\ kc_1 + pc_2 \\ kd_1 + pd_2 \end{bmatrix} \\ &= \begin{bmatrix} ka_1 \\ kb_1 \\ kc_1 \\ kd_1 \end{bmatrix} + \begin{bmatrix} pa_2 \\ pb_2 \\ pc_2 \\ pd_2 \end{bmatrix} \\ &= k\begin{bmatrix} a_1 \\ b_1 \\ c_1 \\ d_1 \end{bmatrix} + p\begin{bmatrix} a_2 \\ b_2 \\ c_2 \\ d_2 \end{bmatrix} \\ &= kT\left(\begin{bmatrix} a_1 & b_1 \\ c_1 & d_1 \end{bmatrix}\right) + pT\left(\begin{bmatrix} a_2 & b_2 \\ c_2 & d_2 \end{bmatrix}\right) \end{aligned} \tag{5.7.2}$$

Therefore T is linear.

T is one-to-one: By Lemma 5.7.1 we need to show that if $T(A) = 0$ then $A = 0$ for some matrix $A \in \mathbb{M}_{22}$.

$$T\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

This clearly only occurs when $a = b = c = d = 0$ which means that

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = 0$$

Hence T is one-to-one.

T is onto: Let

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \in \mathbb{R}^4,$$

and define matrix $A \in \mathbb{M}_{22}$ as follows:

$$A = \begin{bmatrix} x_1 & x_2 \\ x_3 & x_4 \end{bmatrix}.$$

Then $T(A) = \vec{x}$, and therefore T is onto.

Since T is a linear transformation which is one-to-one and onto, T is an isomorphism. Hence $\mathbb{M}_{22}$ and $\mathbb{R}^4$ are isomorphic.

An important property of isomorphisms is that the inverse of an isomorphism is itself an isomorphism and the composition of isomorphisms is an isomorphism. We first recall the definition of composition.

Definition 5.7.5: Composition of Transformations

Let V, W, Z be vector spaces and suppose $T : V \mapsto W$ and $S : W \mapsto Z$ are linear transformations. Then the composite of S and T is

$$S \circ T : V \mapsto Z$$

and is defined by

$$(S \circ T)(\vec{v}) = S(T(\vec{v})) \text{ for all } \vec{v} \in V$$

Consider now the following proposition.

Proposition 5.7.1: Composite and Inverse Isomorphism

Let $T : V \to W$ be an isomorphism. Then $T^{-1} : W \to V$ is also an isomorphism. Also if $T : V \to W$ is an isomorphism and if $S : W \to Z$ is an isomorphism for the vector spaces V, W, Z, then $S \circ T$ defined by $(S \circ T)(v) = S(T(v))$ is also an isomorphism.

Proof available at the end of this section.

Suppose we say that two vector spaces V and W are related if there exists an isomorphism of one to the other, written as $V \sim W$. Then the above proposition suggests that $\sim$ is an equivalence relation. That is: $\sim$ satisfies the following conditions:

- $V \sim V$
- If $V \sim W$, it follows that $W \sim V$
- If $V \sim W$ and $W \sim Z$, then $V \sim Z$

We leave the proof of these to the reader.

The following fundamental lemma describes the relation between bases and isomorphisms.

Lemma 5.7.2: Bases and Isomorphisms

Let $T : V \to W$ be a linear map where V, W are vector spaces. Then a linear transformation T which is one to one has the property that if $\{\vec{u}_1, \cdots, \vec{u}_k\}$ is linearly independent, then so is $\{T(\vec{u}_1), \cdots, T(\vec{u}_k)\}$. More generally, T is an isomorphism if and only if whenever $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a basis for V, it follows that $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ is a basis for W.

Proof available at the end of this section.

The following theorem illustrates a very useful idea for defining an isomorphism. Basically, if you know what it does to a basis, then you can construct the isomorphism.

Theorem 5.7.1: Isomorphic Vector Spaces

Suppose V and W are two vector spaces. Then the two vector spaces are isomorphic if and only if they have the same dimension. In the case that the two vector spaces have the same dimension, then for a linear transformation $T : V \to W$, the following are equivalent.

1. T is one to one.
2. T is onto.
3. T is an isomorphism.

Proof available at the end of this section.

Note the interesting way of defining a linear transformation in the first part of the argument by describing what it does to a basis and then "extending it linearly".

Consider the following example.

Example 5.7.6

Let $V = \mathbb{R}^3$ and let W denote the polynomials of degree at most 2. Show that these two vector spaces are isomorphic.

Solution

First, observe that a basis for W is $\{1, x, x^2\}$ and a basis for V is $\{\vec{e}_1, \vec{e}_2, \vec{e}_3\}$. Since these two have the same dimension, the two are isomorphic. An example of an isomorphism is this:

$$T(\vec{e}_1) = 1, T(\vec{e}_2) = x, T(\vec{e}_3) = x^2$$

and extend T linearly as in the above proof. Thus

$$T(a, b, c) = a + bx + cx^2$$

Answers

Lemma 5.7.1: One to One

Suppose first that T is one to one.

$$T(\vec{0}) = T\left(\vec{0} + \vec{0}\right) = T(\vec{0}) + T(\vec{0})$$

and so, adding the additive inverse of $T(\vec{0})$ to both sides, one sees that $T(\vec{0}) = \vec{0}$. Therefore, if $T(\vec{v}) = \vec{0}$, it must be the case that $\vec{v} = \vec{0}$ because it was just shown that $T(\vec{0}) = \vec{0}$.

Now suppose that if $T(\vec{v}) = \vec{0}$, then $\vec{v} = 0$. If $T(\vec{v}) = T(\vec{u})$, then $T(\vec{v}) - T(\vec{u}) = T(\vec{v} - \vec{u}) = \vec{0}$ which shows that $\vec{v} - \vec{u} = 0$ or in other words, $\vec{v} = \vec{u}$.

Proposition 5.7.1: Composite and Inverse Isomorphism

Consider the first claim. Since T is onto, a typical vector in W is of the form $T(\vec{v})$ where $\vec{v} \in V$. Consider then for a, b scalars,

$$T^{-1}(aT(\vec{v}_1) + bT(\vec{v}_2))$$

where $\vec{v}_1, \vec{v}_2 \in V$. Consider if this is equal to

$$aT^{-1}(T(\vec{v}_1)) + bT^{-1}(T(\vec{v}_2)) = a\vec{v}_1 + b\vec{v}_2?$$

Since T is one to one, this will be so if

$$T(a\vec{v}_1 + b\vec{v}_2) = T\left(T^{-1}(aT(\vec{v}_1) + bT(\vec{v}_2))\right) = aT(\vec{v}_1) + bT(\vec{v}_2)$$

However, the above statement is just the condition that T is a linear map. Thus T^{-1} is indeed a linear map. If $\vec{v} \in V$ is given, then $\vec{v} = T^{-1}(T(\vec{v}))$ and so T^{-1} is onto. If $T^{-1}(\vec{v}) = \vec{0}$, then

$$\vec{v} = T\left(T^{-1}(\vec{v})\right) = T(\vec{0}) = \vec{0}$$

and so T^{-1} is one to one.

Next suppose T and S are as described. Why is $S \circ T$ a linear map? Let for a, b scalars,

$$\begin{aligned} S\circ T\left(a\vec{v}_1+b\vec{v}_2\right) &\equiv S\left(T\left(a\vec{v}_1+b\vec{v}_2\right)\right)=S\left(aT(\vec{v}_1)+bT(\vec{v}_2)\right) \\ &= aS\left(T(\vec{v}_1)\right)+bS\left(T(\vec{v}_2)\right)\equiv a\left(S\circ T\right)(\vec{v}_1)+b\left(S\circ T\right)(\vec{v}_2) \end{aligned} \tag{5.7.3}$$

Hence $S\circ T$ is a linear map. If $(S\circ T)(\vec{v})=0$, then $S\left(T\left(\vec{v}\right)\right)=\vec{0}$ and it follows that $T(\vec{v})=\vec{0}$ and hence by this lemma again, $\vec{v}=\vec{0}$. Thus $S\circ T$ is one to one. It remains to verify that it is onto. Let $\vec{z}\in Z$. Then since S is onto, there exists $\vec{w}\in W$ such that $S(\vec{w})=\vec{z}$. Also, since T is onto, there exists $\vec{v}\in V$ such that $T(\vec{v})=\vec{w}$. It follows that $S\left(T\left(\vec{v}\right)\right)=\vec{z}$ and so $S\circ T$ is also onto.

Lemma 5.7.2**: Bases and Isomorphisms**

First suppose that T is a linear map and is one to one and $\{\vec{u}_1,\cdots,\vec{u}_k\}$ is linearly independent. It is required to show that $\{T(\vec{u}_1),\cdots,T(\vec{u}_k)\}$ is also linearly independent. Suppose then that

$$\sum_{i=1}^{k}c_iT(\vec{u}_i)=\vec{0}$$

Then, since T is linear,

$$T\left(\sum_{i=1}^{n}c_i\vec{u}_i\right)=\vec{0}$$

Since T is one to one, it follows that

$$\sum_{i=1}^{n}c_i\vec{u}_i=0$$

Now the fact that $\{\vec{u}_1,\cdots,\vec{u}_n\}$ is linearly independent implies that each $c_i=0$. Hence $\{T(\vec{u}_1),\cdots,T(\vec{u}_n)\}$ is linearly independent.

Now suppose that T is an isomorphism and $\{\vec{v}_1,\cdots,\vec{v}_n\}$ is a basis for V. It was just shown that $\{T(\vec{v}_1),\cdots,T(\vec{v}_n)\}$ is linearly independent. It remains to verify that the span of $\{T(\vec{v}_1),\cdots,T(\vec{v}_n)\}$ is all of W. This is where T is onto is used. If $\vec{w}\in W$, there exists $\vec{v}\in V$ such that $T(\vec{v})=\vec{w}$. Since $\{\vec{v}_1,\cdots,\vec{v}_n\}$ is a basis, it follows that there exists scalars $\{c_i\}_{i=1}^{n}$ such that

$$\sum_{i=1}^{n}c_i\vec{v}_i=\vec{v}.$$

Hence,

$$\vec{w}=T(\vec{v})=T\left(\sum_{i=1}^{n}c_i\vec{v}_i\right)=\sum_{i=1}^{n}c_iT\vec{v}_i$$

which shows that the span of these vectors $\{T(\vec{v}_1),\cdots,T(\vec{v}_n)\}$ is all of W showing that this set of vectors is a basis for W.

Next suppose that T is a linear map which takes a basis to a basis. Then for $\{\vec{v}_1,\cdots,\vec{v}_n\}$ a basis for V, it follows $\{T(\vec{v}_1),\cdots,T(\vec{v}_n)\}$ is a basis for W. Then if $w\in W$, there exist scalars c_i such that $w=\sum_{i=1}^{n}c_iT(\vec{v}_i)=T\left(\sum_{i=1}^{n}c_i\vec{v}_i\right)$ showing that T is onto. If $T\left(\sum_{i=1}^{n}c_i\vec{v}_i\right)=0$ then $\sum_{i=1}^{n}c_iT(\vec{v}_i)=\vec{0}$ and since the vectors $\{T(\vec{v}_1),\cdots,T(\vec{v}_n)\}$ are linearly independent, it follows that each $c_i=0$. Since $\sum_{i=1}^{n}c_i\vec{v}_i$ is a typical vector in V, this has shown that if $T(\vec{v})=0$ then $\vec{v}=\vec{0}$ and so T is also one to one. Thus T is an isomorphism.

Theorem 5.7.1**: Isomorphic Vector Spaces**

Suppose first these two vector spaces have the same dimension. Let a basis for V be $\{\vec{v}_1,\cdots,\vec{v}_n\}$ and let a basis for W be $\{\vec{w}_1,\cdots,\vec{w}_n\}$. Now define T as follows.

$$T(\vec{v}_i)=\vec{w}_i$$

for $\sum_{i=1}^{n}c_i\vec{v}_i$ an arbitrary vector of V,

$$T\left(\sum_{i=1}^{n}c_i\vec{v}_i\right)=\sum_{i=1}^{n}c_iT(\vec{v}_i)=\sum_{i=1}^{n}c_i\vec{w}_i.$$

It is necessary to verify that this is well defined. Suppose then that

$$\sum_{i=1}^{n}c_i\vec{v}_i=\sum_{i=1}^{n}\hat{c}_i\vec{v}_i$$

Then

$$\sum_{i=1}^{n}\left(c_i-\hat{c}_i\right)\vec{v}_i=0$$

and since $\{\vec{v}_1,\cdots,\vec{v}_n\}$ is a basis, $c_i=\hat{c}_i$ for each i. Hence

$$\sum_{i=1}^{n}c_i\vec{w}_i=\sum_{i=1}^{n}\hat{c}_i\vec{w}_i$$

and so the mapping is well defined. Also if a,b are scalars,

$$\begin{aligned} T\left(a\sum_{i=1}^{n}c_i\vec{v}_i+b\sum_{i=1}^{n}\hat{c}_i\vec{v}_i\right) &= T\left(\sum_{i=1}^{n}\left(ac_i+b\hat{c}_i\right)\vec{v}_i\right)=\sum_{i=1}^{n}\left(ac_i+b\hat{c}_i\right)\vec{w}_i \\ &= a\sum_{i=1}^{n}c_i\vec{w}_i+b\sum_{i=1}^{n}\hat{c}_i\vec{w}_i \\ &= aT\left(\sum_{i=1}^{n}c_i\vec{v}_i\right)+bT\left(\sum_{i=1}^{n}\hat{c}_i\vec{v}_i\right) \end{aligned} \tag{5.7.4}$$

Thus T is a linear map.

Now if

$$T\left(\sum_{i=1}^{n}c_i\vec{v}_i\right)=\sum_{i=1}^{n}c_i\vec{w}_i=\vec{0},$$

then since the $\{\vec{w}_1,\cdots,\vec{w}_n\}$ are independent, each $c_i=0$ and so $\sum_{i=1}^{n}c_i\vec{v}_i=\vec{0}$ also. Hence T is one to one. If $\sum_{i=1}^{n}c_i\vec{w}_i$ is a vector in W, then it equals

$$\sum_{i=1}^{n} c_i T\vec{v}_i = T\left(\sum_{i=1}^{n} c_i \vec{v}_i\right)$$

showing that T is also onto. Hence T is an isomorphism and so V and W are isomorphic.

Next suppose these two vector spaces are isomorphic. Let T be the name of the isomorphism. Then for $\{\vec{v}_1, \cdots, \vec{v}_n\}$ a basis for V, it follows that a basis for W is $\{T\vec{v}_1, \cdots, T\vec{v}_n\}$ showing that the two vector spaces have the same dimension.

Now suppose the two vector spaces have the same dimension.

First consider the claim that $1.) \Rightarrow 2.)$. If T is one to one, then if $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a basis for V, then $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ is linearly independent. If it is not a basis, then it must fail to span W. But then there would exist $\vec{w} \notin span\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ and it follows that $\{T(\vec{v}_1), \cdots, T(\vec{v}_n), \vec{w}\}$ would be linearly independent which is impossible because there exists a basis for W of n vectors. Hence

$$span\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\} = W$$

and so $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ is a basis. Hence, if $\vec{w} \in W$, there exist scalars c_i such that

$$\vec{w} = \sum_{i=1}^{n} c_i T(\vec{v}_i) = T\left(\sum_{i=1}^{n} c_i \vec{v}_i\right)$$

showing that T is onto. This shows that $1.) \Rightarrow 2.)$.

Next consider the claim that $2.) \Rightarrow 3.)$. Since $2.)$ holds, it follows that T is onto. It remains to verify that T is one to one. Since T is onto, there exists a basis of the form $\{T(\vec{v}_i), \cdots, T(\vec{v}_n)\}$. If $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is linearly independent, then this set of vectors must also be a basis for V because if not, there would exist $\vec{u} \notin span\{\vec{v}_1, \cdots, \vec{v}_n\}$ so $\{\vec{v}_1, \cdots, \vec{v}_n, \vec{u}\}$ would be a linearly independent set which is impossible because by assumption, there exists a basis which has n vectors. So why is $\{\vec{v}_1, \cdots, \vec{v}_n\}$ linearly independent? Suppose

$$\sum_{i=1}^{n} c_i \vec{v}_i = \vec{0}$$

Then

$$\sum_{i=1}^{n} c_i T\vec{v}_i = \vec{0}$$

Hence each $c_i = 0$ and so, as just discussed, $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a basis for V. Now it follows that a typical vector in V is of the form $\sum_{i=1}^{n} c_i \vec{v}_i$. If $T\left(\sum_{i=1}^{n} c_i \vec{v}_i\right) = \vec{0}$, it follows that

$$\sum_{i=1}^{n} c_i T(\vec{v}_i) = \vec{0}$$

and so, since $\{T(\vec{v}_i), \cdots, T(\vec{v}_n)\}$ is independent, it follows each $c_i = 0$ and hence $\sum_{i=1}^{n} c_i \vec{v}_i = \vec{0}$. Thus T is one to one as well as onto and so it is an isomorphism.

If T is an isomorphism, it is both one to one and onto by definition so $3.)$ implies both $1.)$ and $2.)$.

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5.8: The Kernel and Image of a Linear Map

Outcomes

A. Describe the kernel and image of a linear transformation.
B. Use the kernel and image to determine if a linear transformation is one to one or onto.

Here we consider the case where the linear map is not necessarily an isomorphism. First here is a definition of what is meant by the image and kernel of a linear transformation.

Definition 5.8.1: Kernel and Image

Let V and W be vector spaces and let $T : V \to W$ be a linear transformation. Then the image of T denoted as $\mathrm{im}\,(T)$ is defined to be the set

$$\{T(\vec{v}) : \vec{v} \in V\}$$

In words, it consists of all vectors in W which equal $T(\vec{v})$ for some $\vec{v} \in V$. The kernel, $\ker(T)$, consists of all $\vec{v} \in V$ such that $T(\vec{v}) = \vec{0}$. That is,

$$\ker(T) = \left\{\vec{v} \in V : T(\vec{v}) = \vec{0}\right\}$$

Then in fact, both $\mathrm{im}\,(T)$ and $\ker(T)$ are subspaces of W and V respectively.

Proposition 5.8.1: Kernel and Image as Subspaces

Let V, W be vector spaces and let $T : V \to W$ be a linear transformation. Then $\ker(T) \subseteq V$ and $\mathrm{im}\,(T) \subseteq W$. In fact, they are both subspaces.

Proof available at the end of this section.

Consider the following example.

Example 5.8.1: Kernel and Image of a Transformation

Let $T : \mathbb{P}_1 \to \mathbb{R}$ be the linear transformation defined by

$$T(p(x)) = p(1) \text{ for all } p(x) \in \mathbb{P}_1.$$

Find the kernel and image of T.

Solution

We will first find the kernel of T. It consists of all polynomials in $\mathbb{P}_1$ that have 1 for a root.

$$\begin{aligned} \ker(T) &= \{p(x) \in \mathbb{P}_1 \mid p(1) = 0\} \\ &= \{ax + b \mid a, b \in \mathbb{R} \text{ and } a + b = 0\} \\ &= \{ax - a \mid a \in \mathbb{R}\} \end{aligned} \tag{5.8.1}$$

Therefore a basis for $\ker(T)$ is

$$\{x - 1\}$$

Notice that this is a subspace of $\mathbb{P}_1$.

Now consider the image. It consists of all numbers which can be obtained by evaluating all polynomials in $\mathbb{P}_1$ at 1.

$$\begin{aligned} \text{im}(T) &= \{p(1) \mid p(x) \in \mathbb{P}_1\} \\ &= \{a+b \mid ax+b \in \mathbb{P}_1\} \\ &= \{a+b \mid a,b \in \mathbb{R}\} \\ &= \mathbb{R} \end{aligned} \tag{5.8.2}$$

Therefore a basis for $\text{im}(T)$ is

$$\{1\}$$

Notice that this is a subspace of $\mathbb{R}$, and in fact is the space $\mathbb{R}$ itself.

Example 5.8.2: Kernel and Image of a Linear Transformation

Let $T : \mathbb{M}_{22} \mapsto \mathbb{R}^2$ be defined by

$$T\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} a-b \\ c+d \end{bmatrix}$$

Then T is a linear transformation. Find a basis for $\ker(T)$ and $\text{im}(T)$.

Solution

You can verify that T represents a linear transformation.

Now we want to find a way to describe all matrices A such that $T(A) = \vec{0}$, that is the matrices in $\ker(T)$. Suppose $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$ is such a matrix. Then

$$T\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} a-b \\ c+d \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

The values of a, b, c, d that make this true are given by solutions to the system

$$\begin{aligned} a-b &= 0 \\ c+d &= 0 \end{aligned} \tag{5.8.3}$$

The solution is $a = s, b = s, c = t, d = -t$ where s, t are scalars. We can describe $\ker(T)$ as follows.

$$\ker(T) = \left\{\begin{bmatrix} s & s \\ t & -t \end{bmatrix}\right\} = \text{span}\left\{\begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & -1 \end{bmatrix}\right\}$$

It is clear that this set is linearly independent and therefore forms a basis for $\ker(T)$.

We now wish to find a basis for $\text{im}(T)$. We can write the image of T as

$$\text{im}(T) = \left\{\begin{bmatrix} a-b \\ c+d \end{bmatrix}\right\}$$

Notice that this can be written as

$$\text{span}\left\{\begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}\right\}$$

However this is clearly not linearly independent. By removing vectors from the set to create an independent set gives a basis of $\text{im}(T)$.

$$\left\{\begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}\right\}$$

Notice that these vectors have the same span as the set above but are now linearly independent.

A major result is the relation between the dimension of the kernel and dimension of the image of a linear transformation. A special case was done earlier in the context of matrices. Recall that for an $m \times n$ matrix it was the case that the dimension of the

kernel of A added to the rank of A equals n.

Theorem 5.8.1: Dimension of Kernel + Image

Let $T : V \to W$ be a linear transformation where V, W are vector spaces. Suppose the dimension of V is n. Then $n = \dim(\ker(T)) + \dim(\text{im}(T))$.

Proof available at the end of this section.

Consider the following definition.

Definition 5.8.2: Rank of Linear Transformation

Let $T : V \to W$ be a linear transformation and suppose V, W are finite dimensional vector spaces. Then the rank of T denoted as $\text{rank}(T)$ is defined as the dimension of $\text{im}(T)$. The nullity of T is the dimension of $\ker(T)$. Thus the above theorem says that $\text{rank}(T) + \dim(\ker(T)) = \dim(V)$.

Recall the following important result.

Theorem 5.8.2: Subspace of Same Dimension

Let V be a vector space of dimension n and let W be a subspace. Then $W = V$ if and only if the dimension of W is also n.

From this theorem follows the next corollary.

Corollary 5.8.1: One to One and Onto Characterization

Let $T : V \to W$ be a linear map where the dimension of V is n and the dimension of W is m. Then T is one to one if and only if $\ker(T) = \left\{\vec{0}\right\}$ and T is onto if and only if $\text{rank}(T) = m$.

Proof available at the end of this section.

Example 5.8.3: One to One Transformation

Let $S : \mathbb{P}_2 \to \mathbb{M}_{22}$ be a linear transformation defined by

$$S(ax^2 + bx + c) = \begin{bmatrix} a+b & a+c \\ b-c & b+c \end{bmatrix} \text{ for all } ax^2 + bx + c \in \mathbb{P}_2.$$

Prove that S is one to one but not onto.

Solution

You may recall this example from earlier in Example 9.7.1. Here we will determine that S is one to one, but not onto, using the method provided in Corollary 5.8.1.

By definition,

$$\ker(S) = \{ax^2 + bx + c \in \mathbb{P}_2 \mid a + b = 0, a + c = 0, b - c = 0, b + c = 0\}.$$

Suppose $p(x) = ax^2 + bx + c \in \ker(S)$. This leads to a homogeneous system of four equations in three variables. Putting the augmented matrix in reduced row-echelon form:

$$\begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 1 & 1 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

Since the unique solution is $a = b = c = 0$, $\ker(S) = \{\vec{0}\}$, and thus S is one-to-one by Corollary 5.8.1.

Similarly, by Corollary 5.8.1, if S is onto it will have $\text{rank}(S) = \dim(\mathbb{M}_{22}) = 4$. The image of S is given by

$$\text{im}(S) = \left\{ \begin{bmatrix} a+b & a+c \\ b-c & b+c \end{bmatrix} \right\} = \text{span} \left\{ \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ -1 & 1 \end{bmatrix} \right\}$$

These matrices are linearly independent which means this set forms a basis for $\text{im}(S)$. Therefore the dimension of $\text{im}(S)$, also called $\text{rank}(S)$, is equal to 3. It follows that S is not onto.

Answers

Proposition 5.8.1: Kernel and Image as Subspaces

First consider $\ker(T)$. It is necessary to show that if $\vec{v}_1, \vec{v}_2$ are vectors in $\ker(T)$ and if a, b are scalars, then $a\vec{v}_1 + b\vec{v}_2$ is also in $\ker(T)$. But

$$T(a\vec{v}_1 + b\vec{v}_2) = aT(\vec{v}_1) + bT(\vec{v}_2) = a\vec{0} + b\vec{0} = \vec{0}$$

Thus $\ker(T)$ is a subspace of V.

Next suppose $T(\vec{v}_1), T(\vec{v}_2)$ are two vectors in $\text{im}(T)$. Then if a, b are scalars,

$$aT(\vec{v}_2) + bT(\vec{v}_2) = T(a\vec{v}_1 + b\vec{v}_2)$$

and this last vector is in $\text{im}(T)$ by definition.

Theorem 5.8.1: Dimension of Kernel + Image

From Proposition 5.8.1, $\text{im}(T)$ is a subspace of W. By Theorem 9.4.8, there exists a basis for $\text{im}(T), \{T(\vec{v}_1), \cdots, T(\vec{v}_r)\}$. Similarly, there is a basis for $\ker(T), \{\vec{u}_1, \cdots, \vec{u}_s\}$. Then if $\vec{v} \in V$, there exist scalars c_i such that

$$T(\vec{v}) = \sum_{i=1}^{r} c_i T(\vec{v}_i)$$

Hence $T\left(\vec{v} - \sum_{i=1}^{r} c_i \vec{v}_i\right) = 0$. It follows that $\vec{v} - \sum_{i=1}^{r} c_i \vec{v}_i$ is in $\ker(T)$. Hence there are scalars a_i such that

$$\vec{v} - \sum_{i=1}^{r} c_i \vec{v}_i = \sum_{j=1}^{s} a_j \vec{u}_j$$

Hence $\vec{v} = \sum_{i=1}^{r} c_i \vec{v}_i + \sum_{j=1}^{s} a_j \vec{u}_j$. Since $\vec{v}$ is arbitrary, it follows that

$$V = \text{span}\{\vec{u}_1, \cdots, \vec{u}_s, \vec{v}_1, \cdots, \vec{v}_r\}$$

If the vectors $\{\vec{u}_1, \cdots, \vec{u}_s, \vec{v}_1, \cdots, \vec{v}_r\}$ are linearly independent, then it will follow that this set is a basis. Suppose then that

$$\sum_{i=1}^{r} c_i \vec{v}_i + \sum_{j=1}^{s} a_j \vec{u}_j = 0$$

Apply T to both sides to obtain

$$\sum_{i=1}^{r} c_i T(\vec{v}_i) + \sum_{j=1}^{s} a_j T(\vec{u}_j) = \sum_{i=1}^{r} c_i T(\vec{v}_i) = \vec{0}$$

Since $\{T(\vec{v}_1), \cdots, T(\vec{v}_r)\}$ is linearly independent, it follows that each $c_i = 0$. Hence $\sum_{j=1}^{s} a_j \vec{u}_j = 0$ and so, since the $\{\vec{u}_1, \cdots, \vec{u}_s\}$ are linearly independent, it follows that each $a_j = 0$ also. It follows that $\{\vec{u}_1, \cdots, \vec{u}_s, \vec{v}_1, \cdots, \vec{v}_r\}$ is a basis for V and so

$$n = s + r = \dim(\ker(T)) + \dim(\text{im}(T))$$

Corollary 5.8.1: One to One and Onto Characterization

The statement $\ker(T) = \left\{\vec{0}\right\}$ is equivalent to saying if $T(\vec{v}) = \vec{0}$, it follows that $\vec{v} = \vec{0}$. Thus by Lemma 9.7.1 T is one to one. If T is onto, then $\text{im}(T) = W$ and so $\text{rank}(T)$ which is defined as the dimension of $\text{im}(T)$ is m. If $\text{rank}(T) = m$, then by Theorem 5.8.2, since $\text{im}(T)$ is a subspace of W, it follows that $\text{im}(T) = W$.

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5.9: The Matrix of a Linear Transformation

Outcomes

A. Find the matrix of a linear transformation with respect to general bases in vector spaces.

You may recall from $\mathbb{R}^n$ that the matrix of a linear transformation depends on the bases chosen. This concept is explored in this section, where the linear transformation now maps from one arbitrary vector space to another.

Let $T : V \mapsto W$ be an isomorphism where V and W are vector spaces. Recall from Lemma 9.7.2 that T maps a basis in V to a basis in W. When discussing this Lemma, we were not specific on what this basis looked like. In this section we will make such a distinction.

Consider now an important definition.

Definition 5.9.1: Coordinate Isomorphism

Let V be a vector space with $\dim(V) = n$, let $B = \{\vec{b}_1, \vec{b}_2, \ldots, \vec{b}_n\}$ be a fixed basis of V, and let $\{\vec{e}_1, \vec{e}_2, \ldots, \vec{e}_n\}$ denote the standard basis of $\mathbb{R}^n$. We define a transformation $C_B : V \to \mathbb{R}^n$ by

$$C_B(a_1\vec{b}_1 + a_2\vec{b}_2 + \cdots + a_n\vec{b}_n) = a_1\vec{e}_1 + a_2\vec{e}_2 + \cdots + a_n\vec{e}_n = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}.$$

Then C_B is a linear transformation such that $C_B(\vec{b}_i) = \vec{e}_i$, $1 \leq i \leq n$.

C_B is an isomorphism, called the coordinate isomorphism corresponding to B.

We continue with another related definition.

Definition 5.9.2: Coordinate Vector

Let V be a finite dimensional vector space with $\dim(V) = n$, and let $B = \{\vec{b}_1, \vec{b}_2, \ldots, \vec{b}_n\}$ be an ordered basis of V (meaning that the order that the vectors are listed is taken into account). The coordinate vector of $\vec{v}$ with respect to B is defined as $C_B(\vec{v})$.

coordinatevector Consider the following example.

Example 5.9.1: Coordinate Vector

Let $V = \mathbb{P}_2$ and $\vec{x} = -x^2 - 2x + 4$. Find $C_B(\vec{x})$ for the following bases B:

1. $B = \{1, x, x^2\}$
2. $B = \{x^2, x, 1\}$
3. $B = \{x + x^2, x, 4\}$

Solution

1. First, note the order of the basis is important. Now we need to find a_1, a_2, a_3 such that $\vec{x} = a_1(1) + a_2(x) + a_3(x^2)$, that is:

$$-x^2-2x+4=a_1(1)+a_2(x)+a_3(x^2)$$

Clearly the solution is

$$\begin{aligned} a_1&=4\\ a_2&=-2\\ a_3&=-1 \end{aligned} \tag{5.9.1}$$

Therefore the coordinate vector is

$$C_B(\vec{x})=\begin{bmatrix} 4\\ -2\\ -1 \end{bmatrix}$$

2. Again remember that the order of B is important. We proceed as above. We need to find a_1, a_2, a_3 such that $\vec{x}=a_1(x^2)+a_2(x)+a_3(1)$, that is:

$$-x^2-2x+4=a_1(x^2)+a_2(x)+a_3(1)$$

Here the solution is

$$\begin{aligned} a_1&=-1\\ a_2&=-2\\ a_3&=4 \end{aligned} \tag{5.9.2}$$

Therefore the coordinate vector is

$$C_B(\vec{x})=\begin{bmatrix} -1\\ -2\\ 4 \end{bmatrix}$$

3. Now we need to find a_1, a_2, a_3 such that $\vec{x}=a_1(x+x^2)+a_2(x)+a_3(4)$, that is:

$$\begin{aligned} -x^2-2x+4&=a_1(x+x^2)+a_2(x)+a_3(4)\\ &=a_1(x^2)+(a_1+a_2)(x)+a_3(4) \end{aligned} \tag{5.9.3}$$

The solution is

$$\begin{aligned} a_1&=-1\\ a_2&=-1\\ a_3&=1 \end{aligned} \tag{5.9.4}$$

and the coordinate vector is

$$C_B(\vec{x})=\begin{bmatrix} -1\\ -1\\ 1 \end{bmatrix}$$

Given that the coordinate transformation $C_B: V\to\mathbb{R}^n$ is an isomorphism, its inverse exists.

Theorem 5.9.1: Inverse of the Coordinate Isomorphism

Let V be a finite dimensional vector space with dimension n and ordered basis $B=\{\vec{b}_1,\vec{b}_2,\ldots,\vec{b}_n\}$. Then $C_B: V\to\mathbb{R}^n$ is an isomorphism whose inverse,

$$C_B^{-1}:\mathbb{R}^n\to V$$

is given by

$$C_B^{-1}\begin{bmatrix} a_1\\ a_2\\ \vdots\\ a_n \end{bmatrix}=a_1\vec{b}_1+a_2\vec{b}_2+\cdots+a_n\vec{b}_n \quad \text{for all} \quad \begin{bmatrix} a_1\\ a_2\\ \vdots\\ a_n \end{bmatrix}\in\mathbb{R}^n.$$

We now discuss the main result of this section, that is how to represent a linear transformation with respect to different bases.

Let V and W be finite dimensional vector spaces, and suppose

- $\dim(V) = n$ and $B_1 = \{\vec{b}_1, \vec{b}_2, \ldots, \vec{b}_n\}$ is an ordered basis of V;
- $\dim(W) = m$ and B_2 is an ordered basis of W.

Let $T : V \to W$ be a linear transformation. If $V = \mathbb{R}^n$ and $W = \mathbb{R}^m$, then we can find a matrix A so that $T_A = T$. For arbitrary vector spaces V and W, our goal is to represent T as a matrix., i.e., find a matrix A so that $T_A : \mathbb{R}^n \to \mathbb{R}^m$ and $T_A = C_{B_2} T C_{B_1}^{-1}$.

To find the matrix A:

$$T_A = C_{B_2} T C_{B_1}^{-1} \text{ implies that } T_A C_{B_1} = C_{B_2} T,$$

and thus for any $\vec{v} \in V$,

$$C_{B_2}[T(\vec{v})] = T_A[C_{B_1}(\vec{v})] = AC_{B_1}(\vec{v}).$$

Since $C_{B_1}(\vec{b}_j) = \vec{e}_j$ for each $\vec{b}_j \in B_1$, $AC_{B_1}(\vec{b}_j) = A\vec{e}_j$, which is simply the j^{th} column of A. Therefore, the j^{th} column of A is equal to $C_{B_2}[T(\vec{b}_j)]$.

The matrix of T corresponding to the ordered bases B_1 and B_2 is denoted $M_{B_2B_1}(T)$ and is given by

$$M_{B_2B_1}(T) = \begin{bmatrix} C_{B_2}[T(\vec{b}_1)] & C_{B_2}[T(\vec{b}_2)] & \cdots & C_{B_2}[T(\vec{b}_n)] \end{bmatrix}.$$

This result is given in the following theorem.

Theorem 5.9.2

Let V and W be vectors spaces of dimension n and m respectively, with $B_1 = \{\vec{b}_1, \vec{b}_2, \ldots, \vec{b}_n\}$ an ordered basis of V and B_2 an ordered basis of W. Suppose $T : V \to W$ is a linear transformation. Then the unique matrix $M_{B_2B_1}(T)$ of T corresponding to B_1 and B_2 is given by

$$M_{B_2B_1}(T) = \begin{bmatrix} C_{B_2}[T(\vec{b}_1)] & C_{B_2}[T(\vec{b}_2)] & \cdots & C_{B_2}[T(\vec{b}_n)] \end{bmatrix}.$$

This matrix satisfies $C_{B_2}[T(\vec{v})] = M_{B_2B_1}(T)C_{B_1}(\vec{v})$ for all $\vec{v} \in V$.

We demonstrate this content in the following examples.

Example 5.9.2: Matrix of a Linear Transformation

Let $T : \mathbb{P}_3 \mapsto \mathbb{R}^4$ be an isomorphism defined by

$$T(ax^3 + bx^2 + cx + d) = \begin{bmatrix} a+b \\ b-c \\ c+d \\ d+a \end{bmatrix}$$

Suppose $B_1 = \{x^3, x^2, x, 1\}$ is an ordered basis of $\mathbb{P}_3$ and

$$B_2 = \left\{ \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right\}$$

be an ordered basis of $\mathbb{R}^4$. Find the matrix $M_{B_2B_1}(T)$.

Solution

To find $M_{B_2B_1}(T)$, we use the following definition.

$$M_{B_2B_1}(T) = \begin{bmatrix} C_{B_2}[T(x^3)] & C_{B_2}[T(x^2)] & C_{B_2}[T(x)] & C_{B_2}[T(x^2)] \end{bmatrix}$$

First we find the result of applying T to the basis B_1.

$$T(x^3) = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix}, T(x^2) = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, T(x) = \begin{bmatrix} 0 \\ -1 \\ 1 \\ 0 \end{bmatrix}, T(1) = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}$$

Next we apply the coordinate isomorphism C_{B_2} to each of these vectors. We will show the first in detail.

$$C_{B_2}\left(\begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix}\right) = a_1 \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} + a_2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} + a_3 \begin{bmatrix} 0 \\ 0 \\ -1 \\ 0 \end{bmatrix} + a_4 \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

This implies that

$$\begin{aligned} a_1 &= 1 \\ a_2 &= 0 \\ a_1 - a_3 &= 0 \\ a_4 &= 1 \end{aligned} \tag{5.9.5}$$

which has a solution given by

$$\begin{aligned} a_1 &= 1 \\ a_2 &= 0 \\ a_3 &= 1 \\ a_4 &= 1 \end{aligned} \tag{5.9.6}$$

Therefore $C_{B_2}[T(x^3)] = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}$.

You can verify that the following are true.

$$C_{B_2}[T(x^2)] = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \end{bmatrix}, C_{B_2}[T(x)] = \begin{bmatrix} 0 \\ -1 \\ -1 \\ 0 \end{bmatrix}, C_{B_2}[T(1)] = \begin{bmatrix} 0 \\ 0 \\ -1 \\ 1 \end{bmatrix}$$

Using these vectors as the columns of $M_{B_2B_1}(T)$ we have

$$M_{B_2B_1}(T) = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 1 & 1 & -1 & -1 \\ 1 & 0 & 0 & 1 \end{bmatrix}$$

The next example demonstrates that this method can be used to solve different types of problems. We will examine the above example and see if we can work backwards to determine the action of T from the matrix $M_{B_2B_1}(T)$.

Example 5.9.3: Finding the Action of a Linear Transformation

Let $T : \mathbb{P}_3 \mapsto \mathbb{R}^4$ be an isomorphism with

$$M_{B_2B_1}(T) = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 1 & 1 & -1 & -1 \\ 1 & 0 & 0 & 1 \end{bmatrix},$$

where $B_1 = \{x^3, x^2, x, 1\}$ is an ordered basis of $\mathbb{P}_3$ and

$$B_2 = \left\{ \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right\}$$

is an ordered basis of $\mathbb{R}^4$. If $p(x) = ax^3 + bx^2 + cx + d$, find $T(p(x))$.

Solution

Recall that $C_{B_2}[T(p(x))] = M_{B_2B_1}(T)C_{B_1}(p(x))$. Then we have

$$\begin{aligned} C_{B_2}[T(p(x))] &= M_{B_2B_1}(T)C_{B_1}(p(x)) \\ &= \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 1 & 1 & -1 & -1 \\ 1 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \\ &= \begin{bmatrix} a+b \\ b-c \\ a+b-c-d \\ a+d \end{bmatrix} \end{aligned} \tag{5.9.7}$$

Therefore

$$\begin{aligned} T(p(x)) &= C_D^{-1} \begin{bmatrix} a+b \\ b-c \\ a+b-c-d \\ a+d \end{bmatrix} \\ &= (a+b) \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} + (b-c) \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} + (a+b-c-d) \begin{bmatrix} 0 \\ 0 \\ -1 \\ 0 \end{bmatrix} + (a+d) \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} a+b \\ b-c \\ c+d \\ a+d \end{bmatrix} \end{aligned} \tag{5.9.8}$$

You can verify that this was the definition of $T(p(x))$ given in the previous example.

We can also find the matrix of the composite of multiple transformations.

Theorem 5.9.3: Matrix of Composition

Let V, W and U be finite dimensional vector spaces, and suppose $T : V \mapsto W$, $S : W \mapsto U$ are linear transformations. Suppose V, W and U have ordered bases of B_1, B_2 and B_3 respectively. Then the matrix of the composite transformation $S \circ T$ (or ST) is given by

$$M_{B_3B_1}(ST) = M_{B_3B_2}(S)M_{B_2B_1}(T).$$

The next important theorem gives a condition on when T is an isomorphism.

Theorem 5.9.4: Isomorphism

Let V and W be vector spaces such that both have dimension n and let $T : V \mapsto W$ be a linear transformation. Suppose B_1 is an ordered basis of V and B_2 is an ordered basis of W.

Then the conditions that $M_{B_2B_1}(T)$ is invertible for **all** B_1 and B_2, and that $M_{B_2B_1}(T)$ is invertible for **some** B_1 and B_2 are equivalent. In fact, these occur if and only if T is an isomorphism.

If T is an isomorphism, the matrix $M_{B_2B_1}(T)$ is invertible and its inverse is given by $[M_{B_2B_1}(T)]^{-1} = M_{B_1B_2}(T^{-1})$.

Consider the following example.

Example 5.9.4

Suppose $T : \mathbb{P}_3 \to \mathbb{M}_{22}$ is a linear transformation defined by

$$T(ax^3 + bx^2 + cx + d) = \begin{bmatrix} a+d & b-c \\ b+c & a-d \end{bmatrix}$$

for all $ax^3 + bx^2 + cx + d \in \mathbb{P}_3$. Let $B_1 = \{x^3, x^2, x, 1\}$ and

$$B_2 = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}$$

be ordered bases of $\mathbb{P}_3$ and $\mathbb{M}_{22}$, respectively.

1. Find $M_{B_2B_1}(T)$.
2. Verify that T is an isomorphism by proving that $M_{B_2B_1}(T)$ is invertible.
3. Find $M_{B_1B_2}(T^{-1})$, and verify that $M_{B_1B_2}(T^{-1}) = [M_{B_2B_1}(T)]^{-1}$.
4. Use $M_{B_1B_2}(T^{-1})$ to find T^{-1}.

Solution

1.
$$\begin{aligned} M_{B_2B_1}(T) &= \begin{bmatrix} C_{B_2}[T(1)] & C_{B_2}[T(x)] & C_{B_2}[T(x^2)] & C_{B_2}[T(x^3)] \end{bmatrix} \\ &= \begin{bmatrix} C_{B_2}\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} & C_{B_2}\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} & C_{B_2}\begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} & C_{B_2}\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \end{bmatrix} \\ &= \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & -1 & 0 \\ 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & -1 \end{bmatrix} \end{aligned} \tag{5.9.9}$$

2. $\det(M_{B_2B_1}(T)) = 4$, so the matrix is invertible, and hence T is an isomorphism.

3.
$$T^{-1}\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = 1, T^{-1}\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = x, T^{-1}\begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} = x^2, T^{-1}\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} = x^3,$$

so

$$T^{-1}\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} = \frac{1+x^3}{2}, T^{-1}\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} = \frac{x-x^2}{2},$$
$$T^{-1}\begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} = \frac{x+x^2}{2}, T^{-1}\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} = \frac{1-x^3}{2}.$$

Therefore,

$$M_{B_1B_2}(T^{-1}) = \frac{1}{2}\begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & -1 & 1 & 0 \\ 1 & 0 & 0 & -1 \end{bmatrix}$$

You should verify that $M_{B_2B_1}(T)M_{B_1B_2}(T^{-1}) = I_4$. From this it follows that $[M_{B_2B_1}(T)]^{-1} = M_{B_1B_2}(T^{-1})$.

4.

$$\begin{aligned} C_{B_1}\left(T^{-1}\begin{bmatrix} p & q \\ r & s \end{bmatrix}\right) &= M_{B_1B_2}(T^{-1})C_{B_2}\left(\begin{bmatrix} p & q \\ r & s \end{bmatrix}\right) \\ T^{-1}\begin{bmatrix} p & q \\ r & s \end{bmatrix} &= C_{B_1}^{-1}\left(M_{B_1B_2}(T^{-1})C_{B_2}\left(\begin{bmatrix} p & q \\ r & s \end{bmatrix}\right)\right) \\ &= C_{B_1}^{-1}\left(\frac{1}{2}\begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & -1 & 1 & 0 \\ 1 & 0 & 0 & -1 \end{bmatrix}\begin{bmatrix} p \\ q \\ r \\ s \end{bmatrix}\right) \\ &= C_{B_1}^{-1}\left(\frac{1}{2}\begin{bmatrix} p+s \\ q+r \\ r-q \\ p-s \end{bmatrix}\right) \\ &= \frac{1}{2}(p+s)x^3 + \frac{1}{2}(q+r)x^2 + \frac{1}{2}(r-q)x + \frac{1}{2}(p-s). \end{aligned} \tag{5.9.10}$$

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5.10: SUPPLEMENTARY NOTES - THE FUNDAMENTAL SUBSPACES

There are a number of vector spaces associated with a matrix. Here we detail those fundamental subspaces of a matrix.

5.10.1: The Fundamental Subspaces

5.10.1.1: Column Space

5.10.1.2: Null Space

5.10.1.3: The Null and Column Spaces- An Example

5.10.1.4: Left Null Space

5.10.1.5: Row Space

5.10.1.6: Exercises- Columns and Null Spaces

Spaces Associated with a Matrix Geogebra Demo by Kevin Hopkins

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5.10.1.1: Column Space

We begin with the simple geometric interpretation of matrix-vector multiplication. Namely, the multiplication of the n-by-1 vector x by the m-by-n matrix A produces a linear combination of the columns of A. More precisely, if a_j denotes the jth column of A then

$$Ax = (a_1 \quad a_2 \quad \cdots \quad a_n) \begin{pmatrix} x_1 \\ x_2 \\ \cdots \\ x_n \end{pmatrix}$$

$$= x_1 a_1 + x_2 a_2 + \cdots + x_n a_n$$

The picture that I wish to place in your mind's eye is that AxAx lies in the subspace spanned by the columns of A. This subspace occurs so frequently that we find it useful to distinguish it with a definition.

Column Space

The column space of the m-by-n matrix S is simply the span of the its columns, i.e. $Ra(S) \equiv \{Sx | x \in \mathbb{R}^n\}$ subspace of $\mathcal{R}^m$ stands for range in this context.The notation R_a stands for range in this context.

Example

Let us examine the matrix:

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

The column space of this matrix is:

$$Ra(A) = \{x_1 \begin{pmatrix} 0 \\ -1 \\ 0 \end{pmatrix} + x_2 \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} + x_3 \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} + x_4 \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} | x \in \mathbb{R}^4\}$$

As the third column is simply a multiple of the first, we may write:

$$Ra(A) = \{x_1 \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} + x_2 \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} + x_3 \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} | x \in \mathbb{R}^3\}$$

As the three remaining columns are linearly independent we may go no further. In this case, $Ra(A)$ comprises all of $\mathbb{R}^3$

Method for Finding a Basis

To determine the basis for $Ra(A)$ (where A is an arbitrary matrix) we must find a way to discard its dependent columns. In the example above, it was easy to see that columns 1 and 3 were colinear. We seek, of course, a more systematic means of uncovering these, and perhaps other less obvious, dependencies. Such dependencies are more easily discerned from the row reduced form. In the reduction of the above problem, we come very easily to the matrix

$$A_{red} = \begin{pmatrix} -1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

Once we have done this, we can recognize that the pivot column are **the** linearly independent columns of A_{red}. One now asks how this might help us distinguish the independent columns of A. For, although the rows of A_{red} are linear combinations of the rows of A **pay attention to the indices of the pivot columns**. In our example, columns $\{1, 2, 4\}$ are the pivot columns of A_{red} and hence the first, second, and fourth columns of A i.e.,

$$\{\begin{pmatrix} 0 \\ -1 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}\}$$

comprise a basis for $Ra(A)$:

Definition: A Basis for the Column Space

Suppose A is m-by-n. If columns $\{c_j | j = 1, \cdots, r\}$ are the pivot columns of A_{red} then columns $\{c_j | j = 1, \cdots, r\}$ of A constitute a basis for $Ra(A)$

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5.10.1: THE FUNDAMENTAL SUBSPACES

5.10.1.1: Column Space

5.10.1.2: Null Space

5.10.1.3: The Null and Column Spaces- An Example

5.10.1.4: Left Null Space

5.10.1.5: Row Space

5.10.1.6: Exercises- Columns and Null Spaces

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5.10.1.2: Null Space

Definition: Null Space

The null space of an m-by-n matrix A is the collection of those vectors in $\mathbb{R}^n$ that A maps to the zero vector in $\mathbb{R}^m$. More precisely,

$$\mathcal{N}(A) = \{x \in \mathbb{R}^n | Ax = 0\}$$

Null Space Example

As an example, we examine the matrix A

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

It is fairly easy to see that the null space of this matrix is:

$$\mathcal{N}(A) = \{t \begin{pmatrix} 1 \\ 0 \\ 1 \\ 0 \end{pmatrix} | t \in \mathbb{R}\}$$

This is a line in $\mathbb{R}^4$

The null space answers the question of uniqueness of solutions to $S\mathbf{x} = \mathbf{f}$. For, if $S\mathbf{x} = \mathbf{f}$ and $S\mathbf{y} = \mathbf{f}$ then $S(\mathbf{x} - \mathbf{y}) = S\mathbf{x} - S\mathbf{y} = \mathbf{f} - \mathbf{f} = 0$ and so $(\mathbf{x} - \mathbf{y}) \in \mathcal{N}(S)$. Hence, a solution to $S\mathbf{x} = \mathbf{f}$ will be unique if, and only if, $\mathcal{N}S = \{0\}$

Method for Finding the Basis

Let us now exhibit a basis for the null space of an arbitrary matrix A. We note that to solve $A\mathbf{x} = 0$ is to solve $A_{red}\mathbf{x} = 0$. With respect to the latter, we suppose that

$$\{c_j | j = \{1, \cdots, r\}\}$$

are the indices of the pivot columns and that

$$\{c_j | j = \{r + 1, \cdots, n\}\}$$

are the indices of the nonpivot columns. We accordingly define the r pivot variables

$$\{x_{c_j} | j = \{1, \cdots, r\}\}$$

and the $n - r$ free variables

$$\{x_{c_j} | j = \{r + 1, \cdots, n\}\}$$

One solves $A_{red}\mathbf{x} = 0$ by expressing each of the pivot variables in terms of the nonpivot, or free, variables. In the example above, x_1, x_2, and x_4 are pivot while x_3 is free. Solving for the pivot in terms of the free, we find $x_4 = 0, x_3 = x_1, x_2 = 0$, or, written as a vector,

$$\mathbf{x} = x_3 \begin{pmatrix} 1 \\ 0 \\ 1 \\ 0 \end{pmatrix}$$

where x_3 is free. As x_3 ranges over all real numbers the x above traces out a line in $\mathbb{R}_4$. This line is precisely the null space of A. Abstracting these calculations we arrive at:

Definition: A Basis for the Null Space

Suppose that A is m-by-n with pivot indices $\{c_j | j = \{1, \cdots, r\}\}$ and free indices $\{c_j | j = \{r+1, \cdots, n\}\}$. A basis for $\mathcal{N}(A)$ may be constructed $n - r$ vectors $\{z^1, z^2, \cdots, z^{n-r}\}$ where z^k, and only z^k possesses a nonzero in its c_{r+k} component.

A MATLAB Observation

As usual, MATLAB has a way to make our lives simpler. If you have defined a matrix A and want to find a basis for its null space, simply call the function `null(A)`. One small note about this function: if one adds an extra flag, `'r'`, as in `null(A, 'r')`, then the basis is displayed "rationally" as opposed to purely mathematically. The MATLAB help pages define the difference between the two modes as the rational mode being useful pedagogically and the mathematical mode of more value **(gasp!)** mathematically.

Final thoughts on null spaces

There is a great deal more to finding null spaces; enough, in fact, to warrant another module. One important aspect and use of null spaces is their ability to inform us about the uniqueness of solutions. If we use the column space to determine the existence of a solution $\mathbf{x}$ to the equation $A\mathbf{x} = b$. Once we know that a solution exists it is a perfectly reasonable question to want to know whether or not this solution is the only solution to this problem. The hard and fast rule is that a solution $\mathbf{x}$ is unique if and only if the null space of A is empty. One way to think about this is to consider that if $A\mathbf{x} = 0$ does not have a unique solution then, by linearity, neither does $A\mathbf{x} = b$. Conversely, if $(Az = 0) \wedge (z \neq 0) \wedge (A\mathbf{y} = b)$ then $A(z + \mathbf{y}) = b$ as well.

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5.10.1.3: The Null and Column Spaces- An Example

Preliminary Information

Let us compute bases for the null and column spaces of the adjacency matrix associated with the ladder below.

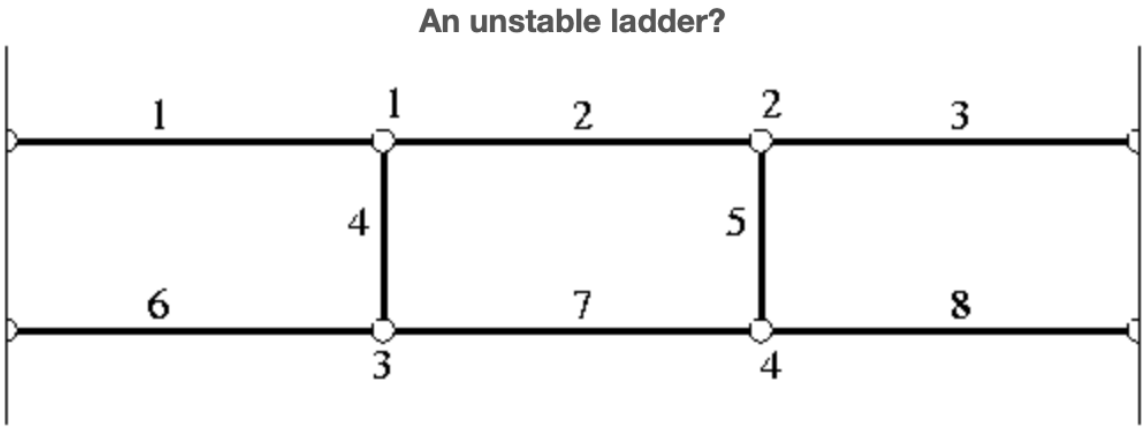


Figure 1.

The ladder has 8 bars and 4 nodes, so 8 degrees of freedom. Denoting the horizontal and vertical displacements of node j by x_{2j-1} and x_{2j} respectively, we arrive at the A matrix

$$A = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 \end{pmatrix}$$

Finding a Basis for the Column Space

To determine a basis for $\mathcal{R}(A)$ we must find a way to discard its dependent columns. A moment's reflection reveals that columns 2 and 6 are colinear, as are columns 4 and 8. We seek, of course, a more systematic means of uncovering these and perhaps other less obvious dependencies. Such dependencies are more easily discerned from the row reduced form

$$A_{red} = rref(A) = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Recall that `rref` performs the elementary row operations necessary to eliminate all nonzeros below the diagonal. For those who can't stand to miss any of the action I recommend `rrefmovie`.

NOT_CONVERTED_YET: para

Each nonzero row of

A_{red} is called a **pivot row**. The first nonzero in each row of A_{red} is called a **pivot**. Each column that contains a pivot is called a **pivot column**. On account of the staircase nature of A_{red} we find that there are as many pivot columns as there are pivot rows. In our example there are six of each and, again on account of the staircase nature, the pivot columns are **the linearly independent** columns of A_{red} One now asks how this might help us distinguish the independent columns of A. For although the rows of A_{red} are linear combinations of the rows of A, no such thing is true with respect to the columns. In our example, columns $\{1, 2, 3, 4, 5, 7\}$ are the pivot columns. In general:

Proposition

Suppose A is m-by-n. If columns $\{c_j | j = 1, \cdots, r\}$ are the pivot columns of A_{red} then columns $\{c_j | j = 1, \cdots, r\}$ of A constitute a basis for $\mathcal{R}(A)$.

Note that the pivot columns of AredAred are, by construction, linearly independent. Suppose, however, that columns $\{c_j | j = 1, \cdots, r\}$ of A are linearly dependent. In this case there exists a nonzero $x \in \mathbb{R}^n$ for which $A\mathbf{x} = \mathbf{0}$ and

$$\forall k, k \notin \{c_j | j = 1, \cdots, r\} : (x_k = 0)$$

Now $A\mathbf{x} = \mathbf{0}$ necessarily implies that $A_{red}\mathbf{x} = \mathbf{0}$ contrary to the fact that columns $\{c_j | j = 1, \cdots, r\}$ are the pivot columns of A_{red}

We now show that the span of columns $\{c_j | j = 1, \cdots, r\}$ of A indeed coincides with $\mathbb{R}(A)$ This is obvious if $r = n$ i.e., if **all** of the columns are linearly independent. If $r < n$ there exists a $q \notin \{c_j | j = 1, \cdots, r\}$ Looking back at A_{red} we note that its qth column is a linear combination of the pivot columns with indices not exceeding q. Hence, there exists an x satisfying Equation and $A_{red}\mathbf{x} = \mathbf{0}$ and $x_q = 1$ This x then necessarily satisfies $A\mathbf{x} = \mathbf{0}$. This states that the qth column of A is a linear combination of columns $\{c_j | j = 1, \cdots, r\}$ of A

Finding a Basis for the Null Space

Let us now exhibit a basis for $\mathcal{N}(A)$ We exploit the already mentioned fact that $\mathcal{N}(A) = \mathcal{N}(A_{red})$. Regarding the latter, we partition the elements of $\mathbf{x}$ into so called **pivot variables**,

$$\{x_{c_j} | j = 1, \cdots, r\}$$

and **free variables**

$$\{x_k | k \notin \{x_j | j = 1, \cdots, r\}\}$$

There are evidently $n - r$ free variables. For convenience, let us denote these in the future by

$$\{x_{c_j} | j = r + 1, \cdots, n\}$$

One solves $A_{red}\mathbf{x} = \mathbf{0}$ by expressing each of the pivot variables in terms of the nonpivot, or free, variables. In the example above, x_1, x_2, x_3, x_4, x_5 and x_7 are pivot while x_6 and x_8 are free. Solving for the pivot in terms of the free we find

$$x_7 = 0 \tag{5.10.1.3.1}$$

$$x_5 = 0 \tag{5.10.1.3.2}$$

$$x_4 = x_8 \tag{5.10.1.3.3}$$

$$x_3 = 0 \tag{5.10.1.3.4}$$

$$x_2 = x_6 \tag{5.10.1.3.5}$$

$$x_1 = 0 \tag{5.10.1.3.6}$$

or, written as a vector,

$$\mathbf{x} = x_6 \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{pmatrix} + x_8 \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}$$

where x_6 and x_8 are free. As x_6 and x_8 range over all real numbers, the $\mathbf{x}$ above traces out a plane in $\mathbb{R}^8$ This plane is precisely the null space of A and Equation describes a generic element as the linear combination of two basis vectors. Compare this to what MATLAB returns when faced with `null(A,'r')`. Abstracting these calculations we arrive at

Proposition

Suppose that A is m-by-n with pivot indices $\{c_j | j = 1, \cdots, r\}$ and free indices $\{c_j | j = r+1, \cdots, n\}$ A basis for $\mathcal{N}(A)$ may be constructed of $n - r$ vectors $\{z^1, z^2, \cdots, z^{n-r}\}$ where z^k and only z^k possesses a nonzero in its c_{r+k} component.

The Physical Meaning of Our Calculations

Let us not end on an abstract note however. We ask what $\mathcal{R}(A)$ and $\mathcal{N}(A)$ tell us about the ladder. Regarding $\mathcal{R}(A)$ the answer will come in the next chapter. The null space calculation however has revealed two independent motions against which the ladder does no work! Do you see that the two vectors in Equation encode rigid vertical motions of bars 4 and 5 respectively? As each of these lies in the null space of A Figure? I hope not, for vertical motion of bar 4 must 'stretch' bars 1, 2, 6, and 7. How does one resolve this (apparent) contradiction?

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5.10.1.4: Left Null Space

If one understands the concept of a null space, the left null space is extremely easy to understand.

Definition: Left Null Space

The Left Null Space of a matrix is the null space of its transpose, i.e.,

$$\mathcal{N}(A^T) = \{\mathbf{y} \in \mathbb{R}^m | A^T\mathbf{y} = 0\}$$

The word "left" in this context stems from the fact that $A^T\mathbf{y} = 0$ is equivalent to $\mathbf{y}^T A = 0$ where $\mathbf{y}$ "acts" on A from the left.

Example

As A_{red} was the key to identifying the null space of A, we shall see that A^T_{red} is the key to the null space of A^T. If

$$A = \begin{pmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \end{pmatrix}$$

then

$$A^T = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 2 & 3 \end{pmatrix}$$

and so

$$A^T_{red} = \begin{pmatrix} 1 & 1 & 1 \\ 0 & 1 & 2 \end{pmatrix}$$

We solve $A^T_{red} = 0$ by recognizing that y_1 and y_2 are pivot variables while y_3 is free. Solving $A^T_{red}\mathbf{y} = 0$ for the pivot in terms of the free we find $y_2 = -(2y_3)$ and $y_1 = y_3$ hence

Erroneous nesting of equation structures

Finding a Basis for the Left Null Space

The procedure is no different than that used to compute the null space of A itself. In fact

Definition: A Basis for the Left Null Space

Suppose that A^T is n-by-m with pivot indices $\{c_j | j = \{1, \cdots, r\}\}$ and free indices $\{c_j | j = \{r+1, \cdots, n\}\}$. A basis for $\mathcal{N}(A^T)$ may be constructed of $m - r$ vectors $\{z^1, z^2, \cdots, z^{m-r}\}$ where z^k and only z^k, possesses a nonzero in its c_{r+k} component.

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5.10.1.5: Row Space

The Row Space

As the columns of A^T are simply the rows of A we call $Ra(A^T)$ the row space of A^T. More precisely

Definition: Row Space

The row space of the m-by-n matrix A is simply the span of its rows, i.e.,

$$Ra(A^T) \equiv \{A^T\mathbf{y} | \mathbf{y} \in \mathbb{R}^m\}$$

This is a subspace of $\mathbb{R}^n$

Let us examine the matrix:

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

The row space of this matrix is:

$$\mathscr{R}a(A^T) = \left\{ y_1 \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \end{pmatrix} + y_2 \begin{pmatrix} -1 \\ 0 \\ 1 \\ 0 \end{pmatrix} + y_3 \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} | y \in \mathbb{R}^3 \right\}$$

As these three rows are linearly independent we may go no further. We "recognize" then $\mathscr{R}a(A^T)$ as a three dimensional subspace of $\mathbb{R}^4$

Method for Finding the Basis of the Row Space

Regarding a basis for $\mathscr{R}a(A^T)$ we recall that the rows of A_{red}, the row reduced form of the matrix A, are merely linear A combinations of the rows of A and hence

$$\mathscr{R}a(A^T) = \mathscr{R}a(A_{red})$$

This leads immediately to:

Definition: A Basis for the Row Space

Suppose A is m-by-n. The pivot rows of A_{red} constitute a basis for $\mathscr{R}a(A^T)$.

With respect to our example,

$$\left\{ \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} -1 \\ 0 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} \right\}$$

comprises a basis for $\mathscr{R}a(A^T)$.

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5.10.1.6: Exercises- Columns and Null Spaces

Exercise 5.10.1.6.1

I encourage you to use `rref` and `null` for the following.

i. Add a diagonal crossbar between nodes 3 and 2 in the unstable ladder figure and compute bases for the column and null spaces of the new adjacency matrix. As this crossbar fails to stabilize the ladder, we shall add one more bar.
ii. To the 9 bar ladder of (i) add a diagonal cross bar between nodes 1 and the left end of bar 6. Compute bases for the column and null spaces of the new adjacency matrix.

Exercise 5.10.1.6.2

We wish to show that $N(A) = N(A^TA)$ regardless of A.

i. We first take a concrete example. Report the findings of `null` when applied to A and A^TA for the A matrix associated with the unstable ladder figure.
ii. Show that $N(A) \subseteq N(A^TA)$ i.e. that if $A\mathbf{x} = \mathbf{0}$ then $A^TA\mathbf{x} = \mathbf{0}$.
iii. Show that $N(A^TA) \subseteq N(A)$ i.e., that if $A^TA\mathbf{x} = \mathbf{0}$ then $A\mathbf{x} = \mathbf{0}$ (Hint: if $A^TA\mathbf{x} = \mathbf{0}$ then $\mathbf{x}^TA^TA\mathbf{x} = \mathbf{0}$

Exercise 5.10.1.6.3

Suppose that A is m-by-n and that $N(A) = \mathbb{R}^n$. Argue that A must be the zero matrix.

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Spaces Associated with a Matrix Geogebra Demo by Kevin Hopkins

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5.11: SUPPLEMENTARY NOTES - A MORE IN-DEPTH LOOK AT VECTOR SPACES

Vector spaces are usually a surprise to most people the first time they see them. Who would think of matrices or polynomials as vectors? Here we have a more detailed treatment of vector spaces that involves some of the surprising generalizations.

5.11.1: Vector Spaces

5.11.1.1: Examples and Basic Properties

5.11.1.1E: Examples and Basic Properties Exercises

5.11.1.2: Subspaces and Spanning Sets

5.11.1.2E: Subspaces and Spanning Sets Exercises

5.11.1.3: Linear Independence and Dimension

5.11.1.3E: Linear Independence and Dimension Exercises

5.11.1.4: Finite Dimensional Spaces

5.11.1.4E: Finite Dimensional Spaces Exercises

5.11.1.5: An Application to Polynomials

5.11.1.5E: An Application to Polynomials Exercises

5.11.1.6: Supplementary Exercises for Chapter 6

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5.11.1.1: EXAMPLES AND BASIC PROPERTIES

Many mathematical entities have the property that they can be added and multiplied by a number. Numbers themselves have this property, as do $m \times n$ matrices: The sum of two such matrices is again $m \times n$ as is any scalar multiple of such a matrix. Polynomials are another familiar example, as are the geometric vectors in Chapter 4. It turns out that there are many other types of mathematical objects that can be added and multiplied by a scalar, and the general study of such systems is introduced in this chapter. Remarkably, much of what we could say in Chapter 5 about the dimension of subspaces in $\mathbb{R}^n$ can be formulated in this generality.

Definition: Vector Spaces

A **vector space** consists of a nonempty set V of objects (called **vectors**) that can be added, that can be multiplied by a real number (called a **scalar** in this context), and for which certain axioms hold.If $\mathbf{v}$ and $\mathbf{w}$ are two vectors in V, their sum is expressed as $\mathbf{v} + \mathbf{w}$, and the scalar product of $\mathbf{v}$ by a real number a is denoted as $a\mathbf{v}$. These operations are called **vector addition** and **scalar multiplication**, respectively, and the following axioms are assumed to hold.

Axioms for vector addition

- *A1 If* $\mathbf{u}$ *and* $\mathbf{v}$ *are in* V*, then* $\mathbf{u} + \mathbf{v}$ *is in* V.
- *A2* $\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u}$ *for all* $\mathbf{u}$ *and* $\mathbf{v}$ *in* V.
- *A3* $\mathbf{u} + (\mathbf{v} + \mathbf{w}) = (\mathbf{u} + \mathbf{v}) + \mathbf{w}$ *for all* $\mathbf{u}$, $\mathbf{v}$, *and* $\mathbf{w}$ *in* V.
- *A4 An element* 0 *in* V *exists such that* $\mathbf{v} + 0 = \mathbf{v} = 0 + \mathbf{v}$ *for every* $\mathbf{v}$ *in* V.
- *A5 For each* $\mathbf{v}$ *in* V*, an element* $-\mathbf{v}$ *in* V *exists such that* $-\mathbf{v} + \mathbf{v} = 0$ *and* $\mathbf{v} + (-\mathbf{v}) = 0$.

Axioms for scalar multiplication

- *S1 If* $\mathbf{v}$ *is in* V*, then* $a\mathbf{v}$ *is in* V *for all* a *in* $\mathbb{R}$.
- *S2* $a(\mathbf{v} + \mathbf{w}) = a\mathbf{v} + a\mathbf{w}$ *for all* $\mathbf{v}$ *and* $\mathbf{w}$ *in* V *and all* a *in* $\mathbb{R}$.
- *S3* $(a + b)\mathbf{v} = a\mathbf{v} + b\mathbf{v}$ *for all* $\mathbf{v}$ *in* V *and all* a *and* b *in* $\mathbb{R}$.
- *S4* \(a(b\mathbf{v}) = (ab)\mathbf{v}\) *for all* $\mathbf{v}$ *in* V *and all* a *and* b *in* $\mathbb{R}$.
- *S5* $1\mathbf{v} = \mathbf{v}$ *for all* $\mathbf{v}$ *in* V.

The content of axioms A1 and S1 is described by saying that V is **closed** under vector addition and scalar multiplication. The element 0 in axiom A4 is called the **zero vector**, and the vector $-\mathbf{v}$ in axiom A5 is called the **negative** of $\mathbf{v}$.

The rules of matrix arithmetic, when applied to $\mathbb{R}^n$, give

Example 5.11.1.1.1

$\mathbb{R}^n$ is a vector space using matrix addition and scalar multiplication.[1]

It is important to realize that, in a general vector space, the vectors need not be n-tuples as in $\mathbb{R}^n$. They can be any kind of objects at all as long as the addition and scalar multiplication are defined and the axioms are satisfied. The following examples illustrate the diversity of the concept.

The space $\mathbb{R}^n$ consists of special types of matrices. More generally, let $\mathbf{M}_{mn}$ denote the set of all $m \times n$ matrices with real entries. Then Definition 2.1.1 gives:

Example 5.11.1.1.2

The set $\mathbf{M}_{mn}$ of all $m \times n$ matrices is a vector space using matrix addition and scalar multiplication. The zero element in this vector space is the zero matrix of size $m \times n$, and the vector space negative of a matrix (required by axiom A5) is the usual matrix negative discussed in Section 2.1. Note that $\mathbf{M}_{mn}$ is just $\mathbb{R}^{mn}$ in different notation.

In Chapter 5 we identified many important subspaces of $\mathbb{R}^n$ such as $im\ A$ and $\text{null}A$ for a matrix A. These are all vector spaces.

Example 5.11.1.1.3

Show that every subspace of $\mathbb{R}^n$ is a vector space in its own right using the addition and scalar multiplication of $\mathbb{R}^n$.

Solution

Axioms A1 and S1 are two of the defining conditions for a subspace U of $\mathbb{R}^n$ (see Section 5.1). The other eight axioms for a vector space are inherited from $\mathbb{R}^n$. For example, if $\mathbf{x}$ and $\mathbf{y}$ are in U and a is a scalar, then $a(\mathbf{x}+\mathbf{y}) = a\mathbf{x} + a\mathbf{y}$ because $\mathbf{x}$ and $\mathbf{y}$ are in $\mathbb{R}^n$. This shows that axiom S2 holds for U; similarly, the other axioms also hold for U.

Example 5.11.1.1.4

Let V denote the set of all ordered pairs (x, y) and define addition in V as in $\mathbb{R}^2$. However, define a new scalar multiplication in V by

$$a(x, y) = (ay, ax)$$

Determine if V is a vector space with these operations.

Solution

Axioms A1 to A5 are valid for V because they hold for matrices. Also $a(x, y) = (ay, ax)$ is again in V, so axiom S1 holds. To verify axiom S2, let $\mathbf{v} = (x, y)$ and $\mathbf{w} = (x_1, y_1)$ be typical elements in V and compute

$$\begin{aligned} a(\mathbf{v}+\mathbf{w}) &= a(x + x_1, y + y_1) = (a(y + y_1), a(x + x_1)) \\ a\mathbf{v} + a\mathbf{w} &= (ay, ax) + (ay_1, ax_1) = (ay + ay_1, ax + ax_1) \end{aligned}$$

Because these are equal, axiom S2 holds. Similarly, the reader can verify that axiom S3 holds. However, axiom S4 fails because

$$a(b(x, y)) = a(by, bx) = (abx, aby)$$

need not equal $ab(x, y) = (aby, abx)$. Hence, V is *not* a vector space. (In fact, axiom S5 also fails.)

Sets of polynomials provide another important source of examples of vector spaces, so we review some basic facts. A **polynomial** in an indeterminate x is an expression

$$p(x) = a_0 + a_1x + a_2x^2 + \cdots + a_nx^n$$

where $a_0, a_1, a_2, \ldots, a_n$ are real numbers called the **coefficients** of the polynomial. If all the coefficients are zero, the polynomial is called the **zero polynomial** and is denoted simply as 0. If $p(x) \neq 0$, the highest power of x with a nonzero coefficient is called the **degree** of $p(x)$ denoted as $\deg p(x)$. The coefficient itself is called the **leading coefficient** of $p(x)$. Hence $\deg(3 + 5x) = 1$, $\deg(1 + x + x^2) = 2$, and $\deg(4) = 0$. (The degree of the zero polynomial is not defined.)

Let $\mathbf{P}$ denote the set of all polynomials and suppose that

$$\begin{aligned} p(x) &= a_0 + a_1x + a_2x^2 + \cdots \\ q(x) &= b_0 + b_1x + b_2x^2 + \cdots \end{aligned}$$

are two polynomials in $\mathbf{P}$ (possibly of different degrees). Then $p(x)$ and $q(x)$ are called **equal** [written $p(x) = q(x)$] if and only if all the corresponding coefficients are equal—that is, $a_0 = b_0$, $a_1 = b_1$, $a_2 = b_2$, and so on. In particular, $a_0 + a_1x + a_2x^2 + \cdots = 0$ means that $a_0 = 0$, $a_1 = 0$, $a_2 = 0$, ..., and this is the reason for calling x an **indeterminate**. The set $\mathbf{P}$ has an addition and scalar multiplication defined on it as follows: if $p(x)$ and $q(x)$ are as before and a is a real number,

$$p(x) + q(x) = (a_0 + b_0) + (a_1 + b_1)x + (a_2 + b_2)x^2 + \cdots$$
$$ap(x) = aa_0 + (aa_1)x + (aa_2)x^2 + \cdots$$

Evidently, these are again polynomials, so $\mathbf{P}$ is closed under these operations, called **pointwise** addition and scalar multiplication. The other vector space axioms are easily verified, and we have

Example 5.11.1.1.5

The set $\mathbf{P}$ of all polynomials is a vector space with the foregoing addition and scalar multiplication. The zero vector is the zero polynomial, and the negative of a polynomial $p(x) = a_0 + a_1x + a_2x^2 + ...$ is the polynomial $-p(x) = -a_0 - a_1x - a_2x^2 - ...$ obtained by negating all the coefficients.

There is another vector space of polynomials that will be referred to later.

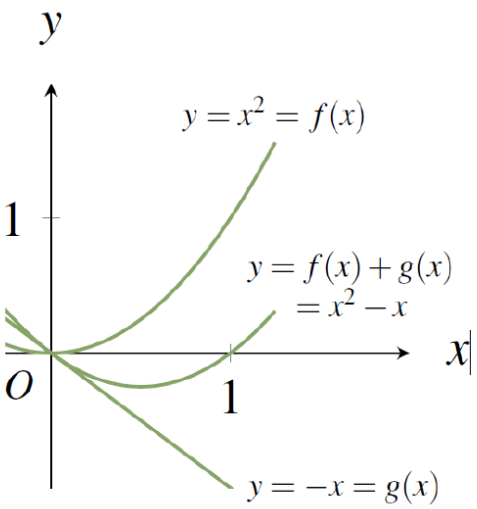
Example 5.11.1.1.6

Given $n \geq 1$, let $\mathbf{P}_n$ denote the set of all polynomials of degree at most n, together with the zero polynomial. That is

$$\mathbf{P}_n = \{a_0 + a_1x + a_2x^2 + \cdots + a_nx^n \mid a_0, a_1, a_2, \ldots, a_n \text{ in } \mathbb{R}\}.$$

Then $\mathbf{P}_n$ is a vector space. Indeed, sums and scalar multiples of polynomials in $\mathbf{P}_n$ are again in $\mathbf{P}_n$, and the other vector space axioms are inherited from $\mathbf{P}$. In particular, the zero vector and the negative of a polynomial in $\mathbf{P}_n$ are the same as those in $\mathbf{P}$.

If a and b are real numbers and $a < b$, the **interval** $[a, b]$ is defined to be the set of all real numbers x such that $a \leq x \leq b$. A (real-valued) **function** f on $[a, b]$ is a rule that associates to every number x in $[a, b]$ a real number denoted $f(x)$. The rule is frequently specified by giving a formula for $f(x)$ in terms of x. For example, $f(x) = 2^x$, $f(x) = \sin x$, and $f(x) = x^2 + 1$ are familiar functions. In fact, every polynomial $p(x)$ can be regarded as the formula for a function p.



The set of all functions on $[a, b]$ is denoted $\mathbf{F}[a, b]$. Two functions f and g in $\mathbf{F}[a, b]$ are **equal** if $f(x) = g(x)$ for every x in $[a, b]$, and we describe this by saying that f and g have the **same action**. Note that two polynomials are equal in $\mathbf{P}$ (defined prior to Example 6.1.5) if and only if they are equal as functions.

If f and g are two functions in $\mathbf{F}[a, b]$, and if r is a real number, define the sum $f + g$ and the scalar product rf by

$$\begin{aligned} 2(f + g)(x) &= f(x) + g(x) \qquad \text{for each } x \text{ in } [a, b] \\ (rf)(x) &= rf(x) \qquad \text{for each } x \text{ in } [a, b] \end{aligned}$$

In other words, the action of $f + g$ upon x is to associate x with the number $f(x) + g(x)$, and rf associates x with $rf(x)$. The sum of $f(x) = x^2$ and $g(x) = -x$ is shown in the diagram. These operations on $\mathbf{F}[a, b]$ are called **pointwise addition and scalar multiplication** of functions and they are the usual operations familiar from elementary algebra and calculus.

Example 5.11.1.1.7

The set $\mathbf{F}[a, b]$ of all functions on the interval $[a, b]$ is a vector space using pointwise addition and scalar multiplication. The zero function (in axiom A4), denoted 0, is the constant function defined by

$$0(x) = 0 \qquad \text{for each } x \text{ in } [a, b]$$

The negative of a function f is denoted $-f$ and has action defined by

$$(-f)(x) = -f(x) \qquad \text{for each } x \text{ in } [a, b]$$

Axioms A1 and S1 are clearly satisfied because, if f and g are functions on $[a, b]$, then $f + g$ and rf are again such functions. The verification of the remaining axioms is left as Exercise 6.1.14.

Other examples of vector spaces will appear later, but these are sufficiently varied to indicate the scope of the concept and to illustrate the properties of vector spaces to be discussed. With such a variety of examples, it may come as a surprise that a well-developed *theory* of vector spaces exists. That is, many properties can be shown to hold for *all* vector spaces and hence hold in every example. Such properties are called *theorems* and can be deduced from the axioms. Here is an important example.

Theorem 5.11.1.1.1: Cancellation

Let $\mathbf{u}$, $\mathbf{v}$, and $\mathbf{w}$ be vectors in a vector space V. If $\mathbf{v} + \mathbf{u} = \mathbf{v} + \mathbf{w}$, then $\mathbf{u} = \mathbf{w}$.

Proof

We are given $\mathbf{v} + \mathbf{u} = \mathbf{v} + \mathbf{w}$. If these were numbers instead of vectors, we would simply subtract $\mathbf{v}$ from both sides of the equation to obtain $\mathbf{u} = \mathbf{w}$. This can be accomplished with vectors by adding $-\mathbf{v}$ to both sides of the equation. The steps (using only the axioms) are as follows:

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This is the desired conclusion.[1]

As with many good mathematical theorems, the technique of the proof of Theorem 6.1.1 is at least as important as the theorem itself. The idea was to mimic the well-known process of numerical subtraction in a vector space V as follows: To subtract a vector $\mathbf{v}$ from both sides of a vector equation, we added $-\mathbf{v}$ to both sides. With this in mind, we define **difference** $\mathbf{u} - \mathbf{v}$ of two vectors in V as

$$\mathbf{u} - \mathbf{v} = \mathbf{u} + (-\mathbf{v})$$

We shall say that this vector is the result of having **subtracted** $\mathbf{v}$ from $\mathbf{u}$ and, as in arithmetic, this operation has the property given in Theorem 6.1.2.

Theorem 5.11.1.1.2

If $\mathbf{u}$ and $\mathbf{v}$ are vectors in a vector space V, the equation

$$\mathbf{x} + \mathbf{v} = \mathbf{u}$$

has one and only one solution $\mathbf{x}$ in V given by

$$\mathbf{x} = \mathbf{u} - \mathbf{v}$$

Proof

The difference $\mathbf{x} = \mathbf{u} - \mathbf{v}$ is indeed a solution to the equation because (using several axioms)

$$\mathbf{x} + \mathbf{v} = (\mathbf{u} - \mathbf{v}) + \mathbf{v} = [\mathbf{u} + (-\mathbf{v})] + \mathbf{v} = \mathbf{u} + (-\mathbf{v} + \mathbf{v}) = \mathbf{u} + \mathbf{0} = \mathbf{u}$$

To see that this is the only solution, suppose $\mathbf{x}_1$ is another solution so that $\mathbf{x}_1 + \mathbf{v} = \mathbf{u}$. Then $\mathbf{x} + \mathbf{v} = \mathbf{x}_1 + \mathbf{v}$ (they both equal $\mathbf{u}$), so $\mathbf{x} = \mathbf{x}_1$ by cancellation.

Similarly, cancellation shows that there is only one zero vector in any vector space and only one negative of each vector (Exercises 6.1.10 and 6.1.11). Hence we speak of *the* zero vector and *the* negative of a vector.

The next theorem derives some basic properties of scalar multiplication that hold in every vector space, and will be used extensively.

Theorem 5.11.1.1.3

Let $\mathbf{v}$ denote a vector in a vector space V and let a denote a real number.

1. $0\mathbf{v} = \mathbf{0}$.
2. $a\mathbf{0} = \mathbf{0}$.
3. If $a\mathbf{v} = \mathbf{0}$, then either $a = 0$ or $\mathbf{v} = \mathbf{0}$.
4. $(-1)\mathbf{v} = -\mathbf{v}$.
5. $(-a)\mathbf{v} = -(a\mathbf{v}) = a(-\mathbf{v})$.

Proof)

1. Observe that $0\mathbf{v} + 0\mathbf{v} = (0 + 0)\mathbf{v} = 0\mathbf{v} = 0\mathbf{v} + \mathbf{0}$ where the first equality is by axiom S3. It follows that $0\mathbf{v} = \mathbf{0}$ by cancellation.
2. The proof is similar to that of (1), and is left as Exercise 6.1.12(a).
3. Assume that $a\mathbf{v} = \mathbf{0}$. If $a = 0$, there is nothing to prove; if $a \neq 0$, we must show that $\mathbf{v} = \mathbf{0}$. But $a \neq 0$ means we can scalar-multiply the equation $a\mathbf{v} = \mathbf{0}$ by the scalar $\frac{1}{a}$. The result (using (2) and Axioms S5 and S4) is
$$\mathbf{v} = 1\mathbf{v} = \left(\frac{1}{a}a\right)\mathbf{v} = \frac{1}{a}(a\mathbf{v}) = \frac{1}{a}\mathbf{0} = \mathbf{0}$$
4. We have $-\mathbf{v} + \mathbf{v} = \mathbf{0}$ by axiom A5. On the other hand,
$$(-1)\mathbf{v} + \mathbf{v} = (-1)\mathbf{v} + 1\mathbf{v} = (-1 + 1)\mathbf{v} = 0\mathbf{v} = \mathbf{0}$$
5. The proof is left as Exercise 6.1.12.

The properties in Theorem 6.1.3 are familiar for matrices; the point here is that they hold in *every* vector space. It is hard to exaggerate the importance of this observation.

Axiom A3 ensures that the sum $\mathbf{u} + (\mathbf{v} + \mathbf{w}) = (\mathbf{u} + \mathbf{v}) + \mathbf{w}$ is the same however it is formed, and we write it simply as $\mathbf{u} + \mathbf{v} + \mathbf{w}$.

Similarly, there are different ways to form any sum $\mathbf{v}_1 + \mathbf{v}_2 + \cdots + \mathbf{v}_n$, and Axiom A3 guarantees that they are all equal. Moreover, Axiom A2 shows that the order in which the vectors are written does not matter (for example: $\mathbf{u} + \mathbf{v} + \mathbf{w} + \mathbf{z} = \mathbf{z} + \mathbf{u} + \mathbf{w} + \mathbf{v}$).

Similarly, Axioms S2 and S3 extend. For example

$$a(\mathbf{u} + \mathbf{v} + \mathbf{w}) = a\left[\mathbf{u} + (\mathbf{v} + \mathbf{w})\right] = a\mathbf{u} + a(\mathbf{v} + \mathbf{w}) = a\mathbf{u} + a\mathbf{v} + a\mathbf{w}$$

for all a, $\mathbf{u}$, $\mathbf{v}$, and $\mathbf{w}$. Similarly $(a + b + c)\mathbf{v} = a\mathbf{v} + b\mathbf{v} + c\mathbf{v}$ hold for all values of a, b, c, and $\mathbf{v}$ (verify). More generally,

$$\begin{aligned} a(\mathbf{v}_1 + \mathbf{v}_2 + \cdots + \mathbf{v}_n) &= a\mathbf{v}_1 + a\mathbf{v}_2 + \cdots + a\mathbf{v}_n \\ (a_1 + a_2 + \cdots + a_n)\mathbf{v} &= a_1\mathbf{v} + a_2\mathbf{v} + \cdots + a_n\mathbf{v} \end{aligned}$$

hold for all $n \geq 1$, all numbers $a, a_1, \ldots, a_n$, and all vectors, $\mathbf{v}, \mathbf{v}_1, \ldots, \mathbf{v}_n$. The verifications are by induction and are left to the reader (Exercise 6.1.13). These facts—together with the axioms, Theorem 6.1.3, and the definition of subtraction—enable us to simplify expressions involving sums of scalar multiples of vectors by collecting like terms, expanding, and taking out common factors. This has been discussed for the vector space of matrices in Section 2.1 (and for geometric vectors in Section 4.1); the manipulations in an arbitrary vector space are carried out in the same way. Here is an illustration.

Example 5.11.1.1.8

If $\mathbf{u}$, $\mathbf{v}$, and $\mathbf{w}$ are vectors in a vector space V, simplify the expression

$$2(\mathbf{u} + 3\mathbf{w}) - 3(2\mathbf{w} - \mathbf{v}) - 3[2(2\mathbf{u} + \mathbf{v} - 4\mathbf{w}) - 4(\mathbf{u} - 2\mathbf{w})]$$

Solution

The reduction proceeds as though $\mathbf{u}$, $\mathbf{v}$, and $\mathbf{w}$ were matrices or variables.

$$\begin{aligned} &2(\mathbf{u} + 3\mathbf{w}) - 3(2\mathbf{w} - \mathbf{v}) - 3[2(2\mathbf{u} + \mathbf{v} - 4\mathbf{w}) - 4(\mathbf{u} - 2\mathbf{w})] \\ &= 2\mathbf{u} + 6\mathbf{w} - 6\mathbf{w} + 3\mathbf{v} - 3[4\mathbf{u} + 2\mathbf{v} - 8\mathbf{w} - 4\mathbf{u} + 8\mathbf{w}] \\ &= 2\mathbf{u} + 3\mathbf{v} - 3[2\mathbf{v}] \\ &= 2\mathbf{u} + 3\mathbf{v} - 6\mathbf{v} \\ &= 2\mathbf{u} - 3\mathbf{v} \end{aligned}$$

Condition (2) in Theorem 6.1.3 points to another example of a vector space.

Example 5.11.1.1.9

A set $\{0\}$ with one element becomes a vector space if we define

$$\mathbf{0} + \mathbf{0} = \mathbf{0} \quad \text{and} \quad a\mathbf{0} = \mathbf{0} \text{ for all scalars } a.$$

The resulting space is called the **zero vector space** and is denoted $\{0\}$.

The vector space axioms are easily verified for $\{0\}$. In any vector space V, Theorem 6.1.3 shows that the zero subspace (consisting of the zero vector of V alone) is a copy of the zero vector space.

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1. Observe that none of the scalar multiplication axioms are needed here.

5.11.1.1E: Examples and Basic Properties Exercises

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5.11.1.1E: Examples and Basic Properties Exercises

Exercise 5.11.1.1E.1

Let V denote the set of ordered triples (x, y, z) and define addition in V as in $\mathbb{R}^3$. For each of the following definitions of scalar multiplication, decide whether V is a vector space.

a. $a(x, y, z) = (ax, y, az)$
b. $a(x, y, z) = (ax, 0, az)$
c. $a(x, y, z) = (0, 0, 0)$
d. $a(x, y, z) = (2ax, 2ay, 2az)$

Answer available at the end of this section.

Exercise 5.11.1.1E.2

Are the following sets vector spaces with the indicated operations? If not, why not?

a. The set V of nonnegative real numbers; ordinary addition and scalar multiplication.
b. The set V of all polynomials of degree ≥ 3, together with 0; operations of $\mathbf{P}$.
c. The set of all polynomials of degree ≤ 3; operations of $\mathbf{P}$.
d. The set $\{1, x, x^2, ...\}$; operations of $\mathbf{P}$.
e. The set V of all 2×2 matrices of the form $\begin{bmatrix} a & b \\ 0 & c \end{bmatrix}$; operations of $\mathbf{M}_{22}$.
f. The set V of 2×2 matrices with equal column sums; operations of $\mathbf{M}_{22}$.
g. The set V of 2×2 matrices with zero determinant; usual matrix operations.
h. The set V of real numbers; usual operations.
i. The set V of complex numbers; usual addition and multiplication by a real number.
j. The set V of all ordered pairs (x, y) with the addition of $\mathbb{R}^2$, but using scalar multiplication $a(x, y) = (ax, -ay)$.
k. The set V of all ordered pairs (x, y) with the addition of $\mathbb{R}^2$, but using scalar multiplication $a(x, y) = (x, y)$ for all a in $\mathbb{R}$.
l. The set V of all functions $f : \mathbb{R} \to \mathbb{R}$ with pointwise addition, but scalar multiplication defined by $(af)(x) = f(ax)$.
m. The set V of all 2×2 matrices whose entries sum to 0; operations of $\mathbf{M}_{22}$.
n. The set V of all 2×2 matrices with the addition of $\mathbf{M}_{22}$ but scalar multiplication $*$ defined by $a * X = aX^T$.

Answer available at the end of this section.

Exercise 5.11.1.1E.3

Let V be the set of positive real numbers with vector addition being ordinary multiplication, and scalar multiplication being $a \cdot v = v^a$. Show that V is a vector space.

Exercise 5.11.1.1E.4

If V is the set of ordered pairs (x, y) of real numbers, show that it is a vector space with addition $(x, y) + (x_1, y_1) = (x + x_1, y + y_1 + 1)$ and scalar multiplication $a(x, y) = (ax, ay + a - 1)$. What is the zero vector in V?

Answer available at the end of this section.

Exercise 5.11.1.1E.5

Find $\mathbf{x}$ and $\mathbf{y}$ (in terms of $\mathbf{u}$ and $\mathbf{v}$) such that:

a. $\begin{aligned} 2\mathbf{x} &+ \mathbf{y} = \mathbf{u} \\ 5\mathbf{x} &+ 3\mathbf{y} = \mathbf{v} \end{aligned}$

b. $\begin{aligned} 3\mathbf{x} &- 2\mathbf{y} = \mathbf{u} \\ 4\mathbf{x} &- 5\mathbf{y} = \mathbf{v} \end{aligned}$

Answer available at the end of this section.

Exercise 5.11.1.1E.6

In each case show that the condition $a\mathbf{u} + b\mathbf{v} + c\mathbf{w} = \mathbf{0}$ in V implies that $a = b = c = 0$.

a. $V = \mathbb{R}^4$; $\mathbf{u} = (2, 1, 0, 2)$, $\mathbf{v} = (1, 1, -1, 0)$, $\mathbf{w} = (0, 1, 2, 1)$

b. $V = \|M_{22}$; $\mathbf{u} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $\mathbf{v} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$, $\mathbf{w} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$

c. $V = \|P$; $\mathbf{u} = x^3 + x$, $\mathbf{v} = x^2 + 1$, $\mathbf{w} = x^3 - x^2 + x + 1$

d. $V = \|F[0, \pi]$; $\mathbf{u} = \sin x$, $\mathbf{v} = \cos x$, $\mathbf{w} = 1$—the constant function

Answer available at the end of this section.

Exercise 5.11.1.1E.7

Simplify each of the following.

a. $3[2(\mathbf{u} - 2\mathbf{v} - \mathbf{w}) + 3(\mathbf{w} - \mathbf{v})] - 7(\mathbf{u} - 3\mathbf{v} - \mathbf{w})$

b. $4(3\mathbf{u} - \mathbf{v} + \mathbf{w}) - 2[(3\mathbf{u} - 2\mathbf{v}) - 3(\mathbf{v} - \mathbf{w})] + 6(\mathbf{w} - \mathbf{u} - \mathbf{v})$

Answer available at the end of this section.

Exercise 5.11.1.1E.8

Show that $\mathbf{x} = \mathbf{v}$ is the only solution to the equation $\mathbf{x} + \mathbf{x} = 2\mathbf{v}$ in a vector space V. Cite all axioms used.

Exercise 5.11.1.1E.9

Show that $-\mathbf{0} = \mathbf{0}$ in any vector space. Cite all axioms used.

Exercise 5.11.1.1E.10

Show that the zero vector $\mathbf{0}$ is uniquely determined by the property in axiom A4.

Answer available at the end of this section.

Exercise 5.11.1.1E.11

Given a vector $\mathbf{v}$, show that its negative $-\mathbf{v}$ is uniquely determined by the property in axiom A5.

Exercise 5.11.1.1E.12

a. Prove (2) of Theorem 6.1.3. [*Hint*: Axiom S2.]
b. Prove that $(-a)\mathbf{v} = -(a\mathbf{v})$ in Theorem 6.1.3 by first computing $(-a)\mathbf{v} + a\mathbf{v}$. Then do it using (4) of Theorem 6.1.3 and axiom S4.
c. Prove that $a(-\mathbf{v}) = -(a\mathbf{v})$ in Theorem 6.1.3 in two ways, as in part (b).

Answer available at the end of this section.

Exercise 5.11.1.1E.13

Let $\mathbf{v}, \mathbf{v}_1, \dots, \mathbf{v}_n$ denote vectors in a vector space V and let $a, a_1, \dots, a_n$ denote numbers. Use induction on n to prove each of the following.

a. $a(\mathbf{v}_1 + \mathbf{v}_2 + \cdots + \mathbf{v}_n) = a\mathbf{v}_1 + a\mathbf{v}_2 + \cdots + a\mathbf{v}_n$
b. $(a_1 + a_2 + \cdots + a_n)\mathbf{v} = a_1\mathbf{v} + a_2\mathbf{v} + \cdots + a_n\mathbf{v}$

Answer available at the end of this section.

Exercise 5.11.1.1E.14

Verify axioms A2—A5 and S2—S5 for the space $\mathbf{F}[a, b]$ of functions on $[a, b]$ (Example 6.1.7).

Exercise 5.11.1.1E.15

Prove each of the following for vectors $\mathbf{u}$ and $\mathbf{v}$ and scalars a and b.

a. If $a\mathbf{v} = \mathbf{0}$, then $a = 0$ or $\mathbf{v} = \mathbf{0}$.
b. If $a\mathbf{v} = b\mathbf{v}$ and $\mathbf{v} \neq \mathbf{0}$, then $a = b$.
c. If $a\mathbf{v} = a\mathbf{w}$ and $a \neq 0$, then $\mathbf{v} = \mathbf{w}$.

Answer available at the end of this section.

Exercise 5.11.1.1E.16

By calculating $(1 + 1)(\mathbf{v} + \mathbf{w})$ in two ways (using axioms S2 and S3), show that axiom A2 follows from the other axioms.

Exercise 5.11.1.1E.17

Let V be a vector space, and define V^n to be the set of all n-tuples $(\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n)$ of n vectors $\mathbf{v}_i$, each belonging to V. Define addition and scalar multiplication in V^n as follows:

$$\begin{aligned}(\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n) + (\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n) \\ = (\mathbf{u}_1 + \mathbf{v}_1, \mathbf{u}_2 + \mathbf{v}_2, \dots, \mathbf{u}_n + \mathbf{v}_n) \\ a(\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n) = (a\mathbf{v}_1, a\mathbf{v}_2, \dots, a\mathbf{v}_n)\end{aligned}$$

Exercise 5.11.1.1E.18

Show that V^n is a vector space.

Exercise $5.11.1.1E.19$

Let V^n be the vector space of n-tuples from the preceding exercise, written as columns. If A is an $m \times n$ matrix, and X is in V^n, define AX in V^m by matrix multiplication. More precisely, if

$$A = [a_{ij}] \text{ and } X = \begin{bmatrix} \mathbf{v}_1 \\ \vdots \\ \mathbf{v}_n \end{bmatrix}, \text{ let } AX = \begin{bmatrix} \mathbf{u}_1 \\ \vdots \\ \mathbf{u}_n \end{bmatrix}$$

where $\mathbf{u}_i = a_{i1}\mathbf{v}_1 + a_{i2}\mathbf{v}_2 + \cdots + a_{in}\mathbf{v}_n$ for each i. Prove that:

a. $B(AX) = (BA)X$
b. $(A + A_1)X = AX + A_1X$
c. $A(X + X_1) = AX + AX_1$
d. $(kA)X = k(AX) = A(kX)$ if k is any number
e. $IX = X$ if I is the $n \times n$ identity matrix
f. Let E be an elementary matrix obtained by performing a row operation on the rows of I_n (see Section 2.5). Show that EX is the column resulting from performing that same row operation on the vectors (call them rows) of X. [*Hint*: Lemma 2.5.1.]

Answers

Exercise $5.11.1.1E.1$

a. No; S5 fails.
d. No; S4 and S5 fail.

Exercise $5.11.1.1E.2$

b. No; only A1 fails.
d. No.
f. Yes.
h. Yes.
j. No.
l. No; only S3 fails.
n. No; only S4 and S5 fail.

Exercise $5.11.1.1E.4$

The zero vector is $(0, -1)$; the negative of (x, y) is $(-x, -2 - y)$.

Exercise $5.11.1.1E.5$

b. $\mathbf{x} = \frac{1}{7}(5\mathbf{u} - 2\mathbf{v}), \mathbf{y} = \frac{1}{7}(4\mathbf{u} - 3\mathbf{v})$

Exercise $5.11.1.1E.6$

b. Equating entries gives $a + c = 0$, $b + c = 0$, $b + c = 0$, $a - c = 0$. The solution is $a = b = c = 0$.
d. If $a \sin x + b \cos y + c = 0$ in $\mathbf{F}[0, \pi]$, then this must hold for *every* x in $[0, \pi]$. Taking $x = 0, \frac{\pi}{2}$, and π, respectively, gives $b + c = 0$, $a + c = 0$, $-b + c = 0$ whence, $a = b = c = 0$.

Exercise $5.11.1.1E.7$

b. $4\mathbf{w}$

Exercise $5.11.1.1E.10$

If $\mathbf{z} + \mathbf{v} = \mathbf{v}$ for all $\mathbf{v}$, then $\mathbf{z} + \mathbf{v} = \mathbf{0} + \mathbf{v}$, so $\mathbf{z} = \mathbf{0}$ by cancellation.

Exercise $5.11.1.1E.12$

b. $(-a)\mathbf{v} + a\mathbf{v} = (-a + a)\mathbf{v} = 0\mathbf{v} = \mathbf{0}$ by Theorem 6.1.3. Because also $-(a\mathbf{v}) + a\mathbf{v} = \mathbf{0}$ (by the definition of $-(a\mathbf{v})$ in axiom A5), this means that $(-a)\mathbf{v} = -(a\mathbf{v})$ by cancellation. Alternatively, use Theorem 6.1.3(4) to give $(-a)\mathbf{v} = [(-1)a]\mathbf{v} = (-1)(a\mathbf{v}) = -(a\mathbf{v})$.

Exercise $5.11.1.1E.13$

b. The case $n = 1$ is clear, and $n = 2$ is axiom S3. If $n > 2$, then $(a_1 + a_2 + \cdots + a_n)\mathbf{v} = [a_1 + (a_2 + \cdots + a_n)]\mathbf{v} = a_1\mathbf{v} + (a_2 + \cdots + a_n)\mathbf{v} = a_1\mathbf{v} + (a_2\mathbf{v} + \cdots + a_n\mathbf{v})$ using the induction hypothesis; so it holds for all n.

Exercise $5.11.1.1E.15$

c. If $a\mathbf{v} = a\mathbf{w}$, then $\mathbf{v} = 1\mathbf{v} = (a^{-1}a)\mathbf{v} = a^{-1}(a\mathbf{v}) = a^{-1}(a\mathbf{w}) = (a^{-1}a)\mathbf{w} = 1\mathbf{w} = \mathbf{w}$.

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5.11.1.2: SUBSPACES AND SPANNING SETS

Chapter 5 is essentially about the subspaces of $\mathbb{R}^n$. We now extend this notion.

Definition: Subspaces of a Vector Space

If V is a vector space, a nonempty subset $U \subseteq V$ is called a **subspace** of V if U is itself a vector space using the addition and scalar multiplication of V.

Subspaces of $\mathbb{R}^n$ (as defined in Section 5.1) are subspaces in the present sense by Example 6.1.3. Moreover, the defining properties for a subspace of $\mathbb{R}^n$ actually *characterize* subspaces in general.

Theorem 5.11.1.2.1: Subspace Test

A subset U of a vector space is a subspace of V if and only if it satisfies the following three conditions:

1. $\mathbf{0}$ lies in U where $\mathbf{0}$ is the zero vector of V.
2. If $\mathbf{u}_1$ and $\mathbf{u}_2$ are in U, then $\mathbf{u}_1 + \mathbf{u}_2$ is also in U.
3. If $\mathbf{u}$ is in U, then $a\mathbf{u}$ is also in U for each scalar a.

Proof

If U is a subspace of V, then (2) and (3) hold by axioms A1 and S1 respectively, applied to the vector space U. Since U is nonempty (it is a vector space), choose $\mathbf{u}$ in U. Then (1) holds because $\mathbf{0} = 0\mathbf{u}$ is in U by (3) and Theorem 6.1.3.

Conversely, if (1), (2), and (3) hold, then axioms A1 and S1 hold because of (2) and (3), and axioms A2, A3, S2, S3, S4, and S5 hold in U because they hold in V. Axiom A4 holds because the zero vector $\mathbf{0}$ of V is actually in U by (1), and so serves as the zero of U. Finally, given $\mathbf{u}$ in U, then its negative $-\mathbf{u}$ in V is again in U by (3) because $-\mathbf{u} = (-1)\mathbf{u}$ (again using Theorem 6.1.3). Hence $-\mathbf{u}$ serves as the negative of $\mathbf{u}$ in U.

$square$

Note that the proof of Theorem 6.2.1 shows that if U is a subspace of V, then U and V share the same zero vector, and that the negative of a vector in the space U is the same as its negative in V.

Example 5.11.1.2.1

If V is any vector space, show that $\{\mathbf{0}\}$ and V are subspaces of V.

Solution

$U = V$ clearly satisfies the conditions of the subspace test. As to $U = \{\mathbf{0}\}$, it satisfies the conditions because $\mathbf{0} + \mathbf{0} = \mathbf{0}$ and $a\mathbf{0} = \mathbf{0}$ for all a in $\mathbb{R}$.

The vector space $\{\mathbf{0}\}$ is called the **zero subspace** of V.

Example 5.11.1.2.2

Let $\mathbf{v}$ be a vector in a vector space V. Show that the set

$$\mathbb{R}\mathbf{v} = \{a\mathbf{v} \mid a \text{ in } \mathbb{R}\}$$

of all scalar multiples of $\mathbf{v}$ is a subspace of V.

Solution

Because $\mathbf{0} = 0\mathbf{v}$, it is clear that $\mathbf{0}$ lies in $\mathbb{R}\mathbf{v}$. Given two vectors $a\mathbf{v}$ and $a_1\mathbf{v}$ in $\mathbb{R}\mathbf{v}$, their sum $a\mathbf{v} + a_1\mathbf{v} = (a + a_1)\mathbf{v}$ is also a scalar multiple of $\mathbf{v}$ and so lies in $\mathbb{R}\mathbf{v}$. Hence $\mathbb{R}\mathbf{v}$ is closed under addition. Finally, given $a\mathbf{v}$, $r(a\mathbf{v}) = (ra)\mathbf{v}$ lies in $\mathbb{R}\mathbf{v}$ for all $r \in \mathbb{R}$, so $\mathbb{R}\mathbf{v}$ is closed under scalar multiplication. Hence the subspace test applies.

In particular, given $\mathbf{d} \neq \mathbf{0}$ in $\mathbb{R}^3$, $\mathbb{R}\mathbf{d}$ is the line through the origin with direction vector $\mathbf{d}$.

The space $\mathbb{R}\mathbf{v}$ in Example 6.2.2 is described by giving the *form* of each vector in $\mathbb{R}\mathbf{v}$. The next example describes a subset U of the space $\mathbf{M}_{nn}$ by giving a *condition* that each matrix of U must satisfy.

Example 5.11.1.2.3

Let A be a fixed matrix in $\mathbf{M}_{nn}$. Show that $U = \{X \text{ in } \|M_{nn} \mid AX = XA\}$ is a subspace of $\mathbf{M}_{nn}$.

Solution

(AX = XA\) and $AX_1 = X_1A$. Then

$$A(X + X_1) = AX + AX_1 = XA + X_1A + (X + X_1)A$$
$$A(aX) = a(AX) = a(XA) = (aX)A$$

for all a in $\mathbb{R}$, so both $X + X_1$ and aX lie in U. Hence U is a subspace of $\mathbf{M}_{nn}$.

If 0 is the $n \times n$ zero matrix, then $A0 = 0A$, so 0 satisfies the condition for membership in U. Next suppose that X and X_1 lie in U so that \

Suppose $p(x)$ is a polynomial and a is a number. Then the number $p(a)$ obtained by replacing x by a in the expression for $p(x)$ is called the **evaluation** of $p(x)$ at a. For example, if $p(x) = 5 - 6x + 2x^2$, then the evaluation of $p(x)$ at $a = 2$ is $p(2) = 5 - 12 + 8 = 1$. If $p(a) = 0$, the number a is called a **root** of $p(x)$.

Example 5.11.1.2.4

Consider the set U of all polynomials in $\mathbf{P}$ that have 3 as a root:

$$U = \{p(x) \in \|P \mid p(3) = 0\}$$

Show that U is a subspace of $\mathbf{P}$.

Solution

Clearly, the zero polynomial lies in U. Now let $p(x)$ and $q(x)$ lie in U so $p(3) = 0$ and $q(3) = 0$. We have $(p + q)(x) = p(x) + q(x)$ for all x, so $(p + q)(3) = p(3) + q(3) = 0 + 0 = 0$, and U is closed under addition. The verification that U is closed under scalar multiplication is similar.

Recall that the space $\mathbf{P}_n$ consists of all polynomials of the form

$$a_0 + a_1x + a_2x^2 + \cdots + a_nx^n$$

where $a_0, a_1, a_2, \ldots, a_n$ are real numbers, and so is closed under the addition and scalar multiplication in $\mathbf{P}$. Moreover, the zero polynomial is included in $\mathbf{P}_n$. Thus the subspace test gives Example 6.2.5.

Example 5.11.1.2.5

$\mathbf{P}_n$ is a subspace of $\mathbf{P}$ for each $n \geq 0$.

The next example involves the notion of the derivative f' of a function f. (If the reader is not familiar with calculus, this example may be omitted.) A function f defined on the interval $[a, b]$ is called **differentiable** if the derivative $f'(r)$ exists at every r in $[a, b]$.

Example 5.11.1.2.6

Show that the subset $\mathbf{D}[a, b]$ of all **differentiable functions** on $[a, b]$ is a subspace of the vector space $\mathbf{F}[a, b]$ of all functions on $[a, b]$.

Solution

The derivative of any constant function is the constant function 0; in particular, 0 itself is differentiable and so lies in $\mathbf{D}[a, b]$. If f and g both lie in $\mathbf{D}[a, b]$ (so that f' and g' exist), then it is a theorem of calculus that $f + g$ and rf are both differentiable for any $r \in \mathbb{R}$. In fact, $(f + g)' = f' + g'$ and $(rf)' = rf'$, so both lie in $\mathbf{D}[a, b]$. This shows that $\mathbf{D}[a, b]$ is a subspace of $\mathbf{F}[a, b]$.

Linear Combinations and Spanning Sets

One of the crucial concept in linear algebra is that of a span of a set of vectors, obtained by considering all possible linear combinations of vectors in that set.

Definition: Linear Combinations and Spanning

Let $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$ be a set of vectors in a vector space V. As in $\mathbb{R}^n$, a vector $\mathbf{v}$ is called a **linear combination** of the vectors $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n$ if it can be expressed in the form

$$\mathbf{v} = a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + \cdots + a_n\mathbf{v}_n$$

where $a_1, a_2, \ldots, a_n$ are scalars, called the **coefficients** of $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n$. The set of all linear combinations of these vectors is called their **span**, and is denoted by

$$span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\} = \{a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + \cdots + a_n\mathbf{v}_n \mid a_i \text{ in } \mathbb{R}\}$$

If it happens that $V = span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$, these vectors are called a **spanning set** for V. For example, the span of two vectors $\mathbf{v}$ and $\mathbf{w}$ is the set

$$span\ \{\mathbf{v}, \mathbf{w}\} = \{s\mathbf{v} + t\mathbf{w} \mid s \text{ and } t \text{ in } \mathbb{R}\}$$

of all sums of scalar multiples of these vectors.

Example 5.11.1.2.7

Consider the vectors $p_1 = 1 + x + 4x^2$ and $p_2 = 1 + 5x + x^2$ in $\mathbf{P}_2$. Determine whether p_1 and p_2 lie in $span\ \{1 + 2x - x^2, 3 + 5x + 2x^2\}$.

Solution

For p_1, we want to determine if s and t exist such that

$$p_1 = s(1 + 2x - x^2) + t(3 + 5x + 2x^2)$$

Equating coefficients of powers of x (where $x^0 = 1$) gives

$$1 = s + 3t, \quad 1 = 2s + 5t, \quad \text{and} \quad 4 = -s + 2t$$

These equations have the solution $s = -2$ and $t = 1$, so p_1 is indeed in $span\ \{1 + 2x - x^2, 3 + 5x + 2x^2\}$.

Turning to $p_2 = 1 + 5x + x^2$, we are looking for s and t such that

$$p_2 = s(1 + 2x - x^2) + t(3 + 5x + 2x^2)$$

Again equating coefficients of powers of x gives equations $1 = s + 3t$, $5 = 2s + 5t$, and $1 = -s + 2t$. But in this case there is no solution, so p_2 is *not* in $span\ \{1 + 2x - x^2, 3 + 5x + 2x^2\}$.

We saw in Example 5.1.6 that $\mathbb{R}^m = span\ \{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_m\}$ where the vectors $\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_m$ are the columns of the $m \times m$ identity matrix. Of course $\mathbb{R}^m = \|M_{m1}$ is the set of all $m \times 1$ matrices, and there is an analogous spanning set for each space $\mathbf{M}_{mn}$. For example, each 2×2 matrix has the form

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} = a\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + b\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + c\begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} + d\begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

so

$$\mathbf{M}_{22} = span\left\{\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}\right\}$$

Similarly, we obtain

Example 5.11.1.2.8

$\mathbf{M}_{mn}$ is the span of the set of all $m \times n$ matrices with exactly one entry equal to 1, and all other entries zero.

The fact that every polynomial in $\mathbf{P}_n$ has the form $a_0 + a_1x + a_2x^2 + \cdots + a_nx^n$ where each a_i is in $\mathbb{R}$ shows that

Example 5.11.1.2.9

$\mathbf{P}_n = span\ \{1, x, x^2, \ldots, x^n\}$.

In Example 6.2.2 we saw that $span\ \{\mathbf{v}\} = \{a\mathbf{v} \mid a \text{ in } \mathbb{R}\} = \mathbb{R}\mathbf{v}$ is a subspace for any vector $\mathbf{v}$ in a vector space V. More generally, the span of *any* set of vectors is a subspace. In fact, the proof of Theorem 5.1.1 goes through to prove:

Theorem 5.11.1.2.2

Let $U = span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$ in a vector space V. Then:

1. U is a subspace of V containing each of $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n$.
2. U is the "smallest" subspace containing these vectors in the sense that any subspace that contains each of $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n$ must contain U.

Here is how condition 2 in Theorem 6.2.2 is used. Given vectors $\mathbf{v}_1, \ldots, \mathbf{v}_k$ in a vector space V and a subspace $U \subseteq V$, then:

$$span\ \{\mathbf{v}_1, \ldots, \mathbf{v}_n\} \subseteq U \Leftrightarrow \text{ each } \mathbf{v}_i \in U$$

The following examples illustrate this.

Example 5.11.1.2.10

Show that $\mathbf{P}_3 = span\ \{x^2 + x^3, x, 2x^2 + 1, 3\}$.

Solution

Write $U = span\ \{x^2 + x^3, x, 2x^2 + 1, 3\}$. Then $U \subseteq \|P_3$, and we use the fact that $\mathbf{P}_3 = span\ \{1, x, x^2, x^3\}$ to show that $\mathbf{P}_3 \subseteq U$. In fact, x and $1 = \frac{1}{3} \cdot 3$ clearly lie in U. But then successively,

$$x^2 = \frac{1}{2}[(2x^2 + 1) - 1] \quad \text{and} \quad x^3 = (x^2 + x^3) - x^2$$

also lie in U. Hence $\mathbf{P}_3 \subseteq U$ by Theorem 6.2.2.

Example 5.11.1.2.11

Let $\mathbf{u}$ and $\mathbf{v}$ be two vectors in a vector space V. Show that

$$span\ \{\mathbf{u}, \mathbf{v}\} = span\ \{\mathbf{u} + 2\mathbf{v}, \mathbf{u} - \mathbf{v}\}$$

Solution

We have $span\ \{\mathbf{u} + 2\mathbf{v}, \mathbf{u} - \mathbf{v}\} \subseteq span\ \{\mathbf{u}, \mathbf{v}\}$ by Theorem 6.2.2 because both $\mathbf{u} + 2\mathbf{v}$ and $\mathbf{u} - \mathbf{v}$ lie in $span\ \{\mathbf{u}, \mathbf{v}\}$. On the other hand,

$$\mathbf{u} = \frac{1}{3}(\mathbf{u} + 2\mathbf{v}) + \frac{2}{3}(\mathbf{u} - \mathbf{v}) \quad \text{and} \quad \mathbf{v} = \frac{1}{3}(\mathbf{u} + 2\mathbf{v}) - \frac{1}{3}(\mathbf{u} - \mathbf{v})$$

so $span\ \{\mathbf{u}, \mathbf{v}\} \subseteq span\ \{\mathbf{u} + 2\mathbf{v}, \mathbf{u} - \mathbf{v}\}$, again by Theorem 6.2.2.

5.11.1.2E: Subspaces and Spanning Sets Exercises

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5.11.1.2E: Subspaces and Spanning Sets Exercises

Exercise $5.11.1.2E.1$

Which of the following are subspaces of $\mathbf{P}_3$? Support your answer.

a. $U = \{f(x) \mid f(x) \in \|P_3, f(2) = 1\}$
b. $U = \{xg(x) \mid g(x) \in \|P_2\}$
c. $U = \{xg(x) \mid g(x) \in \|P_3\}$
d. $U = \{xg(x) + (1-x)h(x) \mid g(x) \text{ and } h(x) \in \|P_2\}$
e. $U =$ The set of all polynomials in $\mathbf{P}_3$ with constant term 0
f. $U = \{f(x) \mid f(x) \in \|P_3, \deg f(x) = 3\}$

Answer available at the end of this section.

Exercise $5.11.1.2E.2$

Which of the following are subspaces of $\mathbf{M}_{22}$? Support your answer.

a. $U = \left\{ \left[\begin{array}{cc} a & b \\ 0 & c \end{array} \right] \middle| \, a, b, \text{ and } c \text{ in } \mathbb{R} \right\}$
b. $U = \left\{ \left[\begin{array}{cc} a & b \\ c & d \end{array} \right] \middle| \, a + b = c + d; \; a, b, c, d \text{ in } \mathbb{R} \right\}$
c. $U = \{A \mid A \in \|M_{22}, A = A^T\}$
d. $U = \{A \mid A \in \|M_{22}, AB = 0\}$, B a fixed 2×2 matrix
e. $U = \{A \mid A \in \|M_{22}, A^2 = A\}$
f. $U = \{A \mid A \in \|M_{22}, A \text{ is not invertible}\}$
g. $U = \{A \mid A \in \|M_{22}, BAC = CAB\}$, B and C fixed 2×2 matrices

Answer available at the end of this section.

Exercise $5.11.1.2E.3$

Which of the following are subspaces of $\mathbf{F}[0, 1]$? Support your answer.

a. $U = \{f \mid f(0) = 0\}$
b. $U = \{f \mid f(0) = 1\}$
c. $U = \{f \mid f(0) = f(1)\}$
d. $U = \{f \mid f(x) \geq 0 \text{ for all } x \text{ in } [0, 1]\}$
e. $U = \{f \mid f(x) = f(y) \text{ for all } x \text{ and } y \text{ in } [0, 1]\}$
f. $U = \{f \mid f(x + y) = f(x) + f(y) \text{ for all } \; x \text{ and } y \text{ in } [0, 1]\}$
g. $U = \{f \mid f \text{ is integrable and } \int_0^1 f(x)dx = 0\}$

Answer available at the end of this section.

Exercise $5.11.1.2E.4$

Let A be an $m \times n$ matrix. For which columns $\mathbf{b}$ in $\mathbb{R}^m$ is $U = \{\mathbf{x} \mid \mathbf{x} \in \mathbb{R}^n, A\mathbf{x} = \mathbf{b}\}$ a subspace of $\mathbb{R}^n$? Support your answer.

Exercise 5.11.1.2E.5

Let $\mathbf{x}$ be a vector in $\mathbb{R}^n$ (written as a column), and define $U = \{A\mathbf{x} \mid A \in \|M_{mn}\}$.

a. Show that U is a subspace of $\mathbb{R}^m$.
b. Show that $U = \mathbb{R}^m$ if $\mathbf{x} \neq \mathbf{0}$.

Answer available at the end of this section.

Exercise 5.11.1.2E.6

Write each of the following as a linear combination of $x + 1$, $x^2 + x$, and $x^2 + 2$.

a. $x^2 + 3x + 2\ 2x^2 - 3x + 1\ x^2 + 1\ x$
b. $-3(x + 1) + 0(x^2 + x) + 2(x^2 + 2)$
c. $\frac{2}{3}(x + 1) + \frac{1}{3}(x^2 + x) - \frac{1}{3}(x^2 + 2)$

Answer available at the end of this section.

Exercise 5.11.1.2E.7

Determine whether $\mathbf{v}$ lies in $span\ \{\mathbf{u}, \mathbf{w}\}$ in each case.

a. $\mathbf{v} = 3x^2 - 2x - 1$; $\mathbf{u} = x^2 + 1$, $\mathbf{w} = x + 2$
b. $\mathbf{v} = x$; $\mathbf{u} = x^2 + 1$, $\mathbf{w} = x + 2$
c. $\mathbf{v} = \begin{bmatrix} 1 & 3 \\ -1 & 1 \end{bmatrix}$; $\mathbf{u} = \begin{bmatrix} 1 & -1 \\ 2 & 1 \end{bmatrix}$, $\mathbf{w} = \begin{bmatrix} 2 & 1 \\ 1 & 0 \end{bmatrix}$
d. $\mathbf{v} = \begin{bmatrix} 1 & -4 \\ 5 & 3 \end{bmatrix}$; $\mathbf{u} = \begin{bmatrix} 1 & -1 \\ 2 & 1 \end{bmatrix}$, $\mathbf{w} = \begin{bmatrix} 2 & 1 \\ 1 & 0 \end{bmatrix}$

Answer available at the end of this section.

Exercise 5.11.1.2E.8

Which of the following functions lie in $span\ \{\cos^2 x, \sin^2 x\}$? (Work in $\mathbf{F}[0, \pi]$.)

a. $\cos 2x$
b. 1
c. x^2
d. $1 + x^2$

Answer available at the end of this section.

Exercise 5.11.1.2E.9

a. Show that $\mathbb{R}^3$ is spanned by $\{(1, 0, 1), (1, 1, 0), (0, 1, 1)\}$.
b. Show that $\mathbf{P}_2$ is spanned by $\{1 + 2x^2, 3x, 1 + x\}$.
c. Show that $\mathbf{M}_{22}$ is spanned by

$$\left\{\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}\right\}.$$

Answer available at the end of this section.

Exercise $5.11.1.2E.10$

If X and Y are two sets of vectors in a vector space V, and if $X \subseteq Y$, show that $span\ X \subseteq span\ Y$.

Exercise $5.11.1.2E.11$

Let $\mathbf{u}$, $\mathbf{v}$, and $\mathbf{w}$ denote vectors in a vector space V. Show that:

a. $span\ \{\mathbf{u}, \mathbf{v}, \mathbf{w}\} = span\ \{\mathbf{u} + \mathbf{v}, \mathbf{u} + \mathbf{w}, \mathbf{v} + \mathbf{w}\}$
b. $span\ \{\mathbf{u}, \mathbf{v}, \mathbf{w}\} = span\ \{\mathbf{u} - \mathbf{v}, \mathbf{u} + \mathbf{w}, \mathbf{w}\}$

Answer available at the end of this section.

Exercise $5.11.1.2E.12$

Show that

$$span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n, \mathbf{0}\} = span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$$

holds for any set of vectors $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$.

Exercise $5.11.1.2E.13$

If X and Y are nonempty subsets of a vector space V such that $span\ X = span\ Y = V$, must there be a vector common to both X and Y? Justify your answer.

Exercise $5.11.1.2E.14$

Is it possible that $\{(1, 2, 0), (1, 1, 1)\}$ can span the subspace $U = \{(a, b, 0) \mid a \text{ and } b \text{ in } \mathbb{R}\}$?

Answer available at the end of this section.

Exercise $5.11.1.2E.15$

Describe $span\ \{\mathbf{0}\}$.

Exercise $5.11.1.2E.16$

Let $\mathbf{v}$ denote any vector in a vector space V. Show that $span\ \{\mathbf{v}\} = span\ \{a\mathbf{v}\}$ for any $a \neq 0$.

Exercise $5.11.1.2E.17$

Determine all subspaces of $\mathbb{R}\mathbf{v}$ where $\mathbf{v} \neq \mathbf{0}$ in some vector space V.

Exercise $5.11.1.2E.18$

Suppose $V = span\ \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$. If $\mathbf{u} = a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + \cdots + a_n\mathbf{v}_n$ where the a_i are in $\mathbb{R}$ and $a_1 \neq 0$, show that $V = span\ \{\mathbf{u}, \mathbf{v}_2, \dots, \mathbf{v}_n\}$.

Answer available at the end of this section.

Exercise $5.11.1.2E.19$

If $\mathbf{M}_{nn} = span\ \{A_1, A_2, \dots, A_k\}$, show that $\mathbf{M}_{nn} = span\ \{A_1^T, A_2^T, \dots, A_k^T\}$.

Exercise $5.11.1.2E.20$

If $\mathbf{P}_n = span\ \{p_1(x), p_2(x), \dots, p_k(x)\}$ and a is in $\mathbb{R}$, show that $p_i(a) \neq 0$ for some i.

Exercise $5.11.1.2E.21$

Let U be a subspace of a vector space V.

a. If $a\mathbf{u}$ is in U where $a \neq 0$, show that $\mathbf{u}$ is in U.
b. If $\mathbf{u}$ and $\mathbf{u} + \mathbf{v}$ are in U, show that $\mathbf{v}$ is in U.

Answer available at the end of this section.

Exercise $5.11.1.2E.22$

Let U be a nonempty subset of a vector space V. Show that U is a subspace of V if and only if $\mathbf{u}_1 + a\mathbf{u}_2$ lies in U for all $\mathbf{u}_1$ and $\mathbf{u}_2$ in U and all a in $\mathbb{R}$.

Answer available at the end of this section.

Exercise $5.11.1.2E.23$

Let $U = \{p(x)$ in $\|P \mid p(3) = 0\}$ be the set in Example 6.2.4. Use the factor theorem (see Section 6.5) to show that U consists of multiples of $x - 3$; that is, show that $U = \{(x-3)q(x) \mid q(x) \in \|P\}$. Use this to show that U is a subspace of $\mathbf{P}$.

Answer available at the end of this section.

Exercise $5.11.1.2E.24$

Let $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$ and $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n\}$ be sets of vectors in a vector space, and let

$$X = \begin{bmatrix} \mathbf{v}_1 \\ \vdots \\ \mathbf{v}_n \end{bmatrix} \quad Y = \begin{bmatrix} \mathbf{u}_1 \\ \vdots \\ \mathbf{u}_n \end{bmatrix}$$

as in Exercise 6.1.18.

a. Show that $span\ \{\mathbf{v}_1, \dots, \mathbf{v}_n\} \subseteq span\ \{\mathbf{u}_1, \dots, \mathbf{u}_n\}$ if and only if $AY = X$ for some $n \times n$ matrix A.

b. If $X = AY$ where A is invertible, show that $span\ \{\mathbf{v}_1, \ldots, \mathbf{v}_n\} = span\ \{\mathbf{u}_1, \ldots, \mathbf{u}_n\}$.

Exercise $5.11.1.2E.25$

If U and W are subspaces of a vector space V, let $U \cup W = \{\mathbf{v} \mid \mathbf{v}$ is in U or $\mathbf{v}$ is in $W\}$. Show that $U \cup W$ is a subspace if and only if $U \subseteq W$ or $W \subseteq U$.

Exercise $5.11.1.2E.27$

Show that $\mathbf{P}$ cannot be spanned by a finite set of polynomials.

Answers

Exercise $5.11.1.2E.1$

b. Yes
d. Yes
f. No; not closed under addition or scalar multiplication, and 0 is not in the set.

Exercise $5.11.1.2E.2$

b. Yes.
d. Yes.
f. No; not closed under addition.

Exercise $5.11.1.2E.3$

b. No; not closed under addition.
d. No; not closed under scalar multiplication.
f. Yes.

Exercise $5.11.1.2E.5$

b. If entry k of $\mathbf{x}$ is $x_k \neq 0$, and if $\mathbf{y}$ is in $\mathbb{R}^n$, then $\mathbf{y} = A\mathbf{x}$ where the column of A is $x_k^{-1}\mathbf{y}$, and the other columns are zero.

Exercise $5.11.1.2E.6$

b. $-3(x+1) + 0\,(x^2+x) + 2\,(x^2+2)$
d. $\frac{2}{3}(x+1) + \frac{1}{3}\,(x^2+x) - \frac{1}{3}\,(x^2+2)$

Exercise $5.11.1.2E.7$

b. No.
d. Yes; $\mathbf{v} = 3\mathbf{u} - \mathbf{w}$.

Exercise $5.11.1.2E.8$

b. Yes; $1 = \cos^2 x + \sin^2 x$
d. No. If $1 + x^2 = a\cos^2 x + b\sin^2 x$, then taking $x = 0$ and $x = \pi$ gives $a = 1$ and $a = 1 + \pi^2$.

Exercise $5.11.1.2E.9$

b. Because $\mathbf{P}_2 = span\ \{1, x, x^2\}$, it suffices to show that $\{1, x, x^2\} \subseteq span\ \{1 + 2x^2, 3x, 1 + x\}$. But $x = \frac{1}{3}(3x); 1 = (1 + x) - x$ and $x^2 = \frac{1}{2}[(1 + 2x^2) - 1]$.

Exercise $5.11.1.2E.11$

b. $\mathbf{u} = (\mathbf{u} + \mathbf{w}) - \mathbf{w}$, $\mathbf{v} = -(\mathbf{u} - \mathbf{v}) + (\mathbf{u} + \mathbf{w}) - \mathbf{w}$, and $\mathbf{w} = \mathbf{w}$

Exercise $5.11.1.2E.14$

No.

Exercise $5.11.1.2E.18$

$\mathbf{v}_1 = \frac{1}{a_1}\mathbf{u} - \frac{a_2}{a_1}\mathbf{v}_2 - \cdots - \frac{a_n}{a_1}\mathbf{v}_n$, so $V \subseteq span\ \{\mathbf{u}, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$

Exercise $5.11.1.2E.21$

b. $\mathbf{v} = (\mathbf{u} + \mathbf{v}) - \mathbf{u}$ is in U.

Exercise $5.11.1.2E.22$

Given the condition and $\mathbf{u} \in U$, $\mathbf{0} = \mathbf{u} + (-1)\mathbf{u} \in U$. The converse holds by the subspace test.

Exercise $5.11.1.2E.23$

Let $A_1, A_2, \ldots, A_m$ denote $n \times n$ matrices. If $\mathbf{0} \neq \mathbf{y} \in \mathbb{R}^n$ and $A_1\mathbf{y} = A_2\mathbf{y} = \cdots = A_m\mathbf{y} = \mathbf{0}$, show that $\{A_1, A_2, \ldots, A_m\}$ cannot $span\ \|M_{nn}$.

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5.11.1.3: LINEAR INDEPENDENCE AND DIMENSION

In addition to the span of a set of vectors covered in the previous section, another central concept in linear algebra is that of an independent set of vectors, meaning roughly that the set does not contain any redundant vector.

Definition: Linear Independence and Dependence

As in $\mathbb{R}^n$, a set of vectors $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$ in a vector space V is called **linearly independent** (or simply **independent**) if it satisfies the following condition:

$$\text{If} \quad s_1\mathbf{v}_1 + s_2\mathbf{v}_2 + \cdots + s_n\mathbf{v}_n = \mathbf{0}, \quad \text{then} \quad s_1 = s_2 = \cdots = s_n = 0.$$

A set of vectors that is not linearly independent is said to be **linearly dependent** (or simply **dependent**).

The **trivial linear combination** of the vectors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$ is the one with every coefficient zero:

$$0\mathbf{v}_1 + 0\mathbf{v}_2 + \cdots + 0\mathbf{v}_n$$

This is obviously one way of expressing $\mathbf{0}$ as a linear combination of the vectors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$, and they are linearly independent when it is the *only* way.

Example 5.11.1.3.1

Show that $\{1 + x, 3x + x^2, 2 + x - x^2\}$ is independent in $\mathbf{P}_2$.

Solution

Suppose a linear combination of these polynomials vanishes.

$$s_1(1 + x) + s_2(3x + x^2) + s_3(2 + x - x^2) = 0$$

Equating the coefficients of 1, x, and x^2 gives a set of linear equations.

$$\begin{array}{rcrcrcl} s_1 & + & & + & 2s_3 & = & 0 \\ s_1 & + & 3s_2 & + & s_3 & = & 0 \\ & & s_2 & - & s_3 & = & 0 \end{array}$$

The only solution is $s_1 = s_2 = s_3 = 0$.

Example 5.11.1.3.2

Show that $\{\sin x, \cos x\}$ is independent in the vector space $\mathbf{F}[0, 2\pi]$ of functions defined on the interval $[0, 2\pi]$.

Solution

Suppose that a linear combination of these functions vanishes.

$$s_1(\sin x) + s_2(\cos x) = 0$$

This must hold for *all* values of x in $[0, 2\pi]$ (by the definition of equality in $\mathbf{F}[0, 2\pi]$). Taking $x = 0$ yields $s_2 = 0$ (because $\sin 0 = 0$ and $\cos 0 = 1$). Similarly, $s_1 = 0$ follows from taking $x = \frac{\pi}{2}$ (because $\sin \frac{\pi}{2} = 1$ and $\cos \frac{\pi}{2} = 0$).

Example 5.11.1.3.3

Suppose that $\{\mathbf{u}, \mathbf{v}\}$ is an independent set in a vector space V. Show that $\{\mathbf{u}+2\mathbf{v}, \mathbf{u}-3\mathbf{v}\}$ is also independent.

Solution

Suppose a linear combination of $\mathbf{u}+2\mathbf{v}$ and $\mathbf{u}-3\mathbf{v}$ vanishes:

$$s(\mathbf{u}+2\mathbf{v})+t(\mathbf{u}-3\mathbf{v})=\mathbf{0}$$

We must deduce that $s=t=0$. Collecting terms involving $\mathbf{u}$ and $\mathbf{v}$ gives

$$(s+t)\mathbf{u}+(2s-3t)\mathbf{v}=\mathbf{0}$$

Because $\{\mathbf{u}, \mathbf{v}\}$ is independent, this yields linear equations $s+t=0$ and $2s-3t=0$. The only solution is $s=t=0$.

Example 5.11.1.3.4

Show that any set of polynomials of distinct degrees is independent.

Solution

Let $p_1, p_2, \ldots, p_m$ be polynomials where $\deg(p_i)=d_i$. By relabelling if necessary, we may assume that $d_1>d_2>\cdots>d_m$. Suppose that a linear combination vanishes:

$$t_1p_1+t_2p_2+\cdots+t_mp_m=0$$

where each t_i is in $\mathbb{R}$. As $\deg(p_1)=d_1$, let ax^{d_1} be the term in p_1 of highest degree, where $a\neq 0$. Since $d_1>d_2>\cdots>d_m$, it follows that $t_1ax^{d_1}$ is the only term of degree d_1 in the linear combination $t_1p_1+t_2p_2+\cdots+t_mp_m=0$. This means that $t_1ax^{d_1}=0$, whence $t_1a=0$, hence $t_1=0$ (because $a\neq 0$). But then $t_2p_2+\cdots+t_mp_m=0$ so we can repeat the argument to show that $t_2=0$. Continuing, we obtain $t_i=0$ for each i, as desired.

Example 5.11.1.3.5

Suppose that A is an $n\times n$ matrix such that $A^k=0$ but $A^{k-1}\neq 0$. Show that $B=\{I, A, A^2, \ldots, A^{k-1}\}$ is independent in $\mathbf{M}_{nn}$.

Solution

Suppose $r_0I+r_1A+r_2A^2+\cdots+r_{k-1}A^{k-1}=0$. Multiply by A^{k-1}:

$$r_0A^{k-1}+r_1A^k+r_2A^{k+1}+\cdots+r_{k-1}A^{2k-2}=0$$

Since $A^k=0$, all the higher powers are zero, so this becomes $r_0A^{k-1}=0$. But $A^{k-1}\neq 0$, so $r_0=0$, and we have $r_1A^1+r_2A^2+\cdots+r_{k-1}A^{k-1}=0$. Now multiply by A^{k-2} to conclude that $r_1=0$. Continuing, we obtain $r_i=0$ for each i, so B is independent.

The next example collects several useful properties of independence for reference.

Example 5.11.1.3.6

Let V denote a vector space.

1. If $\mathbf{v}\neq\mathbf{0}$ in V, then $\{\mathbf{v}\}$ is an independent set.
2. No independent set of vectors in V can contain the zero vector.

Solution

1. Let $t\mathbf{v} = \mathbf{0}$, t in $\mathbb{R}$. If $t \neq 0$, then $\mathbf{v} = 1\mathbf{v} = \frac{1}{t}(t\mathbf{v}) = \frac{1}{t}\mathbf{0} = \mathbf{0}$, contrary to assumption. So $t = 0$.
2. If $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$ is independent and (say) $\mathbf{v}_2 = \mathbf{0}$, then $0\mathbf{v}_1 + 1\mathbf{v}_2 + \cdots + 0\mathbf{v}_k = \mathbf{0}$ is a nontrivial linear combination that vanishes, contrary to the independence of $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$.

A set of vectors is independent if $\mathbf{0}$ is a linear combination in a unique way. The following theorem shows that *every* linear combination of these vectors has uniquely determined coefficients, and so extends Theorem 5.2.1.

Theorem 5.11.1.3.1

Let $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$ be a linearly independent set of vectors in a vector space V. If a vector $\mathbf{v}$ has two (ostensibly different) representations

$$\begin{array}{rcccccccc} \mathbf{v} & = & s_1\mathbf{v}_1 & + & s_2\mathbf{v}_2 & + & \cdots & + & s_n\mathbf{v}_n \\ \mathbf{v} & = & t_1\mathbf{v}_1 & + & t_2\mathbf{v}_2 & + & \cdots & + & t_n\mathbf{v}_n \end{array}$$

as linear combinations of these vectors, then $s_1 = t_1, s_2 = t_2, \ldots, s_n = t_n$. In other words, every vector in V can be written in a unique way as a linear combination of the $\mathbf{v}_i$.

Proof

Subtracting the equations given in the theorem gives

$$(s_1 - t_1)\mathbf{v}_1 + (s_2 - t_2)\mathbf{v}_2 + \cdots + (s_n - t_n)\mathbf{v}_n = \mathbf{0}$$

The independence of $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$ gives $s_i - t_i = 0$ for each i, as required.

□

The following theorem extends (and proves) Theorem 5.2.4, and is one of the most useful results in linear algebra.

Theorem 5.11.1.3.2: Fundamental Theorem

Suppose a vector space V can be spanned by n vectors. If any set of m vectors in V is linearly independent, then $m \leq n$.

Proof

Let $V = span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$, and suppose that $\{\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_m\}$ is an independent set in V. Then $\mathbf{u}_1 = a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + \cdots + a_n\mathbf{v}_n$ where each a_i is in $\mathbb{R}$. As $\mathbf{u}_1 \neq \mathbf{0}$ (Example 6.3.6), not all of the a_i are zero, say $a_1 \neq 0$ (after relabelling the $\mathbf{v}_i$). Then $V = span\ \{\mathbf{u}_1, \mathbf{v}_2, \mathbf{v}_3, \ldots, \mathbf{v}_n\}$ as the reader can verify. Hence, write $\mathbf{u}_2 = b_1\mathbf{u}_1 + c_2\mathbf{v}_2 + c_3\mathbf{v}_3 + \cdots + c_n\mathbf{v}_n$. Then some $c_i \neq 0$ because $\{\mathbf{u}_1, \mathbf{u}_2\}$ is independent; so, as before, $V = span\ \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{v}_3, \ldots, \mathbf{v}_n\}$, again after possible relabelling of the $\mathbf{v}_i$. If $m > n$, this procedure continues until all the vectors $\mathbf{v}_i$ are replaced by the vectors $\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_n$. In particular, $V = span\ \{\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_n\}$. But then $\mathbf{u}_{n+1}$ is a linear combination of $\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_n$ contrary to the independence of the $\mathbf{u}_i$. Hence, the assumption $m > n$ cannot be valid, so $m \leq n$ and the theorem is proved.

□

If $V = span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$, and if $\{\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_m\}$ is an independent set in V, the above proof shows not only that $m \leq n$ but also that m of the (spanning) vectors $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n$ can be replaced by the (independent) vectors $\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_m$ and the resulting set will still $span\ V$. In this form the result is called the **Steinitz Exchange Lemma**.

Definition: Basis of a Vector Space

As in $\mathbb{R}^n$, a set $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ of vectors in a vector space V is called a **basis** of V if it satisfies the following two conditions:

1. $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ is linearly independent
2. $V = span\ \{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$

Thus if a set of vectors $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ is a basis, then *every* vector in V can be written as a linear combination of these vectors in a *unique* way (Theorem 6.3.1). But even more is true: Any two (finite) bases of V contain the same number of vectors.

Theorem 5.11.1.3.3: Invariance Theorem

Let $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ and $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_m\}$ be two bases of a vector space V. Then $n = m$.

Proof

Because $V = span\ \{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ and $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_m\}$ is independent, it follows from Theorem 6.3.2 that $m \leq n$. Similarly $n \leq m$, so $n = m$, as asserted.

$square$

Theorem 6.3.3 guarantees that no matter which basis of V is chosen it contains the same number of vectors as any other basis. Hence there is no ambiguity about the following definition.

Definition: Dimension of a Vector Space

If $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ is a basis of the nonzero vector space V, the number n of vectors in the basis is called the **dimension** of V , and we write

$$dim\ V = n$$

The zero vector space $\{\mathbf{0}\}$ is defined to have dimension 0:

$$dim\ \{\mathbf{0}\} = 0$$

In our discussion to this point we have always assumed that a basis is nonempty and hence that the dimension of the space is at least 1. However, the zero space $\{\mathbf{0}\}$ has *no* basis (by Example 6.3.6 so our insistence that $dim\ \{\mathbf{0}\} = 0$ amounts to saying that the *empty* set of vectors is a basis of $\{\mathbf{0}\}$. Thus the statement that "the dimension of a vector space is the number of vectors in any basis" holds even for the zero space.

We saw in Example 5.2.10 that $dim\ (\mathbb{R}^n) = n$ and, if $\mathbf{e}_j$ denotes column j of I_n, that $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ is a basis (called the standard basis). In Example 6.3.7 below, similar considerations apply to the space $\mathbf{M}_{mn}$ of all $m \times n$ matrices; the verifications are left to the reader.

Example 5.11.1.3.7

The space $\mathbf{M}_{mn}$ has dimension mn, and one basis consists of all $m \times n$ matrices with exactly one entry equal to 1 and all other entries equal to 0. We call this the **standard basis** of $\mathbf{M}_{mn}$.

Example 5.11.1.3.8

Show that $dim\ \mathbf{P}_n = n+1$ and that $\{1, x, x^2, \ldots, x^n\}$ is a basis, called the **standard basis** of $\mathbf{P}_n$.

Solution

Each polynomial $p(x) = a_0 + a_1 x + \cdots + a_n x^n$ in $\mathbf{P}_n$ is clearly a linear combination of $1, x, \ldots, x^n$, so $\mathbf{P}_n = span\ \{1, x, \ldots, x^n\}$. However, if a linear combination of these vectors vanishes, $a_0 1 + a_1 x + \cdots + a_n x^n = 0$, then $a_0 = a_1 = \cdots = a_n = 0$ because x is an indeterminate. So $\{1, x, \ldots, x^n\}$ is linearly independent and hence is a basis containing $n+1$ vectors. Thus, $dim\ (\mathbf{P}_n) = n+1$.

Example 5.11.1.3.9

If $\mathbf{v} \neq \mathbf{0}$ is any nonzero vector in a vector space V, show that $span\ \{\mathbf{v}\} = \mathbb{R}\mathbf{v}$ has dimension 1.

Solution

$\{\mathbf{v}\}$ clearly spans $\mathbb{R}\mathbf{v}$, and it is linearly independent by Example 6.3.6. Hence $\{\mathbf{v}\}$ is a basis of $\mathbb{R}\mathbf{v}$, and so $dim\ \mathbb{R}\mathbf{v} = 1$.

Example 5.11.1.3.10

Let $A = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}$ and consider the subspace

$$U = \{X \text{ in } \|M_{22} \mid AX = XA\}$$

of $\mathbf{M}_{22}$. Show that $dim\ U = 2$ and find a basis of U.

Solution

It was shown in Example 6.2.3 that U is a subspace for any choice of the matrix A. In the present case, if $X = \begin{bmatrix} x & y \\ z & w \end{bmatrix}$ is in U, the condition $AX = XA$ gives $z = 0$ and $x = y + w$. Hence each matrix X in U can be written

$$X = \begin{bmatrix} y+w & y \\ 0 & w \end{bmatrix} = y \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} + w \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

so $U = span\ B$ where $B = \left\{ \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right\}$. Moreover, the set B is linearly independent (verify this), so it is a basis of U and $dim\ U = 2$.

Example 5.11.1.3.11

Show that the set V of all symmetric 2×2 matrices is a vector space, and find the dimension of V.

Solution

A matrix A is symmetric if $A^T = A$. If A and B lie in V, then

$$(A+B)^T = A^T + B^T = A + B \quad \text{and} \quad (kA)^T = kA^T = kA$$

using Theorem 2.1.2. Hence $A + B$ and kA are also symmetric. As the 2×2 zero matrix is also in V, this shows that V is a vector space (being a subspace of $\mathbf{M}_{22}$). Now a matrix A is symmetric when entries directly across the main diagonal are equal, so each 2×2 symmetric matrix has the form

$$\begin{bmatrix} a & c \\ c & b \end{bmatrix} = a \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + b \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + c \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

Hence the set $B = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \right\}$ spans V, and the reader can verify that B is linearly independent. Thus B is a basis of V, so $dim\ V = 3$.

It is frequently convenient to alter a basis by multiplying each basis vector by a nonzero scalar. The next example shows that this always produces another basis. The proof is left as Exercise 6.3.22.

Example 5.11.1.3.12

Let $B = \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$ be nonzero vectors in a vector space V. Given nonzero scalars $a_1, a_2, \dots, a_n$, write $D = \{a_1\mathbf{v}_1, a_2\mathbf{v}_2, \dots, a_n\mathbf{v}_n\}$. If B is independent or spans V, the same is true of D. In particular, if B is a basis of V, so also is D.

5.11.1.3E: Linear Independence and Dimension Exercises

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5.11.1: VECTOR SPACES

In this chapter we introduce vector spaces in full generality. The reader will notice some similarity with the discussion of the space $\mathbb{R}^n$ in Chapter [chap:5]. In fact much of the present material has been developed in that context, and there is some repetition. However, Chapter [chap:6] deals with the notion of an *abstract* vector space, a concept that will be new to most readers. It turns out that there are many systems in which a natural addition and scalar multiplication are defined and satisfy the usual rules familiar from $\mathbb{R}^n$. The study of abstract vector spaces is a way to deal with all these examples simultaneously. The new aspect is that we are dealing with an abstract system in which *all we know* about the vectors is that they are objects that can be added and multiplied by a scalar and satisfy rules familiar from $\mathbb{R}^n$.

The novel thing is the *abstraction*. Getting used to this new conceptual level is facilitated by the work done in Chapter [chap:5]: First, the vector manipulations are familiar, giving the reader more time to become accustomed to the abstract setting; and, second, the mental images developed in the concrete setting of $\mathbb{R}^n$ serve as an aid to doing many of the exercises in Chapter [chap:6].

The concept of a vector space was first introduced in 1844 by the German mathematician Hermann Grassmann (1809-1877), but his work did not receive the attention it deserved. It was not until 1888 that the Italian mathematician Guiseppe Peano (1858-1932) clarified Grassmann's work in his book *Calcolo Geometrico* and gave the vector space axioms in their present form. Vector spaces became established with the work of the Polish mathematician Stephan Banach (1892-1945), and the idea was finally accepted in 1918 when Hermann Weyl (1885-1955) used it in his widely read book *Raum-Zeit-Materie* ("Space-Time-Matter"), an introduction to the general theory of relativity.

5.11.1.1: Examples and Basic Properties

5.11.1.1E: Examples and Basic Properties Exercises

5.11.1.2: Subspaces and Spanning Sets

5.11.1.2E: Subspaces and Spanning Sets Exercises

5.11.1.3: Linear Independence and Dimension

5.11.1.3E: Linear Independence and Dimension Exercises

5.11.1.4: Finite Dimensional Spaces

5.11.1.4E: Finite Dimensional Spaces Exercises

5.11.1.5: An Application to Polynomials

5.11.1.5E: An Application to Polynomials Exercises

5.11.1.6: Supplementary Exercises for Chapter 6

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5.11.1.3E: Linear Independence and Dimension Exercises

Exercise $5.11.1.3E.1$

Show that each of the following sets of vectors is independent.

a. $\{1+x, 1-x, x+x^2\}$ in $\mathbf{P}_2$
b. $\{x^2, x+1, 1-x-x^2\}$ in $\mathbf{P}_2$
c. $\left\{\begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & -1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}\right\}$ in $\mathbf{M}_{22}$
d. $\left\{\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}\right\}$ in $\mathbf{M}_{22}$

Answer available at the end of this section.

Exercise $5.11.1.3E.2$

Which of the following subsets of V are independent?

a. $V = \|P_2; \{x^2+1, x+1, x\}$
b. $V = \|P_2; \{x^2-x+3, 2x^2+x+5, x^2+5x+1\}$
c. $V = \|M_{22}; \left\{\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right\}$
d. $V = \|M_{22}; \left\{\begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}, \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}\right\}$
e. $V = \|F[1,2]; \left\{\frac{1}{x}, \frac{1}{x^2}, \frac{1}{x^3}\right\}$
f. $V = \|F[0,1]; \left\{\frac{1}{x^2+x-6}, \frac{1}{x^2-5x+6}, \frac{1}{x^2-9}\right\}$

Answer available at the end of this section.

Exercise $5.11.1.3E.3$

Which of the following are independent in $\mathbf{F}[0, 2\pi]$?

a. $\{\sin^2 x, \cos^2 x\}$
b. $\{1, \sin^2 x, \cos^2 x\}$
c. $\{x, \sin^2 x, \cos^2 x\}$

Answer available at the end of this section.

Exercise $5.11.1.3E.4$

Find all values of a such that the following are independent in $\mathbb{R}^3$.

a. $\{(1,-1,0), (a,1,0), (0,2,3)\}$
b. $\{(2,a,1), (1,0,1), (0,1,3)\}$

Answer available at the end of this section.

Exercise $5.11.1.3E.5$

Show that the following are bases of the space V indicated.

a. $\{(1,1,0),(1,0,1),(0,1,1)\}$; $V=\mathbb{R}^3$
b. $\{(-1,1,1),(1,-1,1),(1,1,-1)\}$; $V=\mathbb{R}^3$
c. $\left\{\begin{bmatrix}1&0\\0&1\end{bmatrix},\begin{bmatrix}0&1\\1&0\end{bmatrix},\begin{bmatrix}1&1\\0&1\end{bmatrix},\begin{bmatrix}1&0\\0&0\end{bmatrix}\right\}$; $V=\|M_{22}$
d. $\{1+x,x+x^2,x^2+x^3,x^3\}$; $V=\|P_3$

Answer available at the end of this section.

Exercise $5.11.1.3E.6$

Exhibit a basis and calculate the dimension of each of the following subspaces of $\mathbf{P}_2$.

a. $\{a(1+x)+b(x+x^2)\mid a \text{ and } b \text{ in } \mathbb{R}\}$
b. $\{a+b(x+x^2)\mid a \text{ and } b \text{ in } \mathbb{R}\}$
c. $\{p(x)\mid p(1)=0\}$
d. $\{p(x)\mid p(x)=p(-x)\}$

Answer available at the end of this section.

Exercise $5.11.1.3E.7$

Exhibit a basis and calculate the dimension of each of the following subspaces of $\mathbf{M}_{22}$.

a. $\{A\mid A^T=-A\}$
b. $\left\{A\;\middle|\;A\begin{bmatrix}1&1\\-1&0\end{bmatrix}=\begin{bmatrix}1&1\\-1&0\end{bmatrix}A\right\}$
c. $\left\{A\;\middle|\;A\begin{bmatrix}1&0\\-1&0\end{bmatrix}=\begin{bmatrix}0&0\\0&0\end{bmatrix}\right\}$
d. $\left\{A\;\middle|\;A\begin{bmatrix}1&1\\-1&0\end{bmatrix}=\begin{bmatrix}0&1\\-1&1\end{bmatrix}A\right\}$

Answer available at the end of this section.

Exercise $5.11.1.3E.8$

Let $A=\begin{bmatrix}1&1\\0&0\end{bmatrix}$ and define $U=\{X\mid X\in\|M_{22} \text{ and } AX=X\}$.

a. Find a basis of U containing A.
b. Find a basis of U not containing A.

Answer available at the end of this section.

Exercise $5.11.1.3E.9$

Show that the set $\mathbb{C}$ of all complex numbers is a vector space with the usual operations, and find its dimension.

a. Let V denote the set of all 2×2 matrices with equal column sums. Show that V is a subspace of $\mathbf{M}_{22}$, and compute $dim\ V$.
d. Repeat part (a) for 3×3 matrices.
f. Repeat part (a) for $n \times n$ matrices.

Answer available at the end of this section.

Exercise $5.11.1.3E.10$

a. Let V denote the set of all 2×2 matrices with equal column sums. Show that V is a subspace of $\mathbf{M}_{22}$, and compute $\dim V$.
b. Repeat part (a) for 3×3 matrices.
c. Repeat part (a) for $n \times n$ matrices.

Answer available at the end of this section.

Exercise $5.11.1.3E.11$

a. Let $V = \{(x^2 + x + 1)p(x) \mid p(x) \text{ in } \|P_2\}$. Show that V is a subspace of $\mathbf{P}_4$ and find $dim\ V$. [*Hint*: If $f(x)g(x) = 0$ in $\mathbf{P}$, then $f(x) = 0$ or $g(x) = 0$.]
d. Repeat with $V = \{(x^2 - x)p(x) \mid p(x) \text{ in } \|P_3\}$, a subset of $\mathbf{P}_5$.
f. Generalize.

Answer available at the end of this section.

Exercise $5.11.1.3E.12$

In each case, either prove the assertion or give an example showing that it is false.

a. Every set of four nonzero polynomials in $\mathbf{P}_3$ is a basis.
b. $\mathbf{P}_2$ has a basis of polynomials $f(x)$ such that $f(0) = 0$.
c. $\mathbf{P}_2$ has a basis of polynomials $f(x)$ such that $f(0) = 1$.
d. Every basis of $\mathbf{M}_{22}$ contains a noninvertible matrix.
e. No independent subset of $\mathbf{M}_{22}$ contains a matrix A with $A^2 = 0$.
f. If $\{\mathbf{u}, \mathbf{v}, \mathbf{w}\}$ is independent then, $a\mathbf{u} + b\mathbf{v} + c\mathbf{w} = \mathbf{0}$ for some a, b, c.
g. $\{\mathbf{u}, \mathbf{v}, \mathbf{w}\}$ is independent if $a\mathbf{u} + b\mathbf{v} + c\mathbf{w} = \mathbf{0}$ for some a, b, c.
h. If $\{\mathbf{u}, \mathbf{v}\}$ is independent, so is $\{\mathbf{u}, \mathbf{u} + \mathbf{v}\}$.
i. If $\{\mathbf{u}, \mathbf{v}\}$ is independent, so is $\{\mathbf{u}, \mathbf{v}, \mathbf{u} + \mathbf{v}\}$.
j. If $\{\mathbf{u}, \mathbf{v}, \mathbf{w}\}$ is independent, so is $\{\mathbf{u}, \mathbf{v}\}$.
k. If $\{\mathbf{u}, \mathbf{v}, \mathbf{w}\}$ is independent, so is $\{\mathbf{u} + \mathbf{w}, \mathbf{v} + \mathbf{w}\}$.
l. If $\{\mathbf{u}, \mathbf{v}, \mathbf{w}\}$ is independent, so is $\{\mathbf{u} + \mathbf{v} + \mathbf{w}\}$.
m. If $\mathbf{u} \neq \mathbf{0}$ and $\mathbf{v} \neq \mathbf{0}$ then $\{\mathbf{u}, \mathbf{v}\}$ is dependent if and only if one is a scalar multiple of the other.
n. If $dim\ V = n$, then no set of more than n vectors can be independent.
o. If $dim\ V = n$, then no set of fewer than n vectors can span V.

Answer available at the end of this section.

Exercise $5.11.1.3E.13$

Let $A \neq 0$ and $B \neq 0$ be $n \times n$ matrices, and assume that A is symmetric and B is skew-symmetric (that is, $B^T = -B$). Show that $\{A, B\}$ is independent.

Exercise $5.11.1.3E.14$

Show that every set of vectors containing a dependent set is again dependent.

Exercise $5.11.1.3E.15$

Show that every nonempty subset of an independent set of vectors is again independent.

Answer available at the end of this section.

Exercise $5.11.1.3E.16$

Let f and g be functions on $[a, b]$, and assume that $f(a) = 1 = g(b)$ and $f(b) = 0 = g(a)$. Show that $\{f, g\}$ is independent in $\mathbf{F}[a, b]$.

Exercise $5.11.1.3E.17$

Let $\{A_1, A_2, \dots, A_k\}$ be independent in $\mathbf{M}_{mn}$, and suppose that U and V are invertible matrices of size $m \times m$ and $n \times n$, respectively. Show that $\{UA_1V, UA_2V, \dots, UA_kV\}$ is independent.

Exercise $5.11.1.3E.18$

Show that $\{\mathbf{v}, \mathbf{w}\}$ is independent if and only if neither $\mathbf{v}$ nor $\mathbf{w}$ is a scalar multiple of the other.

Exercise $5.11.1.3E.19$

Assume that $\{\mathbf{u}, \mathbf{v}\}$ is independent in a vector space V. Write $\mathbf{u}' = a\mathbf{u} + b\mathbf{v}$ and $\mathbf{v}' = c\mathbf{u} + d\mathbf{v}$, where a, b, c, and d are numbers. Show that $\{\mathbf{u}', \mathbf{v}'\}$ is independent if and only if the matrix $\begin{bmatrix} a & c \\ b & d \end{bmatrix}$ is invertible. [*Hint*: Theorem 2.4.5.]

Answer available at the end of this section.

Exercise $5.11.1.3E.20$

If $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$ is independent and $\mathbf{w}$ is not in $span\ \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$, show that:

a. $\{\mathbf{w}, \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$ is independent.
b. $\{\mathbf{v}_1 + \mathbf{w}, \mathbf{v}_2 + \mathbf{w}, \dots, \mathbf{v}_k + \mathbf{w}\}$ is independent.

Exercise $5.11.1.3E.21$

If $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$ is independent, show that $\{\mathbf{v}_1, \mathbf{v}_1 + \mathbf{v}_2, \dots, \mathbf{v}_1 + \mathbf{v}_2 + \cdots + \mathbf{v}_k\}$ is also independent.

Exercise $5.11.1.3E.22$

Prove Example 6.3.12.

Exercise 5.11.1.3E.23

Let $\{\mathbf{u}, \mathbf{v}, \mathbf{w}, \mathbf{z}\}$ be independent. Which of the following are dependent?

a. $\{\mathbf{u}-\mathbf{v}, \mathbf{v}-\mathbf{w}, \mathbf{w}-\mathbf{u}\}$
b. $\{\mathbf{u}+\mathbf{v}, \mathbf{v}+\mathbf{w}, \mathbf{w}+\mathbf{u}\}$
c. $\{\mathbf{u}-\mathbf{v}, \mathbf{v}-\mathbf{w}, \mathbf{w}-\mathbf{z}, \mathbf{z}-\mathbf{u}\}$
d. $\{\mathbf{u}+\mathbf{v}, \mathbf{v}+\mathbf{w}, \mathbf{w}+\mathbf{z}, \mathbf{z}+\mathbf{u}\}$

Answer available at the end of this section.

Exercise 5.11.1.3E.24

Let U and W be subspaces of V with bases $\{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3\}$ and $\{\mathbf{w}_1, \mathbf{w}_2\}$ respectively. If U and W have only the zero vector in common, show that $\{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \mathbf{w}_1, \mathbf{w}_2\}$ is independent.

Exercise 5.11.1.3E.25

Let $\{p, q\}$ be independent polynomials. Show that $\{p, q, pq\}$ is independent if and only if $\deg p \geq 1$ and $\deg q \geq 1$.

Exercise 5.11.1.3E.26

If z is a complex number, show that $\{z, z^2\}$ is independent if and only if z is not real.

Answer available at the end of this section.

Exercise 5.11.1.3E.27

Let $B = \{A_1, A_2, \ldots, A_n\} \subseteq \|M_{mn}$, and write $B' = \{A_1^T, A_2^T, \ldots, A_n^T\} \subseteq \|M_{nm}$. Show that:

a. B is independent if and only if B' is independent.
b. B spans $\mathbf{M}_{mn}$ if and only if B' spans $\mathbf{M}_{nm}$.

Exercise 5.11.1.3E.28

If $V = \|F[a, b]$ as in Example 6.1.7, show that the set of constant functions is a subspace of dimension 1 (f is **constant** if there is a number c such that $f(x) = c$ for all x).

Exercise 5.11.1.3E.29

a. If U is an invertible $n \times n$ matrix and $\{A_1, A_2, \ldots, A_{mn}\}$ is a basis of $\mathbf{M}_{mn}$, show that $\{A_1U, A_2U, \ldots, A_{mn}U\}$ is also a basis.
b. Show that part (a) fails if U is not invertible. [*Hint*: Theorem 2.4.5.]

Answer available at the end of this section.

Exercise 5.11.1.3E.30

Show that $\{(a, b), (a_1, b_1)\}$ is a basis of $\mathbb{R}^2$ if and only if $\{a + bx, a_1 + b_1x\}$ is a basis of $\mathbf{P}_1$.

Exercise 5.11.1.3E.31

Find the dimension of the subspace $span\ \{1, \sin^2\theta, \cos 2\theta\}$ of $\mathbf{F}[0, 2\pi]$.

Exercise 5.11.1.3E.32

Show that $\mathbf{F}[0, 1]$ is not finite dimensional.

Exercise 5.11.1.3E.33

If U and W are subspaces of V, define their intersection $U \cap W$ as follows:

$$U \cap W = \{\mathbf{v} \mid \mathbf{v} \text{ is in both } U \text{ and } W\}$$

a. Show that $U \cap W$ is a subspace contained in U and W.
b. Show that $U \cap W = \{\mathbf{0}\}$ if and only if $\{\mathbf{u}, \mathbf{w}\}$ is independent for any nonzero vectors $\mathbf{u}$ in U and $\mathbf{w}$ in W.
c. If B and D are bases of U and W, and if $U \cap W = \{\mathbf{0}\}$, show that $B \cup D = \{\mathbf{v} \mid \mathbf{v} \text{ is in } B \text{ or } D\}$ is independent.

Answer available at the end of this section.

Exercise 5.11.1.3E.34

If U and W are vector spaces, let $V = \{(\mathbf{u}, \mathbf{w}) \mid \mathbf{u} \text{ in } U \text{ and } \mathbf{w} \text{ in } W\}$.

a. Show that V is a vector space if $(\mathbf{u}, \mathbf{w}) + (\mathbf{u}_1, \mathbf{w}_1) = (\mathbf{u} + \mathbf{u}_1, \mathbf{w} + \mathbf{w}_1)$ and $a(\mathbf{u}, \mathbf{w}) = (a\mathbf{u}, a\mathbf{w})$.
b. If $dim\ U = m$ and $dim\ W = n$, show that $dim\ V = m + n$.
c. If $V_1, \ldots, V_m$ are vector spaces, let

$$\begin{aligned} V &= V_1 \times \cdots \times V_m \\ &= \{(\mathbf{v}_1, \ldots, \mathbf{v}_m) \mid \mathbf{v}_i \in V_i \text{ for each } i\} \end{aligned}$$

Exercise 5.11.1.3E.35

Let $\mathbf{D}_n$ denote the set of all functions f from the set $\{1, 2, \ldots, n\}$ to $\mathbb{R}$.

a. Show that $\mathbf{D}_n$ is a vector space with pointwise addition and scalar multiplication.
b. Show that $\{S_1, S_2, \ldots, S_n\}$ is a basis of $\mathbf{D}_n$ where, for each $k = 1, 2, \ldots, n$, the function S_k is defined by $S_k(k) = 1$, whereas $S_k(j) = 0$ if $j \neq k$.

Exercise 5.11.1.3E.36

A polynomial $p(x)$ is called **even** if $p(-x) = p(x)$ and **odd** if $p(-x) = -p(x)$. Let E_n and O_n denote the sets of even and odd polynomials in $\mathbf{P}_n$.

a. Show that E_n is a subspace of $\mathbf{P}_n$ and find $dim\ E_n$.
b. Show that O_n is a subspace of $\mathbf{P}_n$ and find $dim\ O_n$.

Answer available at the end of this section.

Exercise $5.11.1.3E.37$

Let $\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ be independent in a vector space V, and let A be an $n \times n$ matrix. Define $\mathbf{u}_1, \ldots, \mathbf{u}_n$ by

$$\begin{bmatrix} \mathbf{u}_1 \\ \vdots \\ \mathbf{u}_n \end{bmatrix} = A \begin{bmatrix} \mathbf{v}_1 \\ \vdots \\ \mathbf{v}_n \end{bmatrix}$$

Show that $\{\mathbf{u}_1, \ldots, \mathbf{u}_n\}$ is independent if and only if A is invertible.

Answers

Exercise $5.11.1.3E.1$

b. If $ax^2 + b(x+1) + c(1 - x - x^2) = 0$, then $a + c = 0$, $b - c = 0$, $b + c = 0$, so $a = b = c = 0$.

d. If $a\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} + b\begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + c\begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} + d\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$, then $a + c + d = 0$, $a + b + d = 0$, $a + b + c = 0$, and $b + c + d = 0$, so $a = b = c = d = 0$.

Exercise $5.11.1.3E.2$

b. $3(x^2 - x + 3) - 2(2x^2 + x + 5) + (x^2 + 5x + 1) = 0$

d. $2\begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} + \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} + \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$

f. $\frac{5}{x^2+x-6} + \frac{1}{x^2-5x+6} - \frac{6}{x^2-9} = 0$

Exercise $5.11.1.3E.3$

b. Dependent: $1 - \sin^2 x - \cos^2 x = 0$

Exercise $5.11.1.3E.4$

b. $x \neq -\frac{1}{3}$

Exercise $5.11.1.3E.5$

b. If $r(-1,1,1) + s(1,-1,1) + t(1,1,-1) = (0,0,0)$, then $-r + s + t = 0$, $r - s + t = 0$, and $r - s - t = 0$, and this implies that $r = s = t = 0$. This proves independence. To prove that they $span\ \mathbb{R}^3$, observe that $(0,0,1) = \frac{1}{2}[(-1,1,1) + (1,-1,1)]$ so $(0,0,1)$ lies in $span\ \{(-1,1,1), (1,-1,1), (1,1,-1)\}$. The proof is similar for $(0,1,0)$ and $(1,0,0)$.

d. If $r(1+x) + s(x+x^2) + t(x^2+x^3) + ux^3 = 0$, then $r = 0$, $r + s = 0$, $s + t = 0$, and $t + u = 0$, so $r = s = t = u = 0$. This proves independence. To show that they $span\ \|P_3$, observe that $x^2 = (x^2 + x^3) - x^3$, $x = (x + x^2) - x^2$, and $1 = (1 + x) - x$, so $\{1, x, x^2, x^3\} \subseteq span\ \{1 + x, x + x^2, x^2 + x^3, x^3\}$.

Exercise $5.11.1.3E.6$

a. $\{1, x + x^2\}$; dimension $= 2$

d. $\{1, x^2\}$; dimension $= 2$

Exercise $5.11.1.3E.7$

a. $\left\{\begin{bmatrix} 1 & 1 \\ -1 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right\}$; dimension $= 2$

d. $\left\{\begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}\right\}$; dimension $= 2$

Exercise $5.11.1.3E.8$

a. $\left\{\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}\right\}$

Exercise $5.11.1.3E.9$

a. $dim\ V = 7$

Exercise $5.11.1.3E.10$

Exercise $5.11.1.3E.11$

a. $\{x^2 - x, x(x^2 - x), x^2(x^2 - x), x^3(x^2 - x)\}$; $dim\ V = 4$

Exercise $5.11.1.3E.12$

a. No. Any linear combination f of such polynomials has $f(0) = 0$.

d. No. $\left\{\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix}\right\}$; consists of invertible matrices.

f. Yes. $0\mathbf{u} + 0\mathbf{v} + 0\mathbf{w} = \mathbf{0}$ for every set $\{\mathbf{u}, \mathbf{v}, \mathbf{w}\}$.

h. Yes. $s\mathbf{u} + t(\mathbf{u} + \mathbf{v}) = \mathbf{0}$ gives $(s + t)\mathbf{u} + t\mathbf{v} = \mathbf{0}$, whence $s + t = 0 = t$.

j. Yes. If $r\mathbf{u} + s\mathbf{v} = \mathbf{0}$, then $r\mathbf{u} + s\mathbf{v} + 0\mathbf{w} = \mathbf{0}$, so $r = 0 = s$.

l. Yes. $\mathbf{u} + \mathbf{v} + \mathbf{w} \neq \mathbf{0}$ because $\{\mathbf{u}, \mathbf{v}, \mathbf{w}\}$ is independent.

n. Yes. If I is independent, then $|I| \leq n$ by the fundamental theorem because any basis spans V.

Exercise $5.11.1.3E.15$

If a linear combination of the subset vanishes, it is a linear combination of the vectors in the larger set (coefficients outside the subset are zero) so it is trivial.

Exercise $5.11.1.3E.19$

Because $\{\mathbf{u}, \mathbf{v}\}$ is linearly independent, $s\mathbf{u}' + t\mathbf{v}' = \mathbf{0}$ is equivalent to $\begin{bmatrix} a & c \\ b & d \end{bmatrix}\begin{bmatrix} s \\ t \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$. Now apply Theorem 2.4.5.

Exercise $5.11.1.3E.23$

b. Independent.

d. Dependent. For example, $(\mathbf{u}+\mathbf{v})-(\mathbf{v}+\mathbf{w})+(\mathbf{w}+\mathbf{z})-(\mathbf{z}+\mathbf{u})=\mathbf{0}$.

Exercise $5.11.1.3E.26$

If z is not real and $az+bz^2=0$, then $a+bz=0(z\neq 0)$. Hence if $b\neq 0$, then $z=-ab^{-1}$ is real. So $b=0$, and so $a=0$. Conversely, if z is real, say $z=a$, then $(-a)z+1z^2=0$, contrary to the independence of $\{z,z^2\}$.

Exercise $5.11.1.3E.29$

b. If $U\mathbf{x}=\mathbf{0}$, $\mathbf{x}\neq\mathbf{0}$ in $\mathbb{R}^n$, then $R\mathbf{x}=\mathbf{0}$ where $R\neq 0$ is row 1 of U. If $B\in\|M_{mn}$ has each row equal to R, then $B\mathbf{x}\neq\mathbf{0}$. But if $B=\sum r_iA_iU$, then $B\mathbf{x}=\sum r_iA_iU\mathbf{x}=\mathbf{0}$. So $\{A_iU\}$ cannot span $\mathbf{M}_{mn}$.

Exercise $5.11.1.3E.33$

b. If $U\cap W=0$ and $r\mathbf{u}+s\mathbf{w}=\mathbf{0}$, then $r\mathbf{u}=-s\mathbf{w}$ is in $U\cap W$, so $r\mathbf{u}=\mathbf{0}=s\mathbf{w}$. Hence $r=0=s$ because $\mathbf{u}\neq\mathbf{0}\neq\mathbf{w}$. Conversely, if $\mathbf{v}\neq\mathbf{0}$ lies in $U\cap W$, then $1\mathbf{v}+(-1)\mathbf{v}=\mathbf{0}$, contrary to hypothesis.

Exercise $5.11.1.3E.36$

b. $dim\ O_n=\frac{n}{2}$ if n is even and $dim\ O_n=\frac{n+1}{2}$ if n is odd.

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5.11.1.4: FINITE DIMENSIONAL SPACES

Up to this point, we have had no guarantee that an arbitrary vector space *has* a basis—and hence no guarantee that one can speak *at all* of the dimension of V. However, Theorem $5.11.1.4.1$ will show that any space that is spanned by a finite set of vectors has a (finite) basis: The proof requires the following basic lemma, of interest in itself, that gives a way to enlarge a given independent set of vectors.

Lemma $5.11.1.4.1$: Independent Lemma

Let $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$ be an independent set of vectors in a vector space V. If $\mathbf{u} \in V$ but $\mathbf{u} \notin span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$, then $\{\mathbf{u}, \mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$ is also independent.

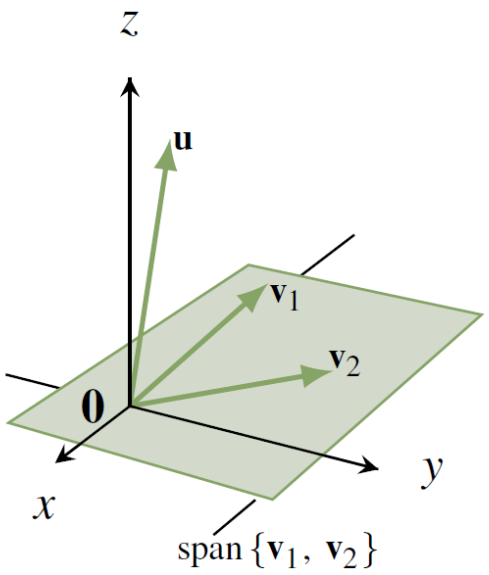
Proof

Let $t\mathbf{u} + t_1\mathbf{v}_1 + t_2\mathbf{v}_2 + \cdots + t_k\mathbf{v}_k = \mathbf{0}$; we must show that all the coefficients are zero. First, $t = 0$ because, otherwise, $\mathbf{u} = -\frac{t_1}{t}\mathbf{v}_1 - \frac{t_2}{t}\mathbf{v}_2 - \cdots - \frac{t_k}{t}\mathbf{v}_k$ is in $span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$, contrary to our assumption. Hence $t = 0$. But then $t_1\mathbf{v}_1 + t_2\mathbf{v}_2 + \cdots + t_k\mathbf{v}_k = \mathbf{0}$ so the rest of the t_i are zero by the independence of $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$. This is what we wanted.

□

Note that the converse of Lemma $5.11.1.4.1$ is also true: if $\{\mathbf{u}, \mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$ is independent, then $\mathbf{u}$ is not in $span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$.

As an illustration, suppose that $\{\mathbf{v}_1, \mathbf{v}_2\}$ is independent in $\mathbb{R}^3$. Then $\mathbf{v}_1$ and $\mathbf{v}_2$ are not parallel, so $span\ \{\mathbf{v}_1, \mathbf{v}_2\}$ is a plane through the origin (shaded in the diagram). By Lemma $5.11.1.4.1$, $\mathbf{u}$ is not in this plane if and only if $\{\mathbf{u}, \mathbf{v}_1, \mathbf{v}_2\}$ is independent.



Definition: Finite Dimensional and Infinite Dimensional Vector Spaces

A vector space V is called **finite dimensional** if it is spanned by a finite set of vectors. Otherwise, V is called **infinite dimensional**.

Thus the zero vector space $\{0\}$ is finite dimensional because $\{0\}$ is a spanning set.

Lemma 5.11.1.4.2

Let V be a finite dimensional vector space. If U is any subspace of V, then any independent subset of U can be enlarged to a finite basis of U.

Proof

Suppose that I is an independent subset of U. If $span\ I = U$ then I is already a basis of U. If $span\ I \neq U$, choose $\mathbf{u}_1 \in U$ such that $\mathbf{u}_1 \notin span\ I$. Hence the set $I \cup \{\mathbf{u}_1\}$ is independent by Lemma 5.11.1.4.1. If $span\ (I \cup \{\mathbf{u}_1\}) = U$ we are done; otherwise choose $\mathbf{u}_2 \in U$ such that $\mathbf{u}_2 \notin span\ (I \cup \{\mathbf{u}_1\})$. Hence $I \cup \{\mathbf{u}_1, \mathbf{u}_2\}$ is independent, and the process continues. We claim that a basis of U will be reached eventually. Indeed, if no basis of U is ever reached, the process creates arbitrarily large independent sets in V. But this is impossible by the fundamental theorem because V is finite dimensional and so is spanned by a finite set of vectors.

□

Theorem 5.11.1.4.1

Let V be a finite dimensional vector space spanned by m vectors.

1. V has a finite basis, and $dim\ V \leq m$.
2. Every independent set of vectors in V can be enlarged to a basis of V by adding vectors from any fixed basis of V.
3. If U is a subspace of V, then
    1. U is finite dimensional and $dim\ U \leq dim\ V$.
    2. If $dim\ U = dim\ V$ then $U = V$.

Proof

1. If $V = \{\mathbf{0}\}$, then V has an empty basis and $dim\ V = 0 \leq m$. Otherwise, let $\mathbf{v} \neq \mathbf{0}$ be a vector in V. Then $\{\mathbf{v}\}$ is independent, so (1) follows from Lemma 6.4.2 with $U = V$.
2. We refine the proof of Lemma 6.4.2. Fix a basis B of V and let I be an independent subset of V. If $span\ I = V$ then I is already a basis of V. If $span\ I \neq V$, then B is not contained in I (because B spans V). Hence choose $\mathbf{b}_1 \in B$ such that $\mathbf{b}_1 \notin span\ I$. Hence the set $I \cup \{\mathbf{b}_1\}$ is independent by Lemma 5.11.1.4.1. If $span\ (I \cup \{\mathbf{b}_1\}) = V$ we are done; otherwise a similar argument shows that $(I \cup \{\mathbf{b}_1, \mathbf{b}_2\})$ is independent for some $\mathbf{b}_2 \in B$. Continue this process. As in the proof of Lemma 6.4.2, a basis of V will be reached eventually.
3. 1. This is clear if $U = \{\mathbf{0}\}$. Otherwise, let $\mathbf{u} \neq \mathbf{0}$ in U. Then $\{\mathbf{u}\}$ can be enlarged to a finite basis B of U by Lemma 6.4.2, proving that U is finite dimensional. But B is independent in V, so $dim\ U \leq dim\ V$ by the fundamental theorem.
    2. This is clear if $U = \{\mathbf{0}\}$ because V *has* a basis; otherwise, it follows from (2).

Theorem 5.11.1.4.1 shows that a vector space V is finite dimensional if and only if it has a finite basis (possibly empty), and that every subspace of a finite dimensional space is again finite dimensional.

Example 5.11.1.4.1

Enlarge the independent set $D = \left\{ \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \right\}$ to a basis of $\mathbf{M}_{22}$.

Solution

The standard basis of $\mathbf{M}_{22}$ is $\left\{\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}\right\}$, so including one of these in D will produce a basis by Theorem 5.11.1.4.1. In fact including *any* of these matrices in D produces an independent set (verify), and hence a basis by Theorem 6.4.1. Of course these vectors are not the only possibilities, for example, including $\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$ works as well.

Example 5.11.1.4.2

Find a basis of $\mathbf{P}_3$ containing the independent set $\{1+x, 1+x^2\}$.

Solution

The standard basis of $\mathbf{P}_3$ is $\{1, x, x^2, x^3\}$, so including two of these vectors will do. If we use 1 and x^3, the result is $\{1, 1+x, 1+x^2, x^3\}$. This is independent because the polynomials have distinct degrees (Example 6.3.4), and so is a basis by Theorem 5.11.1.4.1. Of course, including $\{1, x\}$ or $\{1, x^2\}$ would *not* work!

Example 5.11.1.4.3

Show that the space $\mathbf{P}$ of all polynomials is infinite dimensional.

Solution

For each $n \geq 1$, $\mathbf{P}$ has a subspace $\mathbf{P}_n$ of dimension $n+1$. Suppose $\mathbf{P}$ is finite dimensional, say $dim\ \|P = m$. Then $dim\ \|P_n \leq dim\ \|P$ by Theorem 5.11.1.4.1, that is $n+1 \leq m$. This is impossible since n is arbitrary, so $\mathbf{P}$ must be infinite dimensional.

The next example illustrates how (2) of Theorem 5.11.1.4.1 can be used.

Example 5.11.1.4.1

If $\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_k$ are independent columns in $\mathbb{R}^n$, show that they are the first k columns in some invertible $n \times n$ matrix.

Solution

By Theorem 5.11.1.4.1, expand $\{\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_k\}$ to a basis $\{\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_k, \mathbf{c}_{k+1}, \ldots, \mathbf{c}_n\}$ of $\mathbb{R}^n$. Then the matrix $A = \begin{bmatrix} \mathbf{c}_1 & \mathbf{c}_2 & \ldots & \mathbf{c}_k & \mathbf{c}_{k+1} & \ldots & \mathbf{c}_n \end{bmatrix}$ with this basis as its columns is an $n \times n$ matrix and it is invertible by Theorem 5.2.3.

Theorem 5.11.1.4.2

Let U and W be subspaces of the finite dimensional space V.

1. If $U \subseteq W$, then $dim\ U \leq dim\ W$.
2. If $U \subseteq W$ and $dim\ U = dim\ W$, then $U = W$.

Proof

Since W is finite dimensional, (1) follows by taking $V = W$ in part (3) of Theorem 5.11.1.4.1. Now assume $dim\ U = dim\ W = n$, and let B be a basis of U. Then B is an independent set in W. If $U \neq W$, then $span\ B \neq W$, so B can be extended to an independent set of $n+1$ vectors in W by Lemma 5.11.1.4.1. This contradicts the fundamental theorem (Theorem 6.3.2) because W is spanned by $dim\ W = n$ vectors. Hence $U = W$, proving (2).

□

Theorem 5.11.1.4.2 is very useful. This was illustrated in Example 5.2.13 for $\mathbb{R}^2$ and $\mathbb{R}^3$; here is another example.

Example 5.11.1.4.5

If a is a number, let W denote the subspace of all polynomials in $\mathbf{P}_n$ that have a as a root:

$$W = \{p(x) \mid p(x) \in \| P_n \text{ and } p(a) = 0\}$$

Show that $\{(x-a), (x-a)^2, \ldots, (x-a)^n\}$ is a basis of W.

Solution

Observe first that $(x-a), (x-a)^2, \ldots, (x-a)^n$ are members of W, and that they are independent because they have distinct degrees (Example 6.3.4). Write

$$U = span\ \{(x-a), (x-a)^2, \ldots, (x-a)^n\}$$

Then we have $U \subseteq W \subseteq \| P_n$, $dim\ U = n$, and $dim\ \| P_n = n+1$. Hence $n \leq dim\ W \leq n+1$ by Theorem 5.11.1.4.2. Since $dim\ W$ is an integer, we must have $dim\ W = n$ or $dim\ W = n+1$. But then $W = U$ or $W = \| P_n$, again by Theorem 5.11.1.4.2. Because $W \neq \| P_n$, it follows that $W = U$, as required.

A set of vectors is called **dependent** if it is *not* independent, that is if some nontrivial linear combination vanishes. The next result is a convenient test for dependence.

Lemma 5.11.1.4.3: Dependent Lemma

A set $D = \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$ of vectors in a vector space V is dependent if and only if some vector in D is a linear combination of the others.

Proof

Let $\mathbf{v}_2$ (say) be a linear combination of the rest: $\mathbf{v}_2 = s_1\mathbf{v}_1 + s_3\mathbf{v}_3 + \cdots + s_k\mathbf{v}_k$. Then

$$s_1\mathbf{v}_1 + (-1)\mathbf{v}_2 + s_3\mathbf{v}_3 + \cdots + s_k\mathbf{v}_k = \mathbf{0}$$

is a nontrivial linear combination that vanishes, so D is dependent. Conversely, if D is dependent, let $t_1\mathbf{v}_1 + t_2\mathbf{v}_2 + \cdots + t_k\mathbf{v}_k = \mathbf{0}$ where some coefficient is nonzero. If (say) $t_2 \neq 0$, then $\mathbf{v}_2 = -\frac{t_1}{t_2}\mathbf{v}_1 - \frac{t_3}{t_2}\mathbf{v}_3 - \cdots - \frac{t_k}{t_2}\mathbf{v}_k$ is a linear combination of the others.

□

Lemma 5.11.1.4.1 gives a way to enlarge independent sets to a basis; by contrast, Lemma 5.11.1.4.3 shows that spanning sets can be cut down to a basis.

Lemma 5.11.1.4.3

Let V be a finite dimensional vector space. Any spanning set for V can be cut down (by deleting vectors) to a basis of V.

Proof

Since V is finite dimensional, it has a finite spanning set S. Among all spanning sets contained in S, choose S_0 containing the smallest number of vectors. It suffices to show that S_0 is independent (then S_0 is a basis, proving the theorem). Suppose, on the contrary, that S_0 is not independent. Then, by Lemma 5.11.1.4.3, some vector $\mathbf{u} \in S_0$ is a linear combination of the set $S_1 = S_0 \setminus \{\mathbf{u}\}$ of vectors in S_0 other than $\mathbf{u}$. It follows that $span\ S_0 = span\ S_1$, that is, $V = span\ S_1$. But S_1 has fewer elements than S_0 so this contradicts the choice of S_0. Hence S_0 is independent after all.

□

Note that, with Theorem 5.11.1.4.1, Theorem 5.2.6 completes the promised proof of Theorem 5.2.6 for the case $V = \mathbb{R}^n$.

Example 5.11.1.4.6

Find a basis of $\mathbf{P}_3$ in the spanning set $S = \{1, x + x^2, 2x - 3x^2, 1 + 3x - 2x^2, x^3\}$.

Solution

Since $dim\ \|P_3 = 4$, we must eliminate one polynomial from S. It cannot be x^3 because the span of the rest of S is contained in $\mathbf{P}_2$. But eliminating $1 + 3x - 2x^2$ does leave a basis (verify). Note that $1 + 3x - 2x^2$ is the sum of the first three polynomials in S.

Theorems 6.4.1 and 6.4.3 have other useful consequences.

Theorem 5.11.1.4.4

Let V be a vector space with $dim\ V = n$, and suppose S is a set of exactly n vectors in V. Then S is independent if and only if S spans V.

Proof

Assume first that S is independent. By Theorem 5.11.1.4.1, S is contained in a basis B of V. Hence $|S| = n = |B|$ so, since $S \subseteq B$, it follows that $S = B$. In particular S spans V.

Conversely, assume that S spans V, so S contains a basis B by Theorem 5.2.6. Again $|S| = n = |B|$ so, since $S \supseteq B$, it follows that $S = B$. Hence S is independent.

□

One of independence or spanning is often easier to establish than the other when showing that a set of vectors is a basis. For example if $V = \mathbb{R}^n$ it is easy to check whether a subset S of $\mathbb{R}^n$ is orthogonal (hence independent) but checking spanning can be tedious. Here are three more examples.

Example 5.11.1.4.7

Consider the set $S = \{p_0(x), p_1(x), \ldots, p_n(x)\}$ of polynomials in $\mathbf{P}_n$. If $\deg p_k(x) = k$ for each k, show that S is a basis of $\mathbf{P}_n$.

Solution

The set S is independent—the degrees are distinct—see Example 6.4.4. Hence S is a basis of $\mathbf{P}_n$ by Theorem 6.4.1 because $dim\ \|P_n = n + 1$.

Example 5.11.1.4.8

Let V denote the space of all symmetric 2×2 matrices. Find a basis of V consisting of invertible matrices.

Solution

We know that $dim\ V = 3$ (Example 6.3.11), so what is needed is a set of three invertible, symmetric matrices that (using Theorem 6.4.1) is either independent or spans V. The set $\left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \right\}$ is independent (verify) and so is a basis of the required type.

Example 5.11.1.4.9

Let A be any $n \times n$ matrix. Show that there exist $n^2 + 1$ scalars $a_0, a_1, a_2, \dots, a_{n^2}$ not all zero, such that

$$a_0 I + a_1 A + a_2 A^2 + \cdots + a_{n^2} A^{n^2} = 0$$

where I denotes the $n \times n$ identity matrix.

Solution

The space $\mathbf{M}_{nn}$ of all $n \times n$ matrices has dimension n^2 by Example 6.4.4. Hence the $n^2 + 1$ matrices $I, A, A^2, \dots, A^{n^2}$ cannot be independent by Theorem 6.4.1, so a nontrivial linear combination vanishes. This is the desired conclusion.

The result in Example 6.4.9 can be written as $f(A) = 0$ where $f(x) = a_0 + a_1 x + a_2 x^2 + \cdots + a_{n^2} x^{n^2}$. In other words, A satisfies a nonzero polynomial $f(x)$ of degree at most n^2. In fact we know that A satisfies a nonzero polynomial of degree n (this is the Cayley-Hamilton theorem—see Theorem 8.7.10), but the brevity of the solution in Example 6.4.6 is an indication of the power of these methods.

If U and W are subspaces of a vector space V, there are two related subspaces that are of interest, their **sum** $U + W$ and their **intersection** $U \cap W$, defined by

$$U + W = \{\mathbf{u} + \mathbf{w} \mid \mathbf{u} \in U \text{ and } \mathbf{w} \in W\}$$
$$U \cap W = \{\mathbf{v} \in V \mid \mathbf{v} \in U \text{ and } \mathbf{v} \in W\}$$

It is routine to verify that these are indeed subspaces of V, that $U \cap W$ is contained in both U and W, and that $U + W$ contains both U and W. We conclude this section with a useful fact about the dimensions of these spaces. The proof is a good illustration of how the theorems in this section are used.

Theorem 5.11.1.4.5

Suppose that U and W are finite dimensional subspaces of a vector space V. Then $U + W$ is finite dimensional and

$$dim\ (U + W) = dim\ U + dim\ W - dim\ (U \cap W).$$

Proof

Since $U \cap W \subseteq U$, it has a finite basis, say $\{\mathbf{x}_1, \dots, \mathbf{x}_d\}$. Extend it to a basis $\{\mathbf{x}_1, \dots, \mathbf{x}_d, \mathbf{u}_1, \dots, \mathbf{u}_m\}$ of U by Theorem 5.11.1.4.1. Similarly extend $\{\mathbf{x}_1, \dots, \mathbf{x}_d\}$ to a basis $\{\mathbf{x}_1, \dots, \mathbf{x}_d, \mathbf{w}_1, \dots, \mathbf{w}_p\}$ of W. Then

$$U + W = span\ \{\mathbf{x}_1, \dots, \mathbf{x}_d, \mathbf{u}_1, \dots, \mathbf{u}_m, \mathbf{w}_1, \dots, \mathbf{w}_p\}$$

as the reader can verify, so $U + W$ is finite dimensional. For the rest, it suffices to show that $\{\mathbf{x}_1, \dots, \mathbf{x}_d, \mathbf{u}_1, \dots, \mathbf{u}_m, \mathbf{w}_1, \dots, \mathbf{w}_p\}$ is independent (verify). Suppose that

$$r_1\mathbf{x}_1 + \cdots + r_d\mathbf{x}_d + s_1\mathbf{u}_1 + \cdots + s_m\mathbf{u}_m + t_1\mathbf{w}_1 + \cdots + t_p\mathbf{w}_p = \mathbf{0} \tag{5.11.1.4.1}$$

where the r_i, s_j, and t_k are scalars. Then

$$r_1\mathbf{x}_1 + \cdots + r_d\mathbf{x}_d + s_1\mathbf{u}_1 + \cdots + s_m\mathbf{u}_m = -(t_1\mathbf{w}_1 + \cdots + t_p\mathbf{w}_p)$$

is in U (left side) and also in W (right side), and so is in $U \cap W$. Hence $(t_1\mathbf{w}_1 + \cdots + t_p\mathbf{w}_p)$ is a linear combination of $\{\mathbf{x}_1, \ldots, \mathbf{x}_d\}$, so $t_1 = \cdots = t_p = 0$, because $\{\mathbf{x}_1, \ldots, \mathbf{x}_d, \mathbf{w}_1, \ldots, \mathbf{w}_p\}$ is independent. Similarly, $s_1 = \cdots = s_m = 0$, so (5.11.1.4.1) becomes $r_1\mathbf{x}_1 + \cdots + r_d\mathbf{x}_d = \mathbf{0}$. It follows that $r_1 = \cdots = r_d = 0$, as required.

□

Theorem 6.4.5 is particularly interesting if $U \cap W = \{\mathbf{0}\}$. Then there are *no* vectors $\mathbf{x}_i$ in the above proof, and the argument shows that if $\{\mathbf{u}_1, \ldots, \mathbf{u}_m\}$ and $\{\mathbf{w}_1, \ldots, \mathbf{w}_p\}$ are bases of U and W respectively, then $\{\mathbf{u}_1, \ldots, \mathbf{u}_m, \mathbf{w}_1, \ldots, \mathbf{w}_p\}$ is a basis of U + W. In this case $U + W$ is said to be a **direct sum** (written $U \oplus W$); we return to this in Chapter 9.

5.11.1.4E: Finite Dimensional Spaces Exercises

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5.11.1.4E: Finite Dimensional Spaces Exercises

Exercise $5.11.1.4E.1$

In each case, find a basis for V that includes the vector $\mathbf{v}$.

a. $V = \mathbb{R}^3$, $\mathbf{v} = (1, -1, 1)$
b. $V = \mathbb{R}^3$, $\mathbf{v} = (0, 1, 1)$
c. $V = \|M_{22}$, $\mathbf{v} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$
d. $V = \|P_2$, $\mathbf{v} = x^2 - x + 1$

Answer available at the end of this section.

Exercise $5.11.1.4E.2$

In each case, find a basis for V among the given vectors.

a. $V = \mathbb{R}^3$, $\{(1, 1, -1), (2, 0, 1), (-1, 1, -2), (1, 2, 1)\}$
b. $V = \|P_2$, $\{x^2 + 3, x + 2, x^2 - 2x - 1, x^2 + x\}$

Answer available at the end of this section.

Exercise $5.11.1.4E.3$

In each case, find a basis of V containing $\mathbf{v}$ and $\mathbf{w}$.

a. $V = \mathbb{R}^4$, $\mathbf{v} = (1, -1, 1, -1)$, $\mathbf{w} = (0, 1, 0, 1)$
b. $V = \mathbb{R}^4$, $\mathbf{v} = (0, 0, 1, 1)$, $\mathbf{w} = (1, 1, 1, 1)$
c. $V = \|M_{22}$, $\mathbf{v} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $\mathbf{w} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$
d. $V = \|P_3$, $\mathbf{v} = x^2 + 1$, $\mathbf{w} = x^2 + x$

Answer available at the end of this section.

Exercise $5.11.1.4E.4$

a. If z is not a real number, show that $\{z, z^2\}$ is a basis of the real vector space $\mathbb{C}$ of all complex numbers.
b. If z is neither real nor pure imaginary, show that $\{z, \overline{z}\}$ is a basis of $\mathbb{C}$.

Answer available at the end of this section.

Exercise $5.11.1.4E.5$

In each case use Theorem 6.4.4 to decide if S is a basis of V.

a. $V = \|M_{22}$; $S = \left\{ \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}$
b. $V = \|P_3$; $S = \{2x^2, 1 + x, 3, 1 + x + x^2 + x^3\}$

Answer available at the end of this section.

Exercise $5.11.1.4E.6$

a. Find a basis of $\mathbf{M}_{22}$ consisting of matrices with the property that $A^2 = A$.
b. Find a basis of $\mathbf{P}_3$ consisting of polynomials whose coefficients sum to 4. What if they sum to 0?

Answer available at the end of this section.

Exercise $5.11.1.4E.7$

If $\{\mathbf{u}, \mathbf{v}, \mathbf{w}\}$ is a basis of V, determine which of the following are bases.

a. $\{\mathbf{u} + \mathbf{v}, \mathbf{u} + \mathbf{w}, \mathbf{v} + \mathbf{w}\}$
b. $\{2\mathbf{u} + \mathbf{v} + 3\mathbf{w}, 3\mathbf{u} + \mathbf{v} - \mathbf{w}, \mathbf{u} - 4\mathbf{w}\}$
c. $\{\mathbf{u}, \mathbf{u} + \mathbf{v} + \mathbf{w}\}$
d. $\{\mathbf{u}, \mathbf{u} + \mathbf{w}, \mathbf{u} - \mathbf{w}, \mathbf{v} + \mathbf{w}\}$

Answer available at the end of this section.

Exercise $5.11.1.4E.8$

a. Can two vectors span $\mathbb{R}^3$? Can they be linearly independent? Explain.
b. Can four vectors span $\mathbb{R}^3$? Can they be linearly independent? Explain.

Answer available at the end of this section.

Exercise $5.11.1.4E.9$

Show that any nonzero vector in a finite dimensional vector space is part of a basis.

Exercise $5.11.1.4E.10$

If A is a square matrix, show that $\det A = 0$ if and only if some row is a linear combination of the others.

Answer available at the end of this section.

Exercise $5.11.1.4E.11$

Let D, I, and X denote finite, nonempty sets of vectors in a vector space V. Assume that D is dependent and I is independent. In each case answer yes or no, and defend your answer.

a. If $X \supseteq D$, must X be dependent?
b. If $X \subseteq D$, must X be dependent?
c. If $X \supseteq I$, must X be independent?
d. If $X \subseteq I$, must X be independent?

Answer available at the end of this section.

Exercise 5.11.1.4E.12

If U and W are subspaces of V and $dim\ U = 2$, show that either $U \subseteq W$ or $dim\ (U \cap W) \leq 1$.

Exercise 5.11.1.4E.13

Let A be a nonzero 2×2 matrix and write $U = \{X \text{ in } \|M_{22} \mid XA = AX\}$. Show that $dim\ U \geq 2$. [*Hint*: I and A are in U.]

Exercise 5.11.1.4E.14

If $U \subseteq \mathbb{R}^2$ is a subspace, show that $U = \{\mathbf{0}\}$, $U = \mathbb{R}^2$, or U is a line through the origin.

Exercise 5.11.1.4E.15

Given $\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \ldots, \mathbf{v}_k$, and $\mathbf{v}$, let $U = span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$ and $W = span\ \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k, \mathbf{v}\}$. Show that either $dim\ W = dim\ U$ or $dim\ W = 1 + dim\ U$.

Answer available at the end of this section.

Exercise 5.11.1.4E.16

Suppose U is a subspace of $\mathbf{P}_1$, $U \neq \{0\}$, and $U \neq \|P_1$. Show that either $U = \mathbb{R}$ or $U = \mathbb{R}(a + x)$ for some a in $\mathbb{R}$.

Exercise 5.11.1.4E.17

Let U be a subspace of V and assume $dim\ V = 4$ and $dim\ U = 2$. Does every basis of V result from adding (two) vectors to some basis of U? Defend your answer.

Exercise 5.11.1.4E.18

Let U and W be subspaces of a vector space V.

a. If $dim\ V = 3$, $dim\ U = dim\ W = 2$, and $U \neq W$, show that $dim\ (U \cap W) = 1$.
b. Interpret (a.) geometrically if $V = \mathbb{R}^3$.

Answer available at the end of this section.

Exercise 5.11.1.4E.19

Let $U \subseteq W$ be subspaces of V with $dim\ U = k$ and $dim\ W = m$, where $k < m$. If $k < l < m$, show that a subspace X exists where $U \subseteq X \subseteq W$ and $dim\ X = l$.

Exercise 5.11.1.4E.20

Let $B = \{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ be a *maximal* independent set in a vector space V. That is, no set of more than n vectors S is independent. Show that B is a basis of V.

Exercise $5.11.1.4E.21$

Let $B = \{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ be a *minimal* spanning set for a vector space V. That is, V cannot be spanned by fewer than n vectors. Show that B is a basis of V.

a. Let $p(x)$ and $q(x)$ lie in $\mathbf{P}_1$ and suppose that $p(1) \neq 0$, $q(2) \neq 0$, and $p(2) = 0 = q(1)$. Show that $\{p(x), q(x)\}$ is a basis of $\mathbf{P}_1$. [*Hint*: If $rp(x) + sq(x) = 0$, evaluate at $x = 1$, $x = 2$.]
b. Let $B = \{p_0(x), p_1(x), \ldots, p_n(x)\}$ be a set of polynomials in $\mathbf{P}_n$. Assume that there exist numbers $a_0, a_1, \ldots, a_n$ such that $p_i(a_i) \neq 0$ for each i but $p_i(a_j) = 0$ if i is different from j. Show that B is a basis of $\mathbf{P}_n$.

Exercise $5.11.1.4E.22$

Let V be the set of all infinite sequences $(a_0, a_1, a_2, \ldots)$ of real numbers. Define addition and scalar multiplication by

$$(a_0, a_1, \ldots) + (b_0, b_1, \ldots) = (a_0 + b_0, a_1 + b_1, \ldots)$$

and

$$r(a_0, a_1, \ldots) = (ra_0, ra_1, \ldots)$$

a. Show that V is a vector space.
b. Show that V is not finite dimensional.
c. [For those with some calculus.] Show that the set of convergent sequences (that is, $\lim_{n\to\infty} a_n$ exists) is a subspace, also of infinite dimension.

Answer available at the end of this section.

Exercise $5.11.1.4E.23$

Let A be an $n \times n$ matrix of rank r. If $U = \{X \text{ in } \|M_{nn} \mid AX = 0\}$, show that $dim\ U = n(n - r)$. [*Hint*: Exercise 6.3.34.]

Exercise $5.11.1.4E.24$

Let U and W be subspaces of V.

a. Show that $U + W$ is a subspace of V containing both U and W.
b. Show that $span\ \{\mathbf{u}, \mathbf{w}\} = \mathbb{R}\mathbf{u} + \mathbb{R}\mathbf{w}$ for any vectors $\mathbf{u}$ and $\mathbf{w}$.
c. Show that

$$span\ \{\mathbf{u}_1, \ldots, \mathbf{u}_m, \mathbf{w}_1, \ldots, \mathbf{w}_n = span\ \{\mathbf{u}_1, \ldots, \mathbf{u}_m\} + span\ \{\mathbf{w}_1, \ldots, \mathbf{w}_n\}$$

Answer available at the end of this section.

Exercise $5.11.1.4E.25$

If A and B are $m \times n$ matrices, show that $rank\ (A + B) \leq rank\ A + rank\ B$. [*Hint*: If U and V are the column spaces of A and B, respectively, show that the column space of $A + B$ is contained in $U + V$ and that $dim\ (U + V) \leq dim\ U + dim\ V$. (See Theorem 6.4.5.)]

Answers

Exercise $5.11.1.4E.1$

b. $\{(0, 1, 1), (1, 0, 0), (0, 1, 0)\}$

d. $\{x^2 - x + 1, 1, x\}$

Exercise $5.11.1.4E.2$

b. Any three except $\{x^2 + 3, x + 2, x^2 - 2x - 1\}$

Exercise $5.11.1.4E.3$

b. Add $(0, 1, 0, 0)$ and $(0, 0, 1, 0)$.
d. Add 1 and x^3.

Exercise $5.11.1.4E.4$

b. If $z = a + bi$, then $a \neq 0$ and $b \neq 0$. If $rz + s\overline{z} = 0$, then $(r + s)a = 0$ and $(r - s)b = 0$. This means that $r + s = 0 = r - s$, so $r = s = 0$. Thus $\{z, \overline{z}\}$ is independent; it is a basis because $dim\ \mathbb{C} = 2$.

Exercise $5.11.1.4E.5$

b. The polynomials in S have distinct degrees.

Exercise $5.11.1.4E.6$

b. $\{4, 4x, 4x^2, 4x^3\}$ is one such basis of $\mathbf{P}_3$. However, there is *no* basis of $\mathbf{P}_3$ consisting of polynomials that have the property that their coefficients sum to zero. For if such a basis exists, then every polynomial in $\mathbf{P}_3$ would have this property (because sums and scalar multiples of such polynomials have the same property).

Exercise $5.11.1.4E.7$

b. Not a basis.
d. Not a basis.

Exercise $5.11.1.4E.8$

b. Yes; no.

Exercise $5.11.1.4E.10$

$\det A = 0$ if and only if A is not invertible; if and only if the rows of A are dependent (Theorem 5.2.3); if and only if some row is a linear combination of the others (Lemma 6.4.2).

Exercise $5.11.1.4E.11$

b. No. $\{(0, 1), (1, 0)\} \subseteq \{(0, 1), (1, 0), (1, 1)\}$.
d. Yes. See Exercise 6.3.15.

Exercise $5.11.1.4E.15$

If $\mathbf{v} \in U$ then $W = U$; if $\mathbf{v} \notin U$ then $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k, \mathbf{v}\}$ is a basis of W by the independent lemma.

Exercise $5.11.1.4E.18$

b. Two distinct planes through the origin (U and W) meet in a line through the origin $(U \cap W)$.

Exercise $5.11.1.4E.22$

b. The set $\{(1, 0, 0, 0, \ldots), (0, 1, 0, 0, 0, \ldots), (0, 0, 1, 0, 0, \ldots), \ldots\}$ contains independent subsets of arbitrary size.

Exercise $5.11.1.4E.24$

b. $\mathbb{R}\mathbf{u} + \mathbb{R}\mathbf{w} = \{r\mathbf{u} + s\mathbf{w} \mid r, s \text{ in } \mathbb{R}\} = span\ \{\mathbf{u}, \mathbf{w}\}$

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5.11.1.5: AN APPLICATION TO POLYNOMIALS

The vector space of all polynomials of degree at most n is denoted $\mathbf{P}_n$, and it was established in Section 6.3 that $\mathbf{P}_n$ has dimension $n+1$; in fact, $\{1, x, x^2, \dots, x^n\}$ is a basis. More generally, *any* $n+1$ polynomials of distinct degrees form a basis, by Theorem 6.4.4 (they are independent by Example 6.3.4). This proves

Theorem 5.11.1.5.1

Let $p_0(x), p_1(x), p_2(x), \dots, p_n(x)$ be polynomials in $\mathbf{P}_n$ of degrees $0, 1, 2, \dots, n$, respectively. Then $\{p_0(x), \dots, p_n(x)\}$ is a basis of $\mathbf{P}_n$.

An immediate consequence is that $\{1, (x-a), (x-a)^2, \dots, (x-a)^n\}$ is a basis of $\mathbf{P}_n$ for any number a. Hence we have the following:

Corollary 5.11.1.5.1

If a is any number, every polynomial $f(x)$ of degree at most n has an expansion in powers of $(x-a)$:

$$f(x) = a_0 + a_1(x-a) + a_2(x-a)^2 + \cdots + a_n(x-a)^n \tag{5.11.1.5.1}$$

If $f(x)$ is evaluated at $x = a$, then equation (5.11.1.5.1) becomes

$$f(x) = a_0 + a_1(a-a) + \cdots + a_n(a-a)^n = a_0$$

Hence $a_0 = f(a)$, and equation (5.11.1.5.1) can be written $f(x) = f(a) + (x-a)g(x)$, where $g(x)$ is a polynomial of degree $n-1$ (this assumes that $n \geq 1$). If it happens that $f(a) = 0$, then it is clear that $f(x)$ has the form $f(x) = (x-a)g(x)$. Conversely, every such polynomial certainly satisfies $f(a) = 0$, and we obtain:

Corollary 5.11.1.5.2

Let $f(x)$ be a polynomial of degree $n \geq 1$ and let a be any number. Then:

Remainder Theorem

1. $f(x) = f(a) + (x-a)g(x)$ for some polynomial $g(x)$ of degree $n-1$.

Factor Theorem

2. $f(a) = 0$ if and only if $f(x) = (x-a)g(x)$ for some polynomial $g(x)$.

The polynomial $g(x)$ can be computed easily by using "long division" to divide $f(x)$ by $(x-a)$—see Appendix D.

All the coefficients in the expansion (5.11.1.5.1) of $f(x)$ in powers of $(x-a)$ can be determined in terms of the derivatives of $f(x)$.[1] These will be familiar to students of calculus. Let $f^{(n)}(x)$ denote the nth derivative of the polynomial $f(x)$, and write $f^{(0)}(x) = f(x)$. Then, if

$$f(x) = a_0 + a_1(x-a) + a_2(x-a)^2 + \cdots + a_n(x-a)^n$$

it is clear that $a_0 = f(a) = f^{(0)}(a)$. Differentiation gives

$$f^{(1)}(x) = a_1 + 2a_2(x-a) + 3a_3(x-a)^2 + \cdots + na_n(x-a)^{n-1}$$

and substituting $x = a$ yields $a_1 = f^{(1)}(a)$. This continues to give $a_2 = \frac{f^{(2)}(a)}{2!}, a_3 = \frac{f^{(3)}(a)}{3!}, \dots, a_k = \frac{f^{(k)}(a)}{k!}$, where $k!$ is defined as $k!$

$= k(k-1)\cdots 2\cdot 1$. Hence we obtain the following:

Corollary 5.11.1.5.3: Taylor's Theorem

If $f(x)$ is a polynomial of degree n, then

$$f(x) = f(a) + \frac{f^{(1)}(a)}{1!}(x-a) + \frac{f^{(2)}(a)}{2!}(x-a)^2 + \cdots + \frac{f^{(n)}(a)}{n!}(x-a)^n$$

Example 5.11.1.5.1

Expand $f(x) = 5x^3 + 10x + 2$ as a polynomial in powers of $x - 1$.

Solution

The derivatives are $f^{(1)}(x) = 15x^2 + 10$, $f^{(2)}(x) = 30x$, and $f^{(3)}(x) = 30$. Hence the Taylor expansion is

$$\begin{aligned} f(x) &= f(1) + \frac{f^{(1)}(1)}{1!}(x-1) + \frac{f^{(2)}(1)}{2!}(x-1)^2 + \frac{f^{(3)}(1)}{3!}(x-1)^3 \\ &= 17 + 25(x-1) + 15(x-1)^2 + 5(x-1)^3 \end{aligned}$$

Taylor's theorem is useful in that it provides a formula for the coefficients in the expansion. It is dealt with in calculus texts and will not be pursued here.

Theorem 6.5.1 produces bases of $\mathbf{P}_n$ consisting of polynomials of distinct degrees. A different criterion is involved in the next theorem.

Theorem 5.11.1.5.2

Let $f_0(x), f_1(x), \ldots, f_n(x)$ be nonzero polynomials in $\mathbf{P}_n$. Assume that numbers $a_0, a_1, \ldots, a_n$ exist such that

$$\begin{aligned} f_i(a_i) &\neq 0 \quad \text{for each } i \\ f_i(a_j) &= 0 \quad \text{if } i \neq j \end{aligned}$$

Then

1. $\{f_0(x), \ldots, f_n(x)\}$ is a basis of $\mathbf{P}_n$.
2. If $f(x)$ is any polynomial in $\mathbf{P}_n$, its expansion as a linear combination of these basis vectors is \[f(x) = \frac{f(a_0)}{f_0(a_0)} f_0(x) + \frac{f(a_1)}{f_1(a_1)} f_1(x) + \dots + \frac{f(a_n)}{f_n(a_n)} f_n(x) \nonumber \]

Proof

1. It suffices (by Theorem 6.4.4) to show that $\{f_0(x), \ldots, f_n(x)\}$ is linearly independent (because $dim\ \|P_n = n+1$). Suppose that \[r_0f_0(x) + r_1f_1(x) + \dots + r_nf_n(x) = 0, r_i \in \mathbb{R} \nonumber \]
2. By (1), $f(x) = r_0f_0(x) + \cdots + r_nf_n(x)$ for *some* numbers r_i. Once again, evaluating at a_0 gives $f(a_0) = r_0f_0(a_0)$, so $r_0 = f(a_0)/f_0(a_0)$. Similarly, $r_i = f(a_i)/f_i(a_i)$ for each i.

Example 5.11.1.5.2

Show that $\{x^2 - x, x^2 - 2x, x^2 - 3x + 2\}$ is a basis of $\mathbf{P}_2$.

Solution

Write $f_0(x) = x^2 - x = x(x-1)$, $f_1(x) = x^2 - 2x = x(x-2)$, and $f_2(x) = x^2 - 3x + 2 = (x-1)(x-2)$. Then the conditions of Theorem 6.5.2 are satisfied with $a_0 = 2$, $a_1 = 1$, and $a_2 = 0$.

We investigate one natural choice of the polynomials $f_i(x)$ in Theorem 6.5.2. To illustrate, let a_0, a_1, and a_2 be distinct numbers and write

$$f_0(x) = \frac{(x-a_1)(x-a_2)}{(a_0-a_1)(a_0-a_2)} \quad f_1(x) = \frac{(x-a_0)(x-a_2)}{(a_1-a_0)(a_1-a_2)} \quad f_2(x) = \frac{(x-a_0)(x-a_1)}{(a_2-a_0)(a_2-a_1)}$$

Then $f_0(a_0) = f_1(a_1) = f_2(a_2) = 1$, and $f_i(a_j) = 0$ for $i \neq j$. Hence Theorem 6.5.2 applies, and because $f_i(a_i) = 1$ for each i, the formula for expanding any polynomial is simplified.

In fact, this can be generalized with no extra effort. If $a_0, a_1, \dots, a_n$ are distinct numbers, define the **Lagrange polynomials** $\delta_0(x), \delta_1(x), \dots, \delta_n(x)$ relative to these numbers as follows:

$$\delta_k(x) = \frac{\prod_{i \neq k}(x-a_i)}{\prod_{i \neq k}(a_k-a_i)} \quad k = 0, 1, 2, \dots, n$$

Here the numerator is the product of all the terms $(x-a_0), (x-a_1), \dots, (x-a_n)$ with $(x-a_k)$ omitted, and a similar remark applies to the denominator. If $n = 2$, these are just the polynomials in the preceding paragraph. For another example, if $n = 3$, the polynomial $\delta_1(x)$ takes the form

$$\delta_1(x) = \frac{(x-a_0)(x-a_2)(x-a_3)}{(a_1-a_0)(a_1-a_2)(a_1-a_3)}$$

In the general case, it is clear that $\delta_i(a_i) = 1$ for each i and that $\delta_i(a_j) = 0$ if $i \neq j$. Hence Theorem 6.5.2 specializes as Theorem 6.5.3.

Theorem 5.11.1.5.3: Lagrange Interpolation Expansion

Let $a_0, a_1, \dots, a_n$ be distinct numbers. The corresponding set

$$\{\delta_0(x), \delta_1(x), \dots, \delta_n(x)\}$$

of Lagrange polynomials is a basis of $\mathbf{P}_n$, and any polynomial $f(x)$ in $\mathbf{P}_n$ has the following unique expansion as a linear combination of these polynomials.

$$f(x) = f(a_0)\delta_0(x) + f(a_1)\delta_1(x) + \cdots + f(a_n)\delta_n(x)$$

Example 5.11.1.5.3

Find the Lagrange interpolation expansion for $f(x) = x^2 - 2x + 1$ relative to $a_0 = -1$, $a_1 = 0$, and $a_2 = 1$.

Solution

The Lagrange polynomials are

$$\delta_0 = \frac{(x-0)(x-1)}{(-1-0)(-1-1)} = \frac{1}{2}(x^2 - x)$$
$$\delta_1 = \frac{(x+1)(x-1)}{(0+1)(0-1)} = -(x^2 - 1)$$
$$\delta_2 = \frac{(x+1)(x-0)}{(1+1)(1-0)} = \frac{1}{2}(x^2 + x)$$

Because $f(-1) = 4$, $f(0) = 1$, and $f(1) = 0$, the expansion is

$$f(x) = 2(x^2 - x) - (x^2 - 1)$$

The Lagrange interpolation expansion gives an easy proof of the following important fact.

Theorem 5.11.1.5.1

Let $f(x)$ be a polynomial in $\mathbf{P}_n$, and let $a_0, a_1, \ldots, a_n$ denote distinct numbers. If $f(a_i) = 0$ for all i, then $f(x)$ is the zero polynomial (that is, all coefficients are zero).

Proof

All the coefficients in the Lagrange expansion of $f(x)$ are zero.

---

1. The discussion of Taylor's theorem can be omitted with no loss of continuity.

5.11.1.5E: An Application to Polynomials Exercises

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5.11.1.5E: An Application to Polynomials Exercises

Exercise 5.11.1.5E.1

If polynomials $f(x)$ and $g(x)$ satisfy $f(a) = g(a)$, show that $f(x) - g(x) = (x - a)h(x)$ for some polynomial $h(x)$.

Exercises 6.5.2, 6.5.3, 6.5.4, and 6.5.5 require polynomial differentiation.

Exercise 5.11.1.5E.2

Expand each of the following as a polynomial in powers of $x - 1$.

a. $f(x) = x^3 - 2x^2 + x - 1$
b. $f(x) = x^3 + x + 1$
c. $f(x) = x^4$
d. $f(x) = x^3 - 3x^2 + 3x$

Answer available at the end of this section.

Exercise 5.11.1.5E.3

Prove Taylor's theorem for polynomials.

Exercise 5.11.1.5E.4

Use Taylor's theorem to derive the **binomial theorem**:

$$(1 + x)^n = \binom{n}{0} + \binom{n}{1}x + \binom{n}{2}x^2 + \cdots + \binom{n}{n}x^n$$

Here the **binomial coefficients** $\binom{n}{r}$ are defined by

$$\binom{n}{r} = \frac{n!}{r!(n - r)!}$$

where $n! = n(n - 1) \cdots 2 \cdot 1$ if $n \geq 1$ and $0! = 1$.

Exercise 5.11.1.5E.5

Let $f(x)$ be a polynomial of degree n. Show that, given any polynomial $g(x)$ in $\mathbf{P}_n$, there exist numbers $b_0, b_1, \ldots, b_n$ such that

$$g(x) = b_0 f(x) + b_1 f^{(1)}(x) + \cdots + b_n f^{(n)}(x)$$

where $f^{(k)}(x)$ denotes the kth derivative of $f(x)$.

Exercise 5.11.1.5E.6

Use Theorem 6.5.2 to show that the following are bases of $\mathbf{P}_2$.

a. $\{x^2 - 2x, x^2 + 2x, x^2 - 4\}$
b. $\{x^2 - 3x + 2, x^2 - 4x + 3, x^2 - 5x + 6\}$

Answer available at the end of this section.

Exercise $5.11.1.5E.7$

Find the Lagrange interpolation expansion of $f(x)$ relative to $a_0 = 1$, $a_1 = 2$, and $a_2 = 3$ if:

$f(x) = x^2 + 1$ $f(x) = x^2 + x + 1$

Answer available at the end of this section.

Exercise $5.11.1.5E.8$

Let $a_0, a_1, \ldots, a_n$ be distinct numbers. If $f(x)$ and $g(x)$ in $\mathbf{P}_n$ satisfy $f(a_i) = g(a_i)$ for all i, show that $f(x) = g(x)$. [*Hint*: See Theorem 6.5.4.]

Exercise $5.11.1.5E.9$

Let $a_0, a_1, \ldots, a_n$ be distinct numbers. If $f(x) \in \|P_{n+1}$ satisfies $f(a_i) = 0$ for each $i = 0, 1, \ldots, n$, show that $f(x) = r(x - a_0)(x - a_1) \cdots (x - a_n)$ for some r in $\mathbb{R}$. [*Hint*: r is the coefficient of x^{n+1} in $f(x)$. Consider $f(x) - r(x - a_0) \cdots (x - a_n)$ and use Theorem 6.5.4.]

Exercise $5.11.1.5E.10$

Let a and b denote distinct numbers.

a. Show that $\{(x - a), (x - b)\}$ is a basis of $\mathbf{P}_1$.
b. Show that $\{(x - a)^2, (x - a)(x - b), (x - b)^2\}$ is a basis of $\mathbf{P}_2$.
c. Show that $\{(x - a)^n, (x - a)^{n-1}(x - b), \ldots, (x - a)(x - b)^{n-1}, (x - b)^n\}$ is a basis of $\mathbf{P}_n$. [*Hint*: If a linear combination vanishes, evaluate at $x = a$ and $x = b$. Then reduce to the case $n - 2$ by using the fact that if $p(x)q(x) = 0$ in $\mathbf{P}$, then either $p(x) = 0$ or $q(x) = 0$.]

Answer available at the end of this section.

Exercise $5.11.1.5E.11$

Let a and b be two distinct numbers. Assume that $n \geq 2$ and let

$$U_n = \{f(x) \text{ in } \|P_n \mid f(a) = 0 = f(b)\}.$$

a. Show that

$$U_n = \{(x - a)(x - b)p(x) \mid p(x) \text{ in } \|P_{n-2}\}$$

b. [*Hint*: If $p(x)q(x) = 0$ in $\mathbf{P}$, then either $p(x) = 0$, or $q(x) = 0$.]
c. Show $\{(x - a)^{n-1}(x - b), (x - a)^{n-2}(x - b)^2, \ldots, (x - a)^2(x - b)^{n-2}, (x - a)(x - b)^{n-1}\}$ is a basis of U_n. [*Hint*: Exercise 6.5.10.]

Answer available at the end of this section.

Answers

Exercise $5.11.1.5E.2$

b. $3+4(x-1)+3(x-1)^2+(x-1)^3$

d. $1+(x-1)^3$

Exercise $5.11.1.5E.6$

b. The polynomials are $(x-1)(x-2)$, $(x-1)(x-3)$, $(x-2)(x-3)$. Use $a_0=3$, $a_1=2$, and $a_2=1$.

Exercise $5.11.1.5E.7$

$f(x)=\frac{3}{2}(x-2)(x-3)-7(x-1)(x-3)+\frac{13}{2}(x-1)(x-2)$.

Exercise $5.11.1.5E.10$

b. If $r(x-a)^2+s(x-a)(x-b)+t(x-b)^2=0$, then evaluation at $x=a(x=b)$ gives $t=0(r=0)$. Thus $s(x-a)(x-b)=0$, so $s=0$. Use Theorem 6.4.4.

Exercise $5.11.1.5E.11$

b. Suppose $\{p_0(x),p_1(x),\ldots,p_{n-2}(x)\}$ is a basis of $\mathbf{P}_{n-2}$. We show that $\{(x-a)(x-b)p_0(x),(x-a)(x-b)p_1(x),\ldots,(x-a)(x-b)p_{n-2}(x)\}$ is a basis of U_n. It is a spanning set by part **(a)**, so assume that a linear combination vanishes with coefficients $r_0,r_1,\ldots,r_{n-2}$. Then $(x-a)(x-b)[r_0p_0(x)+\cdots+r_{n-2}p_{n-2}(x)]=0$, so $r_0p_0(x)+\cdots+r_{n-2}p_{n-2}(x)=0$ by the Hint. This implies that $r_0=\cdots=r_{n-2}=0$.

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5.11.1.6: Supplementary Exercises for Chapter 6

Exercise 5.11.1.6.1

(Requires calculus) Let V denote the space of all functions $f : \mathbb{R} \to \mathbb{R}$ for which the derivatives f' and f'' exist. Show that f_1, f_2, and f_3 in V are linearly independent provided that their **wronskian** $w(x)$ is nonzero for some x, where

$$w(x) = \det \begin{bmatrix} f_1(x) & f_2(x) & f_3(x) \\ f_1'(x) & f_2'(x) & f_3'(x) \\ f_1''(x) & f_2''(x) & f_3''(x) \end{bmatrix}$$

Answer available at the end of this section.

Exercise 5.11.1.6.2

Let $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$ be a basis of $\mathbb{R}^n$ (written as columns), and let A be an $n \times n$ matrix.

a. If A is invertible, show that $\{A\mathbf{v}_1, A\mathbf{v}_2, \dots, A\mathbf{v}_n\}$ is a basis of $\mathbb{R}^n$.
b. If $\{A\mathbf{v}_1, A\mathbf{v}_2, \dots, A\mathbf{v}_n\}$ is a basis of $\mathbb{R}^n$, show that A is invertible.

Answer available at the end of this section.

Exercise 5.11.1.6.3

If A is an $m \times n$ matrix, show that A has rank m if and only if col A contains every column of I_m. \end{supex} \begin{supex}

Answer available at the end of this section.

Exercise 5.11.1.6.4

Show that $\text{null}A = \text{null}(A^TA)$ for any real matrix A.

Answer available at the end of this section.

Exercise 5.11.1.6.5

Let A be an $m \times n$ matrix of rank r. Show that $dim\ \ (\text{null}A) = n - r$ (Theorem~???) as follows. Choose a basis $\{\mathbf{x}_1, \dots, \mathbf{x}_k\}$ of $\text{null}A$ and extend it to a basis $\{\mathbf{x}_1, \dots, \mathbf{x}_k, \mathbf{z}_1, \dots, \mathbf{z}_m\}$ of $\mathbb{R}^n$. Show that $\{A\mathbf{z}_1, \dots, A\mathbf{z}_m\}$ is a basis of $\text{col}A$.

Answer available at the end of this section.

Answers

Exercise 5.11.1.6.1

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Exercise 5.11.1.6.2

a. If $YA = 0$, Y a row, we show that $Y = 0$; thus A^T (and hence A) is invertible. Given a column $\mathbf{c}$ in $\mathbb{R}^n$ write $\mathbf{c} = \sum_i r_i(A\mathbf{v}_i)$ where each r_i is in $\mathbb{R}$. Then $Y\mathbf{c} = \sum_i r_i YA\mathbf{v}_i$, so $Y = YI_n = Y \begin{bmatrix} \mathbf{e}_1 & \mathbf{e}_2 & \cdots & \mathbf{e}_n \end{bmatrix} = \begin{bmatrix} Y\mathbf{e}_1 & Y\mathbf{e}_2 & \cdots & Y\mathbf{e}_n \end{bmatrix} = \begin{bmatrix} 0 & 0 & \cdots & 0 \end{bmatrix} = 0$, as required.

Exercise 5.11.1.6.3

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Exercise 5.11.1.6.4

We have $\text{null}A \subseteq \text{null}(A^TA)$ because $A\mathbf{x} = \mathbf{0}$ implies $(A^TA)\mathbf{x} = \mathbf{0}$. Conversely, if $(A^TA)\mathbf{x} = \mathbf{0}$, then $\|A\mathbf{x}\|^2 = (A\mathbf{x})^T(A\mathbf{x}) = \mathbf{x}^TA^TA\mathbf{x} = 0$. Thus $A\mathbf{x} = \mathbf{0}$.

Exercise 5.11.1.6.5

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5.E: Exercises

Exercise 5.E.1

Suppose you have $\mathbb{R}^2$ and the $+$ operation is as follows:

$$(a,b)+(c,d)=(a+d,b+c).$$

Scalar multiplication is defined in the usual way. Is this a vector space? Explain why or why not.

Exercise 5.E.2

Suppose you have $\mathbb{R}^2$ and the $+$ operation is as follows:

$$(a,b)+(c,d)=(0,b+d)$$

Scalar multiplication is defined in the usual way. Is this a vector space? Explain why or why not.

Exercise 5.E.3

Suppose you have $\mathbb{R}^2$ and scalar multiplication is defined as $c(a,b)=(a,cb)$ while vector addition is defined as usual. Is this a vector space? Explain why or why not.

Exercise 5.E.4

Suppose you have $\mathbb{R}^2$ and the $+$ operation is defined as follows.

$$(a,b)+(c,d)=(a-c,b-d)$$

Scalar multiplication is same as usual. Is this a vector space? Explain why or why not.

Exercise 5.E.5

Consider all the functions defined on a non empty set which have values in $\mathbb{R}$. Is this a vector space? Explain. The operations are defined as follows. Here f,g signify functions and a is a scalar

$$\begin{aligned}(f+g)(x)&=f(x)+g(x)\\(af)(x)&=a(f(x))\end{aligned}\tag{5.E.1}$$

Exercise 5.E.6

Denote by $\mathbb{R}^{\mathbb{N}}$ the set of real valued sequences. For $\vec{a}\equiv\{a_n\}_{n=1}^{\infty}$, $\vec{b}\equiv\{b_n\}_{n=1}^{\infty}$ two of these, define their sum to be given by

$$\vec{a}+\vec{b}=\{a_n+b_n\}_{n=1}^{\infty}$$

and define scalar multiplication by

$$c\vec{a}=\{ca_n\}_{n=1}^{\infty}\text{ where }\vec{a}=\{a+n\}_{n=1}^{\infty}$$

Is this a special case of Exercise 5.E.5? Is this a vector space?

Exercise $5.E.7$

Let $\mathbb{C}^2$ be the set of ordered pairs of complex numbers. Define addition and scalar multiplication in the usual way.

$$(z,w)+(\hat{z},\hat{w})=(z+\hat{z},w+\hat{w}),u(z,w)\equiv(uz,uw)$$

Here the scalars are from $\mathbb{C}$. Show this is a vector space.

Exercise $5.E.8$

Let V be the set of functions defined on a nonempty set which have values in a vector space W. Is this a vector space? Explain.

Exercise $5.E.9$

Consider the space of $m\times n$ matrices with operation of addition and scalar multiplication defined the usual way. That is, if A,B are two $m\times n$ matrices and c a scalar,

$$(A+B)_{ij}=A_{ij}+B_{ij},\ (cA)_{ij}\equiv c(A_{ij})$$

Exercise $5.E.10$

Consider the set of $n\times n$ symmetric matrices. That is, $A=A^T$. In other words, $A_{ij}=A_{ji}$. Show that this set of symmetric matrices is a vector space and a subspace of the vector space of $n\times n$ matrices.

Exercise $5.E.11$

Consider the set of all vectors in $\mathbb{R}^2,(x,y)$ such that $x+y\geq 0$. Let the vector space operations be the usual ones. Is this a vector space? Is it a subspace of $\mathbb{R}^2$?

Exercise $5.E.12$

Consider the vectors in $\mathbb{R}^2,(x,y)$ such that $xy=0$. Is this a subspace of $\mathbb{R}^2$? Is it a vector space? The addition and scalar multiplication are the usual operations.

Exercise $5.E.13$

Define the operation of vector addition on $\mathbb{R}^2$ by $(x,y)+(u,v)=(x+u,y+v+1)$. Let scalar multiplication be the usual operation. Is this a vector space with these operations? Explain.

Exercise $5.E.14$

Let the vectors be real numbers. Define vector space operations in the usual way. That is $x+y$ means to add the two numbers and xy means to multiply them. Is $\mathbb{R}$ with these operations a vector space? Explain.

Exercise $5.E.15$

Let the scalars be the rational numbers and let the vectors be real numbers which are the form $a+b\sqrt{2}$ for a,b rational numbers. Show that with the usual operations, this is a vector space.

Exercise $5.E.16$

Let $\mathbb{P}_2$ be the set of all polynomials of degree 2 or less. That is, these are of the form $a+bx+cx^2$. Addition is defined as

$$(a+bx+cx^2)+(\hat{d}+\hat{b}x+\hat{c}x^2)=(a+\hat{a})+(b+\hat{b})x+(c+\hat{c})x^2$$

and scalar multiplication is defined as

$$d(a+bx+cx^2)=da+dbx+cdx^2$$

Show that, with this definition of the vector space operations that $\mathbb{P}_2$ is a vector space. Now let V denote those polynomials $a+bx+cx^2$ such that $a+b+c=0$. Is V a subspace of $\mathbb{P}_2$? Explain.

Exercise $5.E.17$

Let M,N be subspaces of a vector space V and consider $M+N$ defined as the set of all $m+n$ where $m\in M$ and $n\in N$. Show that $M+N$ is a subspace of V.

Exercise $5.E.18$

Let M,N be subspaces of a vector space V. Then $M\cap N$ consists of all vectors which are in both M and N. Show that $M\cap N$ is a subspace of V.

Exercise $5.E.19$

Let M,N be subspaces of a vector space $\mathbb{R}^2$. Then $N\cup M$ consists of all vectors which are in either M or N. Show that $N\cup M$ is not necessarily a subspace of $\mathbb{R}^2$ by giving an example where $N\cup M$ fails to be a subspace.

Exercise $5.E.20$

Let X consist of the real valued functions which are defined on an interval $[a,b]$. For $f,g\in X$, $f+g$ is the name of the function which satisfies $(f+g)(x)=f(x)+g(x)$. For s a real number, $(sf)(x)=s(f(x))$. Show this is a vector space.

Answer available at the end of this section.

Exercise $5.E.21$

Consider functions defined on $\{1,2,\cdots,n\}$ having values in $\mathbb{R}$. Explain how, if V is the set of all such functions, V can be considered as $\mathbb{R}^n$.

Answer available at the end of this section.

Exercise $5.E.22$

Let the vectors be polynomials of degree no more than 3. Show that with the usual definitions of scalar multiplication and addition wherein, for $p(x)$ a polynomial, $(ap)(x) = ap(x)$ and for p, q polynomials $(p+q)(x) = p(x) + q(x)$, this is a vector space.

Answer available at the end of this section.

Exercise $5.E.23$

Let V be a vector space and suppose $\{\vec{x}_1, \cdots, \vec{x}_l\}$ is a set of vectors in V. Show that $\vec{0}$ is in $span\{\vec{x}_1, \cdots, \vec{x}_k\}$.

Answer available at the end of this section.

Exercise $5.E.24$

Determine if $p(x) = 4x^2 - x$ is in the span given by

$$span\{x^2 + x,\ x^2 - 1,\ -x + 2\}$$

Exercise $5.E.25$

Determine if $p(x) = -x^2 + x + 2$ is in the span given by

$$span\{x^2 + x + 1,\ 2x^2 + x\}$$

Exercise $5.E.26$

Determine if $A = \begin{bmatrix} 1 & 3 \\ 0 & 0 \end{bmatrix}$ is in the span given by

$$span\left\{\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix}\right\}$$

Exercise $5.E.27$

Show that the spanning set in Exercise $5.E.26$ is a spanning set for M_{22}, the vector space of all 2×2 matrices.

Exercise $5.E.28$

Consider the vector space of polynomials of degree at most 2, $\mathbb{P}_2$. Determine whether the following is a basis for $\mathbb{P}_2$.

$$\{x^2 + x + 1,\ 2x^2 + 2x + 1,\ x + 1\}$$

Hint: There is a isomorphism from $\mathbb{R}^3$ to $\mathbb{P}_2$. It is defined as follows:

$$T\vec{e}_1 = 1,\ T\vec{e}_2 = x,\ T\vec{e}_3 = x^2$$

Then extend T linearly. Thus

$$T\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = x^2 + x + 1,\ T\begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} = 2x^2 + 2x + 1,\ T\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = 1 + x$$

It follows that if

$$\left\{\begin{bmatrix}1\\1\\1\end{bmatrix},\begin{bmatrix}1\\2\\2\end{bmatrix},\begin{bmatrix}1\\1\\0\end{bmatrix}\right\}$$

is a basis for $\mathbb{R}^3$, then the polynomials will be a basis for $\mathbb{P}_2$ because they will be independent. Recall that an isomorphism takes a linearly independent set to a linearly independent set. Also, since T is an isomorphism, it preserves all linear relations.

Exercise $5.E.29$

Find a basis in $\mathbb{P}_2$ for the subspace

$$span\{1+x+x^2,\ 1+2x,\ 1+5x-3x^2\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others. Hint: This is the situation in which you have a spanning set and you want to cut it down to form a linearly independent set which is also a spanning set. Use the same isomorphism above. Since T is an isomorphism, it preserves all linear relations so if such can be found in $\mathbb{R}^3$, the same linear relations will be present in $\mathbb{P}_2$.

Exercise $5.E.30$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{1+x-x^2+x^3,\ 1+2x+3x^3,\ -1+3x+5x^2+7x^3,\ 1+6x+4x^2+11x^3\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise $5.E.31$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{1+x-x^2+x^3,\ 1+2x+3x^3,\ -1+3x+5x^2+7x^3,\ 1+6x+4x^2+11x^3\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise $5.E.32$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3-2x^2+x+2,\ 3x^3-x^2+2x+2,\ 7x^3+x^2+4x+2,\ 5x^3+3x+2\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise $5.E.33$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3+2x^2+x-2,\ 3x^3+3x^2+2x-2,\ 3x^3+x+2,\ 3x^3+x+2\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise $5.E.34$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3-5x^2+x+5,\ 3x^3-4x^2+2x+5,\ 5x^3+8x^2+2x-5,\ 11x^3+6x+5\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise $5.E.35$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3-3x^2+x+3,\ 3x^3-2x^2+2x+3,\ 7x^3+7x^2+3x-3,\ 7x^3+4x+3\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise $5.E.36$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3-x^2+x+1,\ 3x^3+2x+1,\ 4x^3+x^2+2x+1,\ 3x^3+2x-1\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise $5.E.37$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3-x^2+x+1,\ 3x^3+2x+1,\ 13x^3+x^2+8x+4,\ 3x^3+2x-1\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise $5.E.38$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3-3x^2+x+3,\ 3x^3-2x^2+2x+3,\ -5x^3+5x^2-4x-6,\ 7x^3+4x-3\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise $5.E.39$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3-2x^2+x+2,\ 3x^3-x^2+2x+2,\ 7x^3-x^2+4x+4,\ 5x^3+3x-2\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise $5.E.40$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3-2x^2+x+2,\ 3x^3-x^2+2x+2,\ 3x^3+4x^2+x-2,\ 7x^3-x^2+4x+4\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise $5.E.41$

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3-4x^2+x+4,\ 3x^3-3x^2+2x+4,\ -3x^3+3x^2-2x-4,\ -2x^3+4x^2-2x-4\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise 5.E.42

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3+2x^2+x-2,\ 3x^3+3x^2+2x-2,\ 5x^3+x^2+2x+2,\ 10x^3+10x^2+6x-6\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise 5.E.43

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3+x^2+x-1,\ 3x^3+2x^2+2x-1,\ x^3+1,\ 4x^3+3x^2+2x-1\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise 5.E.44

Find a basis in $\mathbb{P}_3$ for the subspace

$$span\{x^3-x^2+x+1,\ 3x^3+2x+1,\ x^3+2x^2-1,\ 4x^3+x^2+2x+1\}$$

If the above three vectors do not yield a basis, exhibit one of them as a linear combination of the others.

Exercise 5.E.45

Here are some vectors.

$$\{x^3+x^2-x-1,\ 3x^3+2x^2+2x-1\}$$

If these are linearly independent, extend to a basis for all of $\mathbb{P}_3$.

Exercise 5.E.46

Here are some vectors.

$$\{x^3-2x^2-x+2,\ 3x^3-x^2+2x+2\}$$

If these are linearly independent, extend to a basis for all of $\mathbb{P}_3$.

Exercise 5.E.47

Here are some vectors.

$$\{x^3-3x^2-x+3,\ 3x^3-2x^2+2x+3\}$$

If these are linearly independent, extend to a basis for all of $\mathbb{P}_3$.

Exercise 5.E.48

Here are some vectors.

$$\{x^3-2x^2-3x+2,\ 3x^3-x^2-6x+2,\ -8x^3+18x+10\}$$

If these are linearly independent, extend to a basis for all of $\mathbb{P}_3$.

Exercise $5.E.49$

Here are some vectors.

$$\{x^3 - 3x^2 - 3x + 3,\ 3x^3 - 2x^2 - 6x + 3,\ -8x^3 + 18x + 40\}$$

If these are linearly independent, extend to a basis for all of $\mathbb{P}_3$.

Exercise $5.E.50$

Here are some vectors.

$$\{x^3 - x^2 + x + 1,\ 3x^3 + 2x + 1,\ 4x^3 + 2x + 2\}$$

If these are linearly independent, extend to a basis for all of $\mathbb{P}_3$.

Exercise $5.E.51$

Here are some vectors.

$$\{x^3 + x^2 + 2x - 1,\ 3x^3 + 2x^2 + 4x - 1,\ 7x^3 + 8x + 23\}$$

If these are linearly independent, extend to a basis for all of $\mathbb{P}_3$.

Exercise $5.E.52$

Determine if the following set is linearly independent. If it is linearly dependent, write one vector as a linear combination of the other vectors in the set.

$$\{x + 1,\ x^2 + 2,\ x^2 - x - 3\}$$

Exercise $5.E.53$

Determine if the following set is linearly independent. If it is linearly dependent, write one vector as a linear combination of the other vectors in the set.

$$\{x^2 + x,\ -2x^2 - 4x - 6,\ 2x - 2\}$$

Exercise $5.E.54$

Determine if the following set is linearly independent. If it is linearly dependent, write one vector as a linear combination of the other vectors in the set.

$$\left\{\begin{bmatrix} 1 & 2 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} -7 & 2 \\ -2 & -3 \end{bmatrix}, \begin{bmatrix} 4 & 0 \\ 1 & 2 \end{bmatrix}\right\}$$

Exercise $5.E.55$

Determine if the following set is linearly independent. If it is linearly dependent, write one vector as a linear combination of the other vectors in the set.

$$\left\{\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix}\right\}$$

Exercise $5.E.56$

If you have 5 vectors in $\mathbb{R}^5$ and the vectors are linearly independent, can it always be concluded they span $\mathbb{R}^5$?

Answer available at the end of this section.

Exercise $5.E.57$

If you have 6 vectors in $\mathbb{R}^5$, is it possible they are linearly independent? Explain.

Answer available at the end of this section.

Exercise $5.E.58$

Let $\mathbb{P}_3$ be the polynomials of degree no more than 3. Determine which of the following are bases for this vector space.

a. $\{x+1,\ x^3+x^2+2x,\ x^2+x,\ x^3+x^2+x\}$
b. $\{x^3+1,\ x^2+x,\ 2x^3+x^2,\ 2x^3-x^2-3x+1\}$

Answer available at the end of this section.

Exercise $5.E.59$

In the context of the above problem, consider polynomials

$$\{a_i x^3+b_i x^2+c_i x+d_i,\ i=1,2,3,4\}$$

Show that this collection of polynomials is linearly independent on an interval $[s,t]$ if and only if

$$\begin{bmatrix} a_1 & b_1 & c_1 & d_1 \\ a_2 & b_2 & c_2 & d_2 \\ a_3 & b_3 & c_3 & d_3 \\ a_4 & b_4 & c_4 & d_4 \end{bmatrix}$$

is an invertible matrix.

Answer available at the end of this section.

Exercise $5.E.60$

Let the field of scalars be $\mathbb{Q}$, the rational numbers and let the vectors be of the form $a+b\sqrt{2}$ where a,b are rational numbers. Show that this collection of vectors is a vector space with field of scalars $\mathbb{Q}$ and give a basis for this vector space.

Answer available at the end of this section.

Exercise $5.E.61$

Suppose V is a finite dimensional vector space. Based on the exchange theorem above, it was shown that any two bases have the same number of vectors in them. Give a different proof of this fact using the earlier material in the book. Hint: Suppose $\{\vec{x}_1,\cdots,\vec{x}_n\}$ and $\{\vec{y}_1,\cdots,\vec{y}_m\}$ are two bases with $m<n$. Then define

$$\varphi:\mathbb{R}^n\mapsto V,\ \psi:\mathbb{R}^m\mapsto V$$

by

$$\varphi(\vec{a}) = \sum_{k=1}^{n} a_k \vec{x}_k,\ \psi(\vec{b}) = \sum_{j=1}^{m} b_j \vec{y}_j$$

Consider the linear transformation, $\psi^{-1} \circ \varphi$. Argue it is a one to one and onto mapping from $\mathbb{R}^n$ to $\mathbb{R}^m$. Now consider a matrix of this linear transformation and its reduced row-echelon form.

Answer available at the end of this section.

Exercise $5.E.62$

Let $M = \{\vec{u} = (u_1,\ u_2,\ u_3,\ u_4) \in \mathbb{R}^4\ :\ |u_1| \leq 4\}$. Is M a subspace of $\mathbb{R}^4$?

Answer available at the end of this section.

Exercise $5.E.63$

Let $M = \{\vec{u} = (u_1,\ u_2,\ u_3,\ u_4) \in \mathbb{R}^4\ :\ \sin(u_1) = 1\}$. Is M a subspace of $\mathbb{R}^4$?

Answer available at the end of this section.

Exercise $5.E.64$

Let W be a subset of M_{22} given by

$$W = \{A | A \in M_{22}, A^T = A\}$$

In words, W is the set of all symmetric 2×2 matrices. Is W a subspace of M_{22}?

Exercise $5.E.65$

Let W be a subset of M_{22} given by

$$W = \left\{ \begin{bmatrix} a & b \\ c & d \end{bmatrix} | a, b, c, d \in \mathbb{R},\ a + b = c + d \right\}$$

Is W a subspace of M_{22}?

Exercise $5.E.66$

Let W be a subset of P_3 given by

$$W = \{ax^3 + bx^2 + cx + d |\ a, b, c, d \in \mathbb{R}, d = 0\}$$

Is W a subspace of P_3?

Exercise $5.E.67$

Let W be a subset of P_3 given by

$$W = \{p(x) = ax^3 + bx^2 + cx + d |\ a, b, c, d \in \mathbb{R}, p(2) = 1\}$$

Is W a subspace of P_3?

Exercise 5.E.68

Let $T\colon \mathbb{P}_2 \to \mathbb{R}$ be a linear transformation such that

$$T(x^2) = 1;\ T(x^2 + x) = 5;\ T(x^2 + x + 1) = -1.$$

Find $T(ax^2 + bx + c)$.

Answer available at the end of this section.

Exercise 5.E.69

Consider the following functions $T\colon \mathbb{R}^3 \to \mathbb{R}^2$. Explain why each of these functions T is not linear.

a. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x + 2y + 3z + 1 \\ 2y - 3x + z \end{bmatrix}$

b. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x + 2y^2 + 3z \\ 2y + 3z + z \end{bmatrix}$

c. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} \sin x + 2y + 3z \\ 2y + 3z + z \end{bmatrix}$

d. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x + 2y + 3z \\ 2y + 3z - \ln z \end{bmatrix}$

Answer available at the end of this section.

Exercise 5.E.70

Suppose T is a linear transformation such that

$$\begin{aligned} T\begin{bmatrix} 1 \\ 1 \\ -7 \end{bmatrix} &= \begin{bmatrix} 3 \\ 3 \\ 3 \end{bmatrix} \\ T\begin{bmatrix} -1 \\ 0 \\ 6 \end{bmatrix} &= \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \\ T\begin{bmatrix} 0 \\ -1 \\ 2 \end{bmatrix} &= \begin{bmatrix} 1 \\ 3 \\ -1 \end{bmatrix} \end{aligned} \tag{5.E.2}$$

Find the matrix of T. That is find A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise 5.E.71

Suppose T is a linear transformation such that

$$T\begin{bmatrix}1\\2\\-18\end{bmatrix}=\begin{bmatrix}5\\2\\5\end{bmatrix}$$
$$T\begin{bmatrix}-1\\-1\\15\end{bmatrix}=\begin{bmatrix}3\\3\\5\end{bmatrix} \quad (5.E.3)$$
$$T\begin{bmatrix}0\\-1\\4\end{bmatrix}=\begin{bmatrix}2\\5\\-2\end{bmatrix}$$

Find the matrix of T. That is find A such that $T(\vec{x})=A\vec{x}$.

Answer available at the end of this section.

Exercise $5.E.72$

Consider the following functions $T\colon \mathbb{R}^3\to\mathbb{R}^2$. Show that each is a linear transformation and determine for each the matrix A such that $T(\vec{x})=A\vec{x}$.

a. $T\begin{bmatrix}x\\y\\z\end{bmatrix}=\begin{bmatrix}x+2y+3z\\2y-3x+z\end{bmatrix}$

b. $T\begin{bmatrix}x\\y\\z\end{bmatrix}=\begin{bmatrix}7x+2y+z\\3x-11y+2z\end{bmatrix}$

c. $T\begin{bmatrix}x\\y\\z\end{bmatrix}=\begin{bmatrix}3x+2y+z\\x+2y+6z\end{bmatrix}$

d. $T\begin{bmatrix}x\\y\\z\end{bmatrix}=\begin{bmatrix}2y-5x+z\\x+y+z\end{bmatrix}$

Answer available at the end of this section.

Exercise $5.E.73$

Suppose

$$[A_1\cdots A_n]^{-1}$$

exists where each $A_j\in\mathbb{R}^n$ and let vectors $\{B_1,\cdots,B_n\}$ in $\mathbb{R}^m$ be given. Show that there **always** exists a linear transformation T such that $T(A_i)=B_i$.

Exercise $5.E.74$

Let V and W be subspaces of $\mathbb{R}^n$ and $\mathbb{R}^m$ respectively and let $T\colon V\to W$ be a linear transformation. Suppose that $\{T\vec{v}_1,\cdots,T\vec{v}_r\}$ is linearly independent. Show that it must be the case that $\{\vec{v}_1,\cdots,\vec{v}_r\}$ is also linearly independent.

Answer available at the end of this section.

Exercise $5.E.75$

Let

$$V = span\left\{\begin{bmatrix}1\\1\\2\\0\end{bmatrix}, \begin{bmatrix}0\\1\\1\\1\end{bmatrix}, \begin{bmatrix}1\\1\\0\\1\end{bmatrix}\right\}$$

Let $T\vec{x} = A\vec{x}$ where A is the matrix

$$\begin{bmatrix}1 & 1 & 1 & 1\\0 & 1 & 1 & 0\\0 & 1 & 2 & 1\\1 & 1 & 1 & 2\end{bmatrix}$$

Give a basis for $Im(T)$.

Exercise $5.E.76$

Let

$$V = span\left\{\begin{bmatrix}1\\0\\0\\1\end{bmatrix}, \begin{bmatrix}1\\1\\1\\1\end{bmatrix}, \begin{bmatrix}1\\4\\4\\1\end{bmatrix}\right\}$$

Let $T\vec{x} = A\vec{x}$ where A is the matrix

$$\begin{bmatrix}1 & 1 & 1 & 1\\0 & 1 & 1 & 0\\0 & 1 & 2 & 1\\1 & 1 & 1 & 2\end{bmatrix}$$

Find a basis for $Im(T)$. In this case, the original vectors do not form an independent set.

Answer available at the end of this section.

Exercise $5.E.77$

If $\{\vec{v}_1, \cdots, \vec{v}_r\}$ is linearly independent and T is a one to one linear transformation, show that $\{T\vec{v}_1, \cdots, T\vec{v}_r\}$ is also linearly independent. Give an example which shows that if T is only linear, it can happen that, although $\{\vec{v}_1, \cdots, \vec{v}_r\}$ is linearly independent, $\{T\vec{v}_1, \cdots, T\vec{v}_r\}$ is not. In fact, show that it can happen that each of the $T\vec{v}_j$ equals 0.

Exercise $5.E.78$

Let V and W be subspaces of $\mathbb{R}^n$ and $\mathbb{R}^m$ respectively and let T: $V \to W$ be a linear transformation. Show that if T is onto W and if $\{\vec{v}_1, \cdots, \vec{v}_r\}$ is a basis for V, then $span\{T\vec{v}_1, \cdots, T\vec{v}_r\} = W$.

Exercise $5.E.79$

Define T: $\mathbb{R}^4 \to \mathbb{R}^3$ as follows.

$$T\vec{x} = \begin{bmatrix}3 & 2 & 1 & 8\\2 & 2 & -2 & 6\\1 & 1 & -1 & 3\end{bmatrix}\vec{x}$$

Find a basis for $Im(T)$. Also find a basis for $\ker(T)$.

Exercise $5.E.80$

Define T: $\mathbb{R}^4 \to \mathbb{R}^3$ as follows.

$$T\vec{x} = \begin{bmatrix} 1 & 2 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix} \vec{x}$$

where on the right, it is just matrix multiplication of the vector $\vec{x}$ which is meant. Explain why T is an isomorphism of $\mathbb{R}^3$ to $\mathbb{R}^3$.

Exercise $5.E.81$

Suppose T: $\mathbb{R}^3 \to \mathbb{R}^3$ is a linear transformation given by

$$T\vec{x} = A\vec{x}$$

where A is a 3×3 matrix. Show that T is an isomorphism if and only if A is invertible.

Exercise $5.E.82$

Suppose T: $\mathbb{R}^3 \to \mathbb{R}^3$ is a linear transformation given by

$$T\vec{x} = A\vec{x}$$

where A is a $m \times n$ matrix. Show that T is never an isomorphism if $m \neq n$. In particular, show that if $m > n$, T cannot be onto and if $m < n$, then T cannot be one to one.

Exercise $5.E.83$

Define T: $\mathbb{R}^2 \to \mathbb{R}^3$ as follows.

$$T\vec{x} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 0 & 1 \end{bmatrix} \vec{x}$$

where on the right, it is just matrix multiplication of the vector $\vec{x}$ which is meant. Show that T is one to one. Next let $W = Im(T)$. Show that T is an isomorphism of $\mathbb{R}^2$ and $Im(T)$.

Exercise $5.E.84$

In the above problem, find a 2×3 matrix A such that the restriction of A to $Im(T)$ gives the same result as T^{-1} on $Im(T)$. Hint: You might let A be such that

$$A \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, A \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

now find another vector $\vec{v} \in \mathbb{R}^3$ such that

$$\left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}, \vec{v} \right\}$$

is a basis. You could pick

$$\vec{v} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

for example. Explain why this one works or one of your choice works. Then you could define $A\vec{v}$ to equal some vector in $\mathbb{R}^2$. Explain why there will be more than one such matrix A which will deliver the inverse isomorphism T^{-1} on $Im(T)$.

Exercise $5.E.85$

Now let V equal $span\left\{\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}\right\}$ and let T: $V \to W$ be a linear transformation where

$$W = span\left\{\begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \\ 1 \end{bmatrix}\right\}$$

and

$$T\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, T\begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

Explain why T is an isomorphism. Determine a matrix A which, when multiplied on the left gives the same result as T on V and a matrix B which delivers T^{-1} on W. Hint: You need to have

$$A\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 1 \\ 0 & 1 \end{bmatrix}$$

Now enlarge $\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$ to obtain a basis for $\mathbb{R}^3$. You could add in $\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$ for example, and then pick another vector in $\mathbb{R}^4$ and let $A\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$ equal this other vector. Then you would have

$$A\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}$$

This would involve picking for the new vector in $\mathbb{R}^4$ the vector $\begin{bmatrix} 0 & 0 & 0 & 1 \end{bmatrix}^T$. Then you could find A. You can do something similar to find a matrix for T^{-1} denoted as B.

Exercise $5.E.86$

Let $V = \mathbb{R}^3$ and let

$$W = span(S), \text{ where } S = \left\{\begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} -2 \\ 2 \\ -2 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \\ 3 \end{bmatrix}\right\}$$

Find a basis of W consisting of vectors in S.

Answer available at the end of this section.

Exercise $5.E.87$

Let T be a linear transformation given by

$$T\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix}$$

Find a basis for $\ker(T)$ and $Im(T)$.

Answer available at the end of this section.

Exercise $5.E.88$

Let T be a linear transformation given by

$$T\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix}$$

Find a basis for $\ker(T)$ and $Im(T)$.

Answer available at the end of this section.

Exercise $5.E.89$

Let $V = \mathbb{R}^3$ and let

$$W = span\left\{\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 2 \\ -1 \end{bmatrix}\right\}$$

Extend this basis of W to a basis of V.

Answer available at the end of this section.

Exercise $5.E.90$

Let T be a linear transformation given by

$$T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}\begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

What is $\dim(\ker(T))$?

Answer available at the end of this section.

Exercise $5.E.91$

Consider the following functions which map $\mathbb{R}^n$ to $\mathbb{R}^n$.

a. T multiplies the jth component of $\vec{x}$ by a nonzero number b.
b. T replaces the ith component of $\vec{x}$ with b times the jth component added to the ih component.
c. T switches the ith and jth components.

Show these functions are linear transformations and describe their matrices A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $5.E.92$

You are given a linear transformation $T\colon \mathbb{R}^n \to \mathbb{R}^m$ and you know that

$$T(A_i) = B_i$$

where $\begin{bmatrix} A_1 & \cdots & A_n \end{bmatrix}^{-1}$ exists. Show that the matrix of T is of the form

$$\begin{bmatrix} B_1 & \cdots & B_n \end{bmatrix} \begin{bmatrix} A_1 & \cdots & A_n \end{bmatrix}^{-1}$$

Answer available at the end of this section.

Exercise $5.E.93$

Suppose T is a linear transformation such that

$$\begin{aligned} T\begin{bmatrix} 1 \\ 2 \\ -6 \end{bmatrix} &= \begin{bmatrix} 5 \\ 1 \\ 3 \end{bmatrix} \\ T\begin{bmatrix} -1 \\ -1 \\ 5 \end{bmatrix} &= \begin{bmatrix} 1 \\ 1 \\ 5 \end{bmatrix} \\ T\begin{bmatrix} 0 \\ -1 \\ 2 \end{bmatrix} &= \begin{bmatrix} 5 \\ 3 \\ -2 \end{bmatrix} \end{aligned} \tag{5.E.4}$$

Find the matrix of T. That is find A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $5.E.94$

Suppose T is a linear transformation such that

$$\begin{aligned} T\begin{bmatrix} 1 \\ 1 \\ -8 \end{bmatrix} &= \begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix} \\ T\begin{bmatrix} -1 \\ 0 \\ 6 \end{bmatrix} &= \begin{bmatrix} 2 \\ 4 \\ 1 \end{bmatrix} \\ T\begin{bmatrix} 0 \\ -1 \\ 3 \end{bmatrix} &= \begin{bmatrix} 6 \\ 1 \\ -1 \end{bmatrix} \end{aligned} \tag{5.E.5}$$

Find the matrix of T. That is find A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $5.E.95$

Suppose T is a linear transformation such that

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Find the matrix of T. That is find A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $5.E.96$

Suppose T is a linear transformation such that

$$\begin{aligned} T\begin{bmatrix} 1 \\ 1 \\ -7 \end{bmatrix} &= \begin{bmatrix} 3 \\ 3 \\ 3 \end{bmatrix} \\ T\begin{bmatrix} -1 \\ 0 \\ 6 \end{bmatrix} &= \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \\ T\begin{bmatrix} 0 \\ -1 \\ 2 \end{bmatrix} &= \begin{bmatrix} 1 \\ 3 \\ -1 \end{bmatrix} \end{aligned} \tag{5.E.6}$$

Find the matrix of T. That is find A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $5.E.97$

Suppose T is a linear transformation such that

$$\begin{aligned} T\begin{bmatrix} 1 \\ 2 \\ -18 \end{bmatrix} &= \begin{bmatrix} 5 \\ 2 \\ 5 \end{bmatrix} \\ T\begin{bmatrix} -1 \\ -1 \\ 15 \end{bmatrix} &= \begin{bmatrix} 3 \\ 3 \\ 5 \end{bmatrix} \\ T\begin{bmatrix} 0 \\ -1 \\ 4 \end{bmatrix} &= \begin{bmatrix} 2 \\ 5 \\ -2 \end{bmatrix} \end{aligned} \tag{5.E.7}$$

Find the matrix of T. That is find A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $5.E.98$

Consider the following functions $T\colon \mathbb{R}^3 \to \mathbb{R}^2$. Show that each is a linear transformation and determine for each the matrix A such that $T(\vec{x}) = A\vec{x}$.

a. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x + 2y + 3z \\ 2y - 3x + z \end{bmatrix}$

b. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 7x+2y+z \\ 3x-11y+2z \end{bmatrix}$

c. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 3x+2y+z \\ x+2y+6z \end{bmatrix}$

d. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 2y-5x+z \\ x+y+z \end{bmatrix}$

Answer available at the end of this section.

Exercise $5.E.99$

Consider the following functions T: $\mathbb{R}^3 \to \mathbb{R}^2$. Explain why each of these functions T is not linear.

a. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x+2y+3z+1 \\ 2y-3x+z \end{bmatrix}$

b. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x+2y^2+3z \\ 2y+3x+z \end{bmatrix}$

c. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} \sin x+2y+3z \\ 2y+3x+z \end{bmatrix}$

d. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x+2y+3z \\ 2y+3x-\ln z \end{bmatrix}$

Answer available at the end of this section.

Exercise $5.E.100$

Suppose

$$\begin{bmatrix} A_1 & \cdots & A_n \end{bmatrix}^{-1}$$

exists where each $A_j \in \mathbb{R}^n$ and let vectors $\{B_1, \cdots, B_n\}$ in $\mathbb{R}^m$ be given. Show that there always exists a linear transformation T such that $T(A_i) = B_i$.

Exercise $5.E.101$

Find the matrix for $T(\vec{w}) = \text{proj}_{\vec{v}}(\vec{w})$ where $\vec{v} = \begin{bmatrix} 1 & -2 & 3 \end{bmatrix}^T$.

Answer available at the end of this section.

Exercise $5.E.102$

Find the matrix for $T(\vec{w}) = \text{proj}_{\vec{v}}(\vec{w})$ where $\vec{v} = \begin{bmatrix} 1 & 5 & 3 \end{bmatrix}^T$.

Answer available at the end of this section.

Exercise $5.E.103$

Find the matrix for $T(\vec{w}) = \text{proj}_{\vec{v}}(\vec{w})$ where $\vec{v} = \begin{bmatrix} 1 & 0 & 3 \end{bmatrix}^T$.

Answer available at the end of this section.

Exercise $5.E.104$

Let $B = \left\{ \begin{bmatrix} 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ 2 \end{bmatrix} \right\}$ be a basis of $\mathbb{R}^2$ and let $\vec{x} = \begin{bmatrix} 5 \\ -7 \end{bmatrix}$ be a vector in $\mathbb{R}^2$. Find $C_B(\vec{x})$.

Exercise $5.E.105$

Let $B = \left\{ \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 2 \end{bmatrix} \right\}$ be a basis of $\mathbb{R}^3$ and let $\vec{x} = \begin{bmatrix} 5 \\ -1 \\ 4 \end{bmatrix}$ be a vector in $\mathbb{R}^2$. Find $C_B(\vec{x})$.

Answer available at the end of this section.

Exercise $5.E.106$

Let T: $\mathbb{R}^2 \mapsto \mathbb{R}^2$ be a linear transformation defined by $T\left(\begin{bmatrix} a \\ b \end{bmatrix} \right) = \begin{bmatrix} a+b \\ a-b \end{bmatrix}$.

Consider the two bases

$$B_1 = \{\vec{v}_1, \vec{v}_2\} = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \end{bmatrix} \right\}$$

and

$$B_2 = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$$

Find the matrix M_{B_2,B_1} of T with respect to the bases B_1 and B_2.

Answer available at the end of this section.

Answers

Exercise $5.E.20$

The axioms of a vector space all hold because they hold for a vector space. The only thing left to verify is the assertions about the things which are supposed to exist. 0 would be the zero function which sends everything to 0. This is an additive identity. Now if f is a function, $-f(x) \equiv (-f(x))$. Then

$$(f + (-f))(x) \equiv f(x) + (-f)(x) \equiv f(x) + (-f(x)) = 0$$

Hence $f + -f = 0$. For each $x \in [a, b]$, let $f_x(x) = 1$ and $f_x(y) = 0$ if $y \neq x$. Then these vectors are obviously linearly independent.

Exercise $5.E.21$

Let $f(i)$ be the ith component of a vector $\vec{x} \in \mathbb{R}^n$. Thus a typical element in $\mathbb{R}^n$ is $(f(1), \cdots, f(n))$.

Exercise $5.E.22$

This is just a subspace of the vector space of functions because it is closed with respect to vector addition and scalar multiplication. Hence this is a vector space.

Exercise $5.E.23$

$\sum_{i=1}^{k} 0\vec{x}_k = \vec{0}$

Exercise $5.E.56$

Yes. If not, there would exist a vector not in the span. But then you could add in this vector and obtain a linearly independent set of vectors with more vectors than a basis.

Exercise $5.E.57$

No. They can't be.

Exercise $5.E.58$

a.

b. Suppose

$$c_1(x^3+1)+c_2(x^2+x)+c_3(2x^3+x^2)+c_4(2x^3-x^2-3x+1)=0$$

Then combine the terms according to power of x.

$$(c_1+2c_3+2c_4)x^3+(c_2+c_3-c_4)x^2+(c_2-3c_4)x+(c_1+c_4)=0$$

Is there a non zero solution to the system

$$\begin{aligned} c_1+2c_3+2c_4&=0\\ c_2+c_3-c_4&=0\\ c_2-3c_4&=0\\ c_1+c_4&=0 \end{aligned} \tag{5.E.8}$$

, Solution is:

$$[c_1=0,\ c_2=0,\ c_3=0,\ c_4=0]$$

Therefore, these are linearly independent.

Exercise $5.E.59$

Let $p_i(x)$ denote the ith of these polynomials. Suppose $\sum_i C_i p_i(x)=0$. Then collecting terms according to the exponent of x, you need to have

$$\begin{aligned} C_1a_1+C_2a_2+C_3a_3+C_4a_4&=0\\ C_1b_1+C_2b_2+C_3b_3+C_4b_4&=0\\ C_1c_1+C_2c_2+C_3c_3+C_4c_4&=0\\ C_1d_1+C_2d_2+C_3d_3+C_4d_4&=0 \end{aligned} \tag{5.E.9}$$

The matrix of coefficients is just the transpose of the above matrix. There exists a non trivial solution if and only if the determinant of this matrix equals 0.

Exercise $5.E.60$

When you add two of these you get one and when you multiply one of these by a scalar, you get another one. A basis is $\{1,\sqrt{2}\}$. By definition, the span of these gives the collection of vectors. Are they independent? Say $a+b\sqrt{2}=0$ where a,b are rational numbers. If $a\neq 0$, then $b\sqrt{2}=-a$ which can't happen since a is rational. If $b\neq 0$, then $-a=b\sqrt{2}$ which again can't happen because on the left is a rational number and on the right is an irrational. Hence both $a,b=0$ and so this is a basis.

Exercise $5.E.61$

This is obvious because when you add two of these you get one and when you multiply one of these by a scalar, you get another one. A basis is $\{1,\sqrt{2}\}$. By definition, the span of these gives the collection of vectors. Are they independent? Say $a+b\sqrt{2}=0$ where a,b are rational numbers. If $a\neq 0$, then $b\sqrt{2}=-a$ which can't happen since a is rational. If $b\neq 0$, then $-a=b\sqrt{2}$ which again can't happen because on the left is a rational number and on the right is an irrational. Hence both $a,b=0$ and so this is a basis.

Exercise $5.E.62$

This is not a subspace. $\begin{bmatrix}1\\1\\1\\1\end{bmatrix}$ is in it, but $20\begin{bmatrix}1\\1\\1\\1\end{bmatrix}$ is not.

Exercise $5.E.63$

This is not a subspace.

Exercise $5.E.68$

By linearity we have $T(x^2)=1,\ T(x)=T(x^2+x-x^2)=T(x^2+x)-T(x^2)=5-1=5$, and $T(1)=T(x^2+x+1-(x^2+x))=T(x^2+x+1)-T(x^2+x))=-1-5=-6$. Thus $T(ax^2+bx+c)=aT(x^2)+bT(x)+cT(1)=a+5b-6c$.

Exercise $5.E.69$

Exercise $5.E.70$

$$\begin{bmatrix}3&1&1\\3&2&3\\3&3&-1\end{bmatrix}\begin{bmatrix}6&2&1\\5&2&1\\6&1&1\end{bmatrix}=\begin{bmatrix}29&9&5\\46&13&8\\27&11&5\end{bmatrix}$$

Exercise $5.E.71$

$$\begin{bmatrix}5&3&2\\2&3&5\\5&5&-2\end{bmatrix}\begin{bmatrix}11&4&1\\10&4&1\\12&3&1\end{bmatrix}=\begin{bmatrix}109&38&10\\112&35&10\\81&34&8\end{bmatrix}$$

Exercise $5.E.72$

Exercise $5.E.74$

If $\sum_i^r a_i\vec{v}_r=0$, then using linearity properties of T we get

$$0=T(0)=T\left(\sum_i^r a_i\vec{v}_r\right)=\sum_i^r a_iT(\vec{v}_r).$$

Since we assume that $\{T\vec{v}_1,\cdots,T\vec{v}_r\}$ is linearly independent, we must have all $a_i=0$, and therefore we conclude that $\{\vec{v}_1,\cdots,\vec{v}_r\}$ is also linearly independent.

Exercise $5.E.76$

Since the third vector is a linear combinations of the first two, then the image of the third vector will also be a linear combinations of the image of the first two. However the image of the first two vectors are linearly independent (check!), and hence form a basis of the image. Thus a basis for $Im(T)$ is:

$$V = span\left\{\begin{bmatrix}2\\0\\1\\3\end{bmatrix}, \begin{bmatrix}4\\2\\4\\5\end{bmatrix}\right\}$$

Exercise $5.E.86$

In this case $\dim(W) = 1$ and a basis for W consisting of vectors in S can be obtained by taking any (nonzero) vector from S.

Exercise $5.E.87$

A basis for $\ker(T)$ is $\left\{\begin{bmatrix}1\\-1\end{bmatrix}\right\}$ and a basis for $Im(T)$ is $\left\{\begin{bmatrix}1\\1\end{bmatrix}\right\}$. There are many other possibilities for the specific bases, but in this case $\dim(\ker(T)) = 1$ and $\dim(Im(T)) = 1$.

Exercise $5.E.88$

In this case $\ker(T) = \{0\}$ and $Im(T) = \mathbb{R}^2$ (pick any basis of $\mathbb{R}^2$).

Exercise $5.E.89$

There are many possible such extensions, one is (how do we know?):

$$\left\{\begin{bmatrix}1\\1\\1\end{bmatrix}, \begin{bmatrix}-1\\2\\-1\end{bmatrix}, \begin{bmatrix}0\\0\\1\end{bmatrix}\right\}$$

Exercise $5.E.90$

We can easily see that $\dim(Im(T)) = 1$, and thus $\dim(\ker(T)) = 3 - \dim(Im(T)) = 3 - 1 = 2$.

Exercise $5.E.91$

a. The matrix of T is the elementary matrix which multiplies the jth diagonal entry of the identity matrix by b.
b. The matrix of T is the elementary matrix which takes b times the jth row and adds to the ith row.
c. The matrix of T is the elementary matrix which switches the ith and the jth rows where the two components are in the ith and jth positions.

Exercise $5.E.92$

Suppose

$$\begin{bmatrix}\vec{c}_1^{\,T}\\ \vdots \\ \vec{c}_n^{\,T}\end{bmatrix} = \begin{bmatrix}\vec{a}_1 & \cdots & \vec{a}_n\end{bmatrix}^{-1}$$

Thus $\vec{c}_i^{\,T}\vec{a}_j = \delta_{ij}$. Therefore

$$\begin{aligned}\begin{bmatrix}\vec{b}_1 & \cdots & \vec{b}_n\end{bmatrix}\begin{bmatrix}\vec{a}_1 & \cdots & \vec{a}_n\end{bmatrix}^{-1}\vec{a}_i &= \begin{bmatrix}\vec{b}_1 & \cdots & \vec{b}_n\end{bmatrix}\begin{bmatrix}\vec{c}_1^{\,T}\\ \vdots \\ \vec{c}_n^{\,T}\end{bmatrix}\vec{a}_i\\ &= \begin{bmatrix}\vec{b}_1 & \cdots & \vec{b}_n\end{bmatrix}\vec{e}_i\\ &= \vec{b}_i\end{aligned} \tag{5.E.10}$$

Thus $T\vec{a}_i = \begin{bmatrix}\vec{b}_1 & \cdots & \vec{b}_n\end{bmatrix}\begin{bmatrix}\vec{a}_1 & \cdots & \vec{a}_n\end{bmatrix}^{-1}\vec{a}_i = A\vec{a}_i$. If $\vec{x}$ is arbitrary, then since the matrix $\begin{bmatrix}\vec{a}_1 & \cdots & \vec{a}_n\end{bmatrix}$ is invertible, there exists a unique $\vec{y}$ such that $\begin{bmatrix}\vec{a}_1 & \cdots & \vec{a}_n\end{bmatrix}\vec{y} = \vec{x}$ Hence

$$T\vec{x} = T\left(\sum_{i=1}^{n} y_i\vec{a}_i\right) = \sum_{i=1}^{n} y_i T\vec{a}_i = \sum_{i=1}^{n} y_1 A\vec{a}_i = A\left(\sum_{i=1}^{n} y_i\vec{a}_i\right) = A\vec{x}$$

Exercise $5.E.93$

$$\begin{bmatrix}5 & 1 & 5\\1 & 1 & 3\\3 & 5 & -2\end{bmatrix}\begin{bmatrix}3 & 2 & 1\\2 & 2 & 1\\4 & 1 & 1\end{bmatrix} = \begin{bmatrix}37 & 17 & 11\\17 & 7 & 5\\11 & 14 & 6\end{bmatrix}$$

Exercise $5.E.94$

$$\begin{bmatrix}1 & 2 & 6\\3 & 4 & 1\\1 & 1 & -1\end{bmatrix}\begin{bmatrix}6 & 3 & 1\\5 & 3 & 1\\6 & 2 & 1\end{bmatrix} = \begin{bmatrix}52 & 21 & 9\\44 & 23 & 8\\5 & 4 & 1\end{bmatrix}$$

Exercise $5.E.95$

$$\begin{bmatrix}-3 & 1 & 5\\1 & 3 & 3\\3 & -3 & -3\end{bmatrix}\begin{bmatrix}2 & 2 & 1\\1 & 2 & 1\\4 & 1 & 1\end{bmatrix} = \begin{bmatrix}15 & 1 & 3\\17 & 11 & 7\\-9 & -3 & -3\end{bmatrix}$$

Exercise $5.E.96$

$$\begin{bmatrix}3 & 1 & 1\\3 & 2 & 3\\3 & 3 & -1\end{bmatrix}\begin{bmatrix}6 & 2 & 1\\5 & 2 & 1\\6 & 1 & 1\end{bmatrix} = \begin{bmatrix}29 & 9 & 5\\46 & 13 & 8\\27 & 11 & 5\end{bmatrix}$$

Exercise $5.E.97$

$$\begin{bmatrix} 5 & 3 & 2 \\ 2 & 3 & 5 \\ 5 & 5 & -2 \end{bmatrix} \begin{bmatrix} 11 & 4 & 1 \\ 10 & 4 & 1 \\ 12 & 3 & 1 \end{bmatrix} = \begin{bmatrix} 109 & 38 & 10 \\ 112 & 35 & 10 \\ 81 & 34 & 8 \end{bmatrix}$$

Exercise $5.E.98$

Exercise $5.E.99$

Exercise $5.E.101$

Recall that $\text{proj}_{\vec{u}}(\vec{v}) = \frac{\vec{v} \bullet \vec{u}}{||\vec{u}||^2} \vec{u}$ and so the desired matrix has ith column equal to $\text{proj}_{\vec{u}}(\vec{e}_i)$. Therefore, the matrix desired is

$$\frac{1}{14} \begin{bmatrix} 1 & -2 & 3 \\ -2 & 4 & -6 \\ 3 & -6 & 9 \end{bmatrix}$$

Exercise $5.E.102$

$$\frac{1}{35} \begin{bmatrix} 1 & 5 & 3 \\ 5 & 25 & 15 \\ 3 & 15 & 9 \end{bmatrix}$$

Exercise $5.E.103$

$$\frac{1}{10} \begin{bmatrix} 1 & 0 & 3 \\ 0 & 0 & 0 \\ 3 & 0 & 9 \end{bmatrix}$$

Exercise $5.E.105$

$C_B(\vec{x}) = \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix}$.

Exercise $5.E.106$

$M_{B_2 B_1} = \begin{bmatrix} 1 & 0 \\ -1 & 1 \end{bmatrix}$

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6: LINEAR TRANSFORMATIONS

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6.1: Linear Transformations

Outcomes

A. Understand the definition of a linear transformation, and that all linear transformations are determined by matrix multiplication.

Recall that when we multiply an $m \times n$ matrix by an $n \times 1$ column vector, the result is an $m \times 1$ column vector. In this section we will discuss how, through matrix multiplication, an $m \times n$ matrix **transforms** an $n \times 1$ column vector into an $m \times 1$ column vector.

Recall that the $n \times 1$ vector given by

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

is said to belong to $\mathbb{R}^n$, which is the set of all $n \times 1$ vectors. In this section, we will discuss transformations of vectors in $\mathbb{R}^n$.

Consider the following example.

Example 6.1.1: A Function Which Transforms Vectors

Consider the matrix $A = \begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 0 \end{bmatrix}$. Show that by matrix multiplication A transforms vectors in $\mathbb{R}^3$ into vectors in $\mathbb{R}^2$.

Solution

First, recall that vectors in $\mathbb{R}^3$ are vectors of size 3×1, while vectors in $\mathbb{R}^2$ are of size 2×1. If we multiply A, which is a 2×3 matrix, by a 3×1 vector, the result will be a 2×1 vector. This what we mean when we say that A *transforms* vectors.

Now, for $\begin{bmatrix} x \\ y \\ z \end{bmatrix}$ in $\mathbb{R}^3$, multiply on the left by the given matrix to obtain the new vector. This product looks like

$$\begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x + 2y \\ 2x + y \end{bmatrix}$$

The resulting product is a 2×1 vector which is determined by the choice of x and y. Here are some numerical examples.

$$\begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 5 \\ 4 \end{bmatrix}$$

Here, the vector $\begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$ in $\mathbb{R}^3$ was transformed by the matrix into the vector $\begin{bmatrix} 5 \\ 4 \end{bmatrix}$ in $\mathbb{R}^2$.

Here is another example:

$$\begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 0 \end{bmatrix} \begin{bmatrix} 10 \\ 5 \\ -3 \end{bmatrix} = \begin{bmatrix} 20 \\ 25 \end{bmatrix}$$

The idea is to define a function which takes vectors in $\mathbb{R}^3$ and delivers new vectors in $\mathbb{R}^2$. In this case, that function is

multiplication by the matrix A.

Let T denote such a function. The notation $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ means that the function T transforms vectors in $\mathbb{R}^n$ into vectors in $\mathbb{R}^m$. The notation $T(\vec{x})$ means the transformation T applied to the vector $\vec{x}$. The above example demonstrated a transformation achieved by matrix multiplication. In this case, we often write

$$T_A(\vec{x}) = A\vec{x}$$

Therefore, T_A is the transformation determined by the matrix A. In this case we say that T is a matrix transformation.

Recall the property of matrix multiplication that states that for k and p scalars,

$$A(kB + pC) = kAB + pAC$$

In particular, for A an $m \times n$ matrix and B and C, $n \times 1$ vectors in $\mathbb{R}^n$, this formula holds.

In other words, this means that matrix multiplication gives an example of a linear transformation, which we will now define.

Definition 6.1.1: Linear Transformation

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a function, where for each $\vec{x} \in \mathbb{R}^n, T(\vec{x}) \in \mathbb{R}^m$. Then T is a **linear transformation** if whenever k, p are scalars and $\vec{x}_1$ and $\vec{x}_2$ are vectors in $\mathbb{R}^n$ ($n \times 1$ vectors),

$$T(k\vec{x}_1 + p\vec{x}_2) = kT(\vec{x}_1) + pT(\vec{x}_2)$$

Consider the following example.

Example 6.1.2: Linear Transformation

Let T be a transformation defined by $T : \mathbb{R}^3 \to \mathbb{R}^2$ is defined by

$$T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x + y \\ x - z \end{bmatrix} \text{ for all } \begin{bmatrix} x \\ y \\ z \end{bmatrix} \in \mathbb{R}^3$$

Show that T is a linear transformation.

Solution

By Definition 6.1.1 we need to show that $T(k\vec{x}_1 + p\vec{x}_2) = kT(\vec{x}_1) + pT(\vec{x}_2)$ for all scalars k, p and vectors $\vec{x}_1, \vec{x}_2$. Let

$$\vec{x}_1 = \begin{bmatrix} x_1 \\ y_1 \\ z_1 \end{bmatrix}, \vec{x}_2 = \begin{bmatrix} x_2 \\ y_2 \\ z_2 \end{bmatrix}$$

Then

$$\begin{aligned} T\left(k\vec{x}_1+p\vec{x}_2\right) &= T\left(k\begin{bmatrix} x_1 \\ y_1 \\ z_1 \end{bmatrix} + p\begin{bmatrix} x_2 \\ y_2 \\ z_2 \end{bmatrix}\right) \\ &= T\left(\begin{bmatrix} kx_1 \\ ky_1 \\ kz_1 \end{bmatrix} + \begin{bmatrix} px_2 \\ py_2 \\ pz_2 \end{bmatrix}\right) \\ &= T\left(\begin{bmatrix} kx_1+px_2 \\ ky_1+py_2 \\ kz_1+pz_2 \end{bmatrix}\right) \\ &= \begin{bmatrix} (kx_1+px_2)+(ky_1+py_2) \\ (kx_1+px_2)-(kz_1+pz_2) \end{bmatrix} \\ &= \begin{bmatrix} (kx_1+ky_1)+(px_2+py_2) \\ (kx_1-kz_1)+(px_2-pz_2) \end{bmatrix} \\ &= \begin{bmatrix} kx_1+ky_1 \\ kx_1-kz_1 \end{bmatrix} + \begin{bmatrix} px_2+py_2 \\ px_2-pz_2 \end{bmatrix} \\ &= k\begin{bmatrix} x_1+y_1 \\ x_1-z_1 \end{bmatrix} + p\begin{bmatrix} x_2+y_2 \\ x_2-z_2 \end{bmatrix} \\ &= kT(\vec{x}_1)+pT(\vec{x}_2) \end{aligned}$$

Therefore T is a linear transformation.

Two important examples of linear transformations are the zero transformation and identity transformation. The zero transformation defined by $T\left(\vec{x}\right)=\vec{0}$ for all $\vec{x}$ is an example of a linear transformation. Similarly the identity transformation defined by $T\left(\vec{x}\right)=\vec{x}$ is also linear. Take the time to prove these using the method demonstrated in Example 6.1.2.

We began this section by discussing matrix transformations, where multiplication by a matrix transforms vectors. These matrix transformations are in fact linear transformations.

Theorem 6.1.1: Matrix Transformations are Linear Transformations

Let $T:\mathbb{R}^n\mapsto\mathbb{R}^m$ be a transformation defined by $T(\vec{x})=A\vec{x}$. Then T is a linear transformation.

It turns out that every linear transformation can be expressed as a matrix transformation, and thus linear transformations are exactly the same as matrix transformations.

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6.2: The Matrix of a Linear Transformation I

Outcomes

A. Find the matrix of a linear transformation with respect to the standard basis.
B. Determine the action of a linear transformation on a vector in $\mathbb{R}^n$.

In the above examples, the action of the linear transformations was to multiply by a matrix. It turns out that this is always the case for linear transformations. If T is **any** linear transformation which maps $\mathbb{R}^n$ to $\mathbb{R}^m$, there is **always** an $m \times n$ matrix A with the property that

$$T\left(\vec{x}\right) = A\vec{x} \tag{6.2.1}$$

for all $\vec{x} \in \mathbb{R}^n$.

Theorem 6.2.1: Matrix of a Linear Transformation

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation. Then we can find a matrix A such that $T(\vec{x}) = A\vec{x}$. In this case, we say that T is *determined* or *induced* by the matrix A.

Here is why. Suppose $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ is a linear transformation and you want to find the matrix defined by this linear transformation as described in (6.2.1). Note that

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = x_1 \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + x_2 \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix} + \cdots + x_n \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix} = \sum_{i=1}^{n} x_i \vec{e}_i$$

where $\vec{e}_i$ is the i^{th} column of I_n, that is the $n \times 1$ vector which has zeros in every slot but the i^{th} and a 1 in this slot.

Then since T is linear,

$$\begin{aligned} T\left(\vec{x}\right) &= \sum_{i=1}^{n} x_i T\left(\vec{e}_i\right) \\ &= \begin{bmatrix} | & & | \\ T\left(\vec{e}_1\right) & \cdots & T\left(\vec{e}_n\right) \\ | & & | \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \\ &= A \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \end{aligned} \tag{6.2.2}$$

The desired matrix is obtained from constructing the i^{th} column as $T\left(\vec{e}_i\right)$. Recall that the set $\left\{\vec{e}_1, \vec{e}_2, \cdots, \vec{e}_n\right\}$ is called the standard basis of $\mathbb{R}^n$. Therefore the matrix of T is found by applying T to the standard basis. We state this formally as the following theorem.

Theorem 6.2.2: Matrix of a Linear Transformation

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation. Then the matrix A satisfying $T\left(\vec{x}\right) = A\vec{x}$ is given by

$$A = \begin{bmatrix} | & & | \\ T\left(\vec{e}_1\right) & \cdots & T\left(\vec{e}_n\right) \\ | & & | \end{bmatrix}$$

where $\vec{e}_i$ is the i^{th} column of I_n, and then $T\left(\vec{e}_i\right)$ is the i^{th} column of A.

The following Corollary is an essential result.

Corollary 6.2.1: Matrix and Linear Transformation

A transformation $T : \mathbb{R}^n \to \mathbb{R}^m$ is a linear transformation if and only if it is a matrix transformation.

Consider the following example.

Example 6.2.1: The Matrix of a Linear Transformation

Suppose T is a linear transformation, $T : \mathbb{R}^3 \to \mathbb{R}^2$ where

$$T\begin{bmatrix}1\\0\\0\end{bmatrix} = \begin{bmatrix}1\\2\end{bmatrix}, \; T\begin{bmatrix}0\\1\\0\end{bmatrix} = \begin{bmatrix}9\\-3\end{bmatrix}, \; T\begin{bmatrix}0\\0\\1\end{bmatrix} = \begin{bmatrix}1\\1\end{bmatrix}$$

Find the matrix A of T such that $T(\vec{x}) = A\vec{x}$ for all $\vec{x}$.

Solution

By Theorem 6.2.2 we construct A as follows:

$$A = \begin{bmatrix} | & & | \\ T(\vec{e}_1) & \cdots & T(\vec{e}_n) \\ | & & | \end{bmatrix}$$

In this case, A will be a 2×3 matrix, so we need to find $T(\vec{e}_1), T(\vec{e}_2)$, and $T(\vec{e}_3)$. Luckily, we have been given these values so we can fill in A as needed, using these vectors as the columns of A. Hence,

$$A = \begin{bmatrix}1 & 9 & 1\\2 & -3 & 1\end{bmatrix}$$

In this example, we were given the resulting vectors of $T(\vec{e}_1), T(\vec{e}_2)$, and $T(\vec{e}_3)$. Constructing the matrix A was simple, as we could simply use these vectors as the columns of A. The next example shows how to find A when we are not given the $T(\vec{e}_i)$ so clearly.

Example 6.2.2: The Matrix of Linear Transformation: Inconveniently Defined

Suppose T is a linear transformation, $T : \mathbb{R}^2 \to \mathbb{R}^2$ and

$$T\begin{bmatrix}1\\1\end{bmatrix} = \begin{bmatrix}1\\2\end{bmatrix}, \; T\begin{bmatrix}0\\-1\end{bmatrix} = \begin{bmatrix}3\\2\end{bmatrix}$$

Find the matrix A of T such that $T(\vec{x}) = A\vec{x}$ for all $\vec{x}$.

Solution

By Theorem 6.2.2 to find this matrix, we need to determine the action of T on $\vec{e}_1$ and $\vec{e}_2$. In Example 9.9.2, we were given these resulting vectors. However, in this example, we have been given T of two different vectors. How can we find out the action of T on $\vec{e}_1$ and $\vec{e}_2$? In particular for $\vec{e}_1$, suppose there exist x and y such that

$$\begin{bmatrix}1\\0\end{bmatrix} = x\begin{bmatrix}1\\1\end{bmatrix} + y\begin{bmatrix}0\\-1\end{bmatrix} \tag{6.2.3}$$

Then, since T is linear,

$$T\begin{bmatrix}1\\0\end{bmatrix} = xT\begin{bmatrix}1\\1\end{bmatrix} + yT\begin{bmatrix}0\\-1\end{bmatrix}$$

Substituting in values, this sum becomes

$$T\begin{bmatrix}1\\0\end{bmatrix} = x\begin{bmatrix}1\\2\end{bmatrix} + y\begin{bmatrix}3\\2\end{bmatrix} \tag{6.2.4}$$

Therefore, if we know the values of x and y which satisfy (6.2.3), we can substitute these into equation (6.2.4). By doing so, we find $T(\vec{e}_1)$ which is the first column of the matrix A.

We proceed to find x and y. We do so by solving (6.2.3), which can be done by solving the system

$$\begin{aligned} x &= 1 \\ x - y &= 0 \end{aligned}$$

We see that $x = 1$ and $y = 1$ is the solution to this system. Substituting these values into equation (6.2.4), we have

$$T\begin{bmatrix}1\\0\end{bmatrix} = 1\begin{bmatrix}1\\2\end{bmatrix} + 1\begin{bmatrix}3\\2\end{bmatrix} = \begin{bmatrix}1\\2\end{bmatrix} + \begin{bmatrix}3\\2\end{bmatrix} = \begin{bmatrix}4\\4\end{bmatrix}$$

Therefore $\begin{bmatrix}4\\4\end{bmatrix}$ is the first column of A.

Computing the second column is done in the same way, and is left as an exercise.

The resulting matrix A is given by

$$A = \begin{bmatrix}4 & -3\\4 & -2\end{bmatrix}$$

This example illustrates a very long procedure for finding the matrix of A. While this method is reliable and will always result in the correct matrix A, the following procedure provides an alternative method.

Procedure 6.2.1: Finding the Matrix of Inconveniently Defined Linear Transformation

Suppose $T : \mathbb{R}^n \to \mathbb{R}^m$ is a linear transformation. Suppose there exist vectors $\{\vec{a}_1, \cdots, \vec{a}_n\}$ in $\mathbb{R}^n$ such that $\begin{bmatrix}\vec{a}_1 & \cdots & \vec{a}_n\end{bmatrix}^{-1}$ exists, and

$$T(\vec{a}_i) = \vec{b}_i$$

Then the matrix of T must be of the form

$$\begin{bmatrix}\vec{b}_1 & \cdots & \vec{b}_n\end{bmatrix}\begin{bmatrix}\vec{a}_1 & \cdots & \vec{a}_n\end{bmatrix}^{-1}$$

We will illustrate this procedure in the following example. You may also find it useful to work through Example 6.2.2 using this procedure.

Example 6.2.3: Matrix of a Linear Transformation Given Inconveniently

Suppose $T : \mathbb{R}^3 \to \mathbb{R}^3$ is a linear transformation and

$$T\begin{bmatrix}1\\3\\1\end{bmatrix} = \begin{bmatrix}0\\1\\1\end{bmatrix}, T\begin{bmatrix}0\\1\\1\end{bmatrix} = \begin{bmatrix}2\\1\\3\end{bmatrix}, T\begin{bmatrix}1\\1\\0\end{bmatrix} = \begin{bmatrix}0\\0\\1\end{bmatrix}$$

Find the matrix of this linear transformation.

Solution

By Procedure 6.2.1, $A = \begin{bmatrix} 1 & 0 & 1 \\ 3 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix}^{-1}$ and $B = \begin{bmatrix} 0 & 2 & 0 \\ 1 & 1 & 0 \\ 1 & 3 & 1 \end{bmatrix}$

Then, Procedure 6.2.1 claims that the matrix of T is

$$C = BA^{-1} = \begin{bmatrix} 2 & -2 & 4 \\ 0 & 0 & 1 \\ 4 & -3 & 6 \end{bmatrix}$$

Indeed you can first verify that $T(\vec{x}) = C\vec{x}$ for the 3 vectors above:

$$\begin{bmatrix} 2 & -2 & 4 \\ 0 & 0 & 1 \\ 4 & -3 & 6 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}, \quad \begin{bmatrix} 2 & -2 & 4 \\ 0 & 0 & 1 \\ 4 & -3 & 6 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix}$$

$$\begin{bmatrix} 2 & -2 & 4 \\ 0 & 0 & 1 \\ 4 & -3 & 6 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

But more generally $T(\vec{x}) = C\vec{x}$ for any $\vec{x}$. To see this, let $\vec{y} = A^{-1}\vec{x}$ and then using linearity of T:

$$T(\vec{x}) = T(A\vec{y}) = T\left(\sum_i \vec{y}_i \vec{a}_i\right) = \sum \vec{y}_i T(\vec{a}_i) \sum \vec{y}_i \vec{b}_i = B\vec{y} = BA^{-1}\vec{x} = C\vec{x}$$

Recall the dot product discussed earlier. Consider the map $\vec{v} \mapsto \text{proj}_{\vec{u}}(\vec{v})$ which takes a vector a transforms it to its projection onto a given vector $\vec{u}$. It turns out that this map is linear, a result which follows from the properties of the dot product. This is shown as follows.

$$\begin{aligned} \text{proj}_{\vec{u}}(k\vec{v} + p\vec{w}) &= \left(\frac{(k\vec{v} + p\vec{w}) \bullet \vec{u}}{\vec{u} \bullet \vec{u}}\right) \vec{u} \\ &= k\left(\frac{\vec{v} \bullet \vec{u}}{\vec{u} \bullet \vec{u}}\right) \vec{u} + p\left(0.05in\frac{\vec{w} \bullet \vec{u}}{\vec{u} \bullet \vec{u}}\right) \vec{u} \\ &= k \,\text{proj}_{\vec{u}}(\vec{v}) + p \,\text{proj}_{\vec{u}}(\vec{w}) \end{aligned} \tag{6.2.5}$$

Consider the following example.

Example 6.2.4: Matrix of a Projection Map

Let $\vec{u} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$ and let T be the projection map $T : \mathbb{R}^3 \mapsto \mathbb{R}^3$ defined by

$$T(\vec{v}) = \text{proj}_{\vec{u}}(\vec{v})$$

for any $\vec{v} \in \mathbb{R}^3$.

1. Does this transformation come from multiplication by a matrix?
2. If so, what is the matrix?

Solution

1. First, we have just seen that $T(\vec{v}) = \text{proj}_{\vec{u}}(\vec{v})$ is linear. Therefore by Theorem 6.2.1, we can find a matrix A such that $T(\vec{x}) = A\vec{x}$.
2. The columns of the matrix for T are defined above as $T(\vec{e}_i)$. It follows that $T(\vec{e}_i) = \text{proj}_{\vec{u}}(\vec{e}_i)$ gives the i^{th} column of the desired matrix. Therefore, we need to find

$$\text{proj}_{\vec{u}}(\vec{e}_i) = \left(\frac{\vec{e}_i \bullet \vec{u}}{\vec{u} \bullet \vec{u}}\right) \vec{u}$$

For the given vector $\vec{u}$, this implies the columns of the desired matrix are

$$\frac{1}{14}\begin{bmatrix}1\\2\\3\end{bmatrix}, \frac{2}{14}\begin{bmatrix}1\\2\\3\end{bmatrix}, \frac{3}{14}\begin{bmatrix}1\\2\\3\end{bmatrix}$$

which you can verify. Hence the matrix of T is

$$\frac{1}{14}\begin{bmatrix}1&2&3\\2&4&6\\3&6&9\end{bmatrix}$$

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6.3: Properties of Linear Transformations

Outcomes

A. Use properties of linear transformations to solve problems.
B. Find the composite of transformations and the inverse of a transformation.

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation. Then there are some important properties of T which will be examined in this section. Consider the following theorem.

Theorem 6.3.1: Properties of Linear Transformations

Properties of Linear Transformationsproperties Let $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation and let $\vec{x} \in \mathbb{R}^n$.

- T preserves the zero vector.

$$T(0\vec{x}) = 0T(\vec{x}). \text{ Hence } T(\vec{0}) = \vec{0}$$

- T preserves the negative of a vector:

$$T((-1)\vec{x}) = (-1)T(\vec{x}). \text{ Hence } T(-\vec{x}) = -T(\vec{x}).$$

- T preserves linear combinations:

$$\text{Let } \vec{x}_1, ..., \vec{x}_k \in \mathbb{R}^n \text{ and } a_1, ..., a_k \in \mathbb{R}.$$
$$\text{Then if } \vec{y} = a_1\vec{x}_1 + a_2\vec{x}_2 + ... + a_k\vec{x}_k, \text{ it follows that}$$
$$T(\vec{y}) = T(a_1\vec{x}_1 + a_2\vec{x}_2 + ... + a_k\vec{x}_k) = a_1T(\vec{x}_1) + a_2T(\vec{x}_2) + ... + a_kT(\vec{x}_k).$$

These properties are useful in determining the action of a transformation on a given vector. Consider the following example.

Example 6.3.1: Linear Combination

Let $T : \mathbb{R}^3 \mapsto \mathbb{R}^4$ be a linear transformation such that

$$T\begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 4 \\ 0 \\ -2 \end{bmatrix}, T\begin{bmatrix} 4 \\ 0 \\ 5 \end{bmatrix} = \begin{bmatrix} 4 \\ 5 \\ -1 \\ 5 \end{bmatrix}$$

Find $T\begin{bmatrix} -7 \\ 3 \\ -9 \end{bmatrix}$.

Solution

Using the third property in Theorem 9.6.1, we can find $T\begin{bmatrix} -7 \\ 3 \\ -9 \end{bmatrix}$ by writing $\begin{bmatrix} -7 \\ 3 \\ -9 \end{bmatrix}$ as a linear combination of $\begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix}$ and $\begin{bmatrix} 4 \\ 0 \\ 5 \end{bmatrix}$.

Therefore we want to find $a, b \in \mathbb{R}$ such that

$$\begin{bmatrix} -7 \\ 3 \\ -9 \end{bmatrix} = a \begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix} + b \begin{bmatrix} 4 \\ 0 \\ 5 \end{bmatrix}$$

The necessary augmented matrix and resulting reduced row-echelon form are given by:

$$\begin{bmatrix} 1 & 4 & -7 \\ 3 & 0 & 3 \\ 1 & 5 & -9 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & -2 \\ 0 & 0 & 0 \end{bmatrix}$$

Hence $a = 1, b = -2$ and

$$\begin{bmatrix} -7 \\ 3 \\ -9 \end{bmatrix} = 1 \begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix} + (-2) \begin{bmatrix} 4 \\ 0 \\ 5 \end{bmatrix}$$

Now, using the third property above, we have

$$\begin{aligned} T \begin{bmatrix} -7 \\ 3 \\ -9 \end{bmatrix} &= T \left(1 \begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix} + (-2) \begin{bmatrix} 4 \\ 0 \\ 5 \end{bmatrix} \right) \\ &= 1T \begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix} - 2T \begin{bmatrix} 4 \\ 0 \\ 5 \end{bmatrix} \\ &= \begin{bmatrix} 4 \\ 4 \\ 0 \\ -2 \end{bmatrix} - 2 \begin{bmatrix} 4 \\ 5 \\ -1 \\ 5 \end{bmatrix} \\ &= \begin{bmatrix} -4 \\ -6 \\ 2 \\ -12 \end{bmatrix} \end{aligned} \tag{6.3.1}$$

Therefore, $T \begin{bmatrix} -7 \\ 3 \\ -9 \end{bmatrix} = \begin{bmatrix} -4 \\ -6 \\ 2 \\ -12 \end{bmatrix}$.

Suppose two linear transformations act in the same way on $\vec{x}$ for all vectors. Then we say that these transformations are equal.

Definition 6.3.1: Equal Transformations

Let S and T be linear transformations from $\mathbb{R}^n$ to $\mathbb{R}^m$. Then $S = T$ if and only if for every $\vec{x} \in \mathbb{R}^n$,

$$S(\vec{x}) = T(\vec{x})$$

Suppose two linear transformations act on the same vector $\vec{x}$, first the transformation T and then a second transformation given by S. We can find the **composite** transformation that results from applying both transformations.

Definition 6.3.2: Composition of Linear Transformations

Let $T : \mathbb{R}^k \mapsto \mathbb{R}^n$ and $S : \mathbb{R}^n \mapsto \mathbb{R}^m$ be linear transformations. Then the **composite** of S and T is

$$S \circ T : \mathbb{R}^k \mapsto \mathbb{R}^m$$

The action of $S \circ T$ is given by

$$(S \circ T)(\vec{x}) = S(T(\vec{x})) \text{ for all } \vec{x} \in \mathbb{R}^k$$

Notice that the resulting vector will be in $\mathbb{R}^m$. Be careful to observe the order of transformations. We write $S \circ T$ but apply the transformation T first, followed by S.

Theorem 6.3.2: Composition of Transformations

Let $T : \mathbb{R}^k \mapsto \mathbb{R}^n$ and $S : \mathbb{R}^n \mapsto \mathbb{R}^m$ be linear transformations such that T is induced by the matrix A and S is induced by the matrix B. Then $S \circ T$ is a linear transformation which is induced by the matrix BA.

Consider the following example.

Example 6.3.2: Composition of Transformations

Let T be a linear transformation induced by the matrix

$$A = \begin{bmatrix} 1 & 2 \\ 2 & 0 \end{bmatrix}$$

and S a linear transformation induced by the matrix

$$B = \begin{bmatrix} 2 & 3 \\ 0 & 1 \end{bmatrix}$$

Find the matrix of the composite transformation $S \circ T$. Then, find $(S \circ T)(\vec{x})$ for $\vec{x} = \begin{bmatrix} 1 \\ 4 \end{bmatrix}$.

Solution

By Theorem 6.3.2, the matrix of $S \circ T$ is given by BA.

$$BA = \begin{bmatrix} 2 & 3 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 2 & 0 \end{bmatrix} = \begin{bmatrix} 8 & 4 \\ 2 & 0 \end{bmatrix}$$

To find $(S \circ T)(\vec{x})$, multiply $\vec{x}$ by BA as follows

$$\begin{bmatrix} 8 & 4 \\ 2 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 4 \end{bmatrix} = \begin{bmatrix} 24 \\ 2 \end{bmatrix}$$

To check, first determine $T(\vec{x})$:

$$\begin{bmatrix} 1 & 2 \\ 2 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 4 \end{bmatrix} = \begin{bmatrix} 9 \\ 2 \end{bmatrix}$$

Then, compute $S(T(\vec{x}))$ as follows:

$$\begin{bmatrix} 2 & 3 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 9 \\ 2 \end{bmatrix} = \begin{bmatrix} 24 \\ 2 \end{bmatrix}$$

Consider a composite transformation $S \circ T$, and suppose that this transformation acted such that $(S \circ T)(\vec{x}) = \vec{x}$. That is, the transformation S took the vector $T(\vec{x})$ and returned it to $\vec{x}$. In this case, S and T are inverses of each other. Consider the following definition.

Definition 6.3.3: Inverse of a Transformation

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^n$ and $S : \mathbb{R}^n \mapsto \mathbb{R}^n$ be linear transformations. Suppose that for each $\vec{x} \in \mathbb{R}^n$,

$$(S \circ T)(\vec{x}) = \vec{x}$$

and

$$(T \circ S)(\vec{x}) = \vec{x}$$

Then, S is called an inverse of T and T is called an inverse of S. Geometrically, they reverse the action of each other.

The following theorem is crucial, as it claims that the above inverse transformations are unique.

Theorem 6.3.3: Inverse of a Transformation

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^n$ be a linear transformation induced by the matrix A. Then T has an inverse transformation if and only if the matrix A is invertible. In this case, the inverse transformation is unique and denoted $T^{-1} : \mathbb{R}^n \mapsto \mathbb{R}^n$. T^{-1} is induced by the matrix A^{-1}.

Consider the following example.

Example 6.3.3: Inverse of a Transformation

Let $T : \mathbb{R}^2 \mapsto \mathbb{R}^2$ be a linear transformation induced by the matrix

$$A = \begin{bmatrix} 2 & 3 \\ 3 & 4 \end{bmatrix}$$

Show that T^{-1} exists and find the matrix B which it is induced by.

Solution

Since the matrix A is invertible, it follows that the transformation T is invertible. Therefore, T^{-1} exists.

You can verify that A^{-1} is given by:

$$A^{-1} = \begin{bmatrix} -4 & 3 \\ 3 & -2 \end{bmatrix}$$

Therefore the linear transformation T^{-1} is induced by the matrix A^{-1}.

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6.4: SPECIAL LINEAR TRANSFORMATIONS IN R²

Outcomes

A. Find the matrix of rotations and reflections in $\mathbb{R}^2$ and determine the action of each on a vector in $\mathbb{R}^2$.

In this section, we will examine some special examples of linear transformations in $\mathbb{R}^2$ including rotations and reflections. We will use the geometric descriptions of vector addition and scalar multiplication discussed earlier to show that a rotation of vectors through an angle and reflection of a vector across a line are examples of linear transformations.

More generally, denote a transformation given by a rotation by T. Why is such a transformation linear? Consider the following picture which illustrates a rotation. Let $\vec{u}, \vec{v}$ denote vectors.

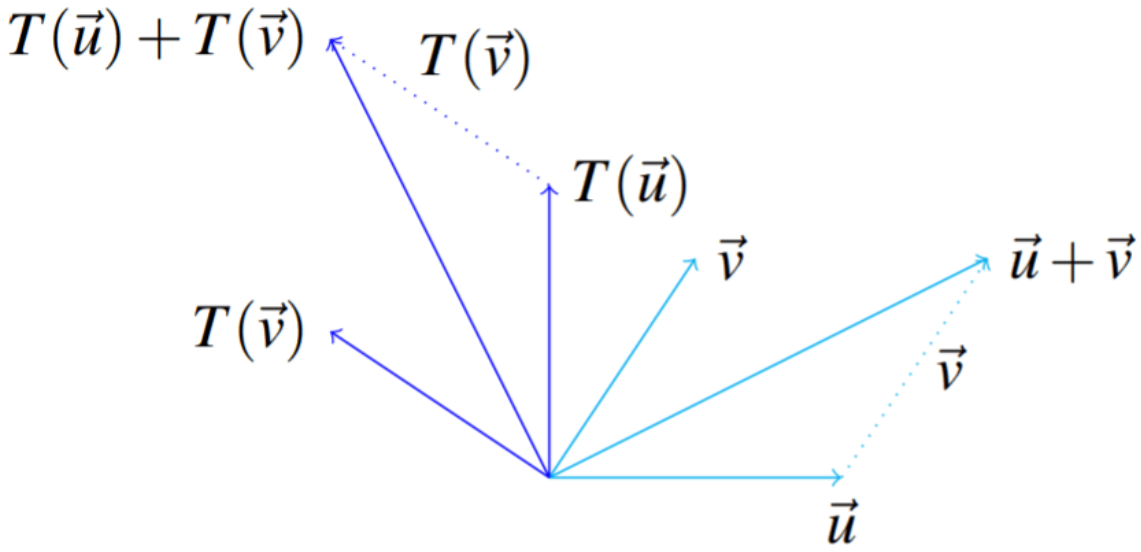


Figure 6.4.1

Let's consider how to obtain $T\left[\vec{u}+\vec{v}\right]$. Simply, you add $T(\vec{u})$ and $T(\vec{v})$. Here is why. If you add $T(\vec{u})$ to $T(\vec{v})$ you get the diagonal of the parallelogram determined by $T(\vec{u})$ and $T(\vec{v})$, as this action is our usual vector addition. Now, suppose we first add $\vec{u}$ and $\vec{v}$, and then apply the transformation T to $\vec{u}+\vec{v}$. Hence, we find $T(\vec{u}+\vec{v})$. As shown in the diagram, this will result in the same vector. In other words, $T(\vec{u}+\vec{v})=T(\vec{u})+T(\vec{v})$.

This is because the rotation preserves all angles between the vectors as well as their lengths. In particular, it preserves the shape of this parallelogram. Thus both $T\left[\vec{u}\right]+T\left[\vec{v}\right]$ and $T\left[\vec{u}+\vec{v}\right]$ give the same vector. It follows that T distributes across addition of the vectors of $\mathbb{R}^2$.

Similarly, if k is a scalar, it follows that $T\left[k\vec{u}\right]=kT\left[\vec{u}\right]$. Thus rotations are an example of a linear transformation by Definition 9.6.1.

The following theorem gives the matrix of a linear transformation which rotates all vectors through an angle of θ.

Theorem 6.4.1: Rotation

Let $R_\theta : \mathbb{R}^2 \to \mathbb{R}^2$ be a linear transformation given by rotating vectors through an angle of θ. Then the matrix A of R_θ is given by

$$\begin{bmatrix} \cos\left[\theta\right] & -\sin\left[\theta\right] \\ \sin\left[\theta\right] & \cos\left[\theta\right] \end{bmatrix}$$

Proof available at the end of this section.

Consider the following example.

Example 6.4.1: Rotation in $\mathbb{R}^2$

Let $R_{\frac{\pi}{2}} : \mathbb{R}^2 \to \mathbb{R}^2$ denote rotation through $\pi/2$. Find the matrix of $R_{\frac{\pi}{2}}$. Then, find $R_{\frac{\pi}{2}}(\vec{x})$ where $\vec{x} = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$.

Solution

By Theorem 6.4.1, the matrix of $R_{\frac{\pi}{2}}$ is given by

$$\begin{bmatrix} \cos[\theta] & -\sin[\theta] \\ \sin[\theta] & \cos[\theta] \end{bmatrix} = \begin{bmatrix} \cos[\pi/2] & -\sin[\pi/2] \\ \sin[\pi/2] & \cos[\pi/2] \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

To find $R_{\frac{\pi}{2}}(\vec{x})$, we multiply the matrix of $R_{\frac{\pi}{2}}$ by $\vec{x}$ as follows

$$\begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ -2 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

We now look at an example of a linear transformation involving two angles.

Example 6.4.2: The Rotation Matrix of the Sum of Two Angles

Find the matrix of the linear transformation which is obtained by first rotating all vectors through an angle of ϕ and then through an angle θ. Hence the linear transformation rotates all vectors through an angle of $\theta + \phi$.

Solution

Let $R_{\theta+\phi}$ denote the linear transformation which rotates every vector through an angle of $\theta + \phi$. Then to obtain $R_{\theta+\phi}$, we first apply R_ϕ and then R_θ where R_ϕ is the linear transformation which rotates through an angle of ϕ and R_θ is the linear transformation which rotates through an angle of θ. Denoting the corresponding matrices by $A_{\theta+\phi}$, A_ϕ, and A_θ, it follows that for every $\vec{u}$

$$R_{\theta+\phi}[\vec{u}] = A_{\theta+\phi}\vec{u} = A_\theta A_\phi \vec{u} = R_\theta R_\phi [\vec{u}]$$

Notice the order of the matrices here!

Consequently, you must have

$$\begin{aligned} A_{\theta+\phi} &= \begin{bmatrix} \cos[\theta+\phi] & -\sin[\theta+\phi] \\ \sin[\theta+\phi] & \cos[\theta+\phi] \end{bmatrix} \\ &= \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} \cos\phi & -\sin\phi \\ \sin\phi & \cos\phi \end{bmatrix} = A_\theta A_\phi \end{aligned} \tag{6.4.1}$$

The usual matrix multiplication yields

$$\begin{aligned} A_{\theta+\phi} &= \begin{bmatrix} \cos[\theta+\phi] & -\sin[\theta+\phi] \\ \sin[\theta+\phi] & \cos[\theta+\phi] \end{bmatrix} \\ &= \begin{bmatrix} \cos\theta\cos\phi - \sin\theta\sin\phi & -\cos\theta\sin\phi - \sin\theta\cos\phi \\ \sin\theta\cos\phi + \cos\theta\sin\phi & \cos\theta\cos\phi - \sin\theta\sin\phi \end{bmatrix} \\ &= A_\theta A_\phi \end{aligned} \tag{6.4.2}$$

Don't these look familiar? They are the usual trigonometric identities for the sum of two angles derived here using linear algebra concepts.

Here we have focused on rotations in two dimensions. However, you can consider rotations and other geometric concepts in any number of dimensions. This is one of the major advantages of linear algebra. You can break down a difficult geometrical procedure into small steps, each corresponding to multiplication by an appropriate matrix. Then by multiplying the matrices, you can obtain a single matrix which can give you numerical information on the results of applying the given sequence of simple procedures.

Linear transformations which reflect vectors across a line are a second important type of transformations in $\mathbb{R}^2$. Consider the following theorem.

Theorem 6.4.2: Reflection

Let $Q_m : \mathbb{R}^2 \to \mathbb{R}^2$ be a linear transformation given by reflecting vectors over the line $\vec{y} = m\vec{x}$. Then the matrix of Q_m is given by

$$\frac{1}{1+m^2}\begin{bmatrix} 1-m^2 & 2m \\ 2m & m^2-1 \end{bmatrix}$$

Consider the following example.

Example 6.4.3: Reflection in $\mathbb{R}^2$

Let $Q_2 : \mathbb{R}^2 \to \mathbb{R}^2$ denote reflection over the line $\vec{y} = 2\vec{x}$. Then Q_2 is a linear transformation. Find the matrix of Q_2. Then, find $Q_2(\vec{x})$ where $\vec{x} = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$.

Solution

By Theorem 6.4.2, the matrix of Q_2 is given by

$$\frac{1}{1+m^2}\begin{bmatrix} 1-m^2 & 2m \\ 2m & m^2-1 \end{bmatrix} = \frac{1}{1+(2)^2}\begin{bmatrix} 1-(2)^2 & 2(2) \\ 2(2) & (2)^2-1 \end{bmatrix} = \frac{1}{5}\begin{bmatrix} -3 & 8 \\ 8 & 3 \end{bmatrix}$$

To find $Q_2(\vec{x})$ we multiply $\vec{x}$ by the matrix of Q_2 as follows:

$$\frac{1}{5}\begin{bmatrix} -3 & 8 \\ 8 & 3 \end{bmatrix}\begin{bmatrix} 1 \\ -2 \end{bmatrix} = \begin{bmatrix} -\frac{19}{5} \\ \frac{2}{5} \end{bmatrix}$$

Consider the following example which incorporates a reflection as well as a rotation of vectors.

Example 6.4.4: Rotation Followed by a Reflection

Find the matrix of the linear transformation which is obtained by first rotating all vectors through an angle of $\pi/6$ and then reflecting through the x axis.

Solution

By Theorem 6.4.1, the matrix of the transformation which involves rotating through an angle of $\pi/6$ is

$$\begin{bmatrix} \cos[\pi/6] & -\sin[\pi/6] \\ \sin[\pi/6] & \cos[\pi/6] \end{bmatrix} = \begin{bmatrix} \frac{1}{2}\sqrt{3} & -\frac{1}{2} \\ \frac{1}{2} & \frac{1}{2}\sqrt{3} \end{bmatrix}$$

Reflecting across the x axis is the same action as reflecting vectors over the line $\vec{y} = m\vec{x}$ with $m = 0$. By Theorem 6.4.2, the matrix for the transformation which reflects all vectors through the x axis is

$$\frac{1}{1+m^2}\begin{bmatrix} 1-m^2 & 2m \\ 2m & m^2-1 \end{bmatrix} = \frac{1}{1+(0)^2}\begin{bmatrix} 1-(0)^2 & 2(0) \\ 2(0) & (0)^2-1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

Therefore, the matrix of the linear transformation which first rotates through $\pi/6$ and then reflects through the x axis is given by

$$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}\begin{bmatrix} \frac{1}{2}\sqrt{3} & -\frac{1}{2} \\ \frac{1}{2} & \frac{1}{2}\sqrt{3} \end{bmatrix} = \begin{bmatrix} \frac{1}{2}\sqrt{3} & -\frac{1}{2} \\ -\frac{1}{2} & -\frac{1}{2}\sqrt{3} \end{bmatrix}$$

Answers

Theorem 6.4.1**: Rotation**

Let $\vec{e}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ and $\vec{e}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$. These identify the geometric vectors which point along the positive x axis and positive y axis as shown.

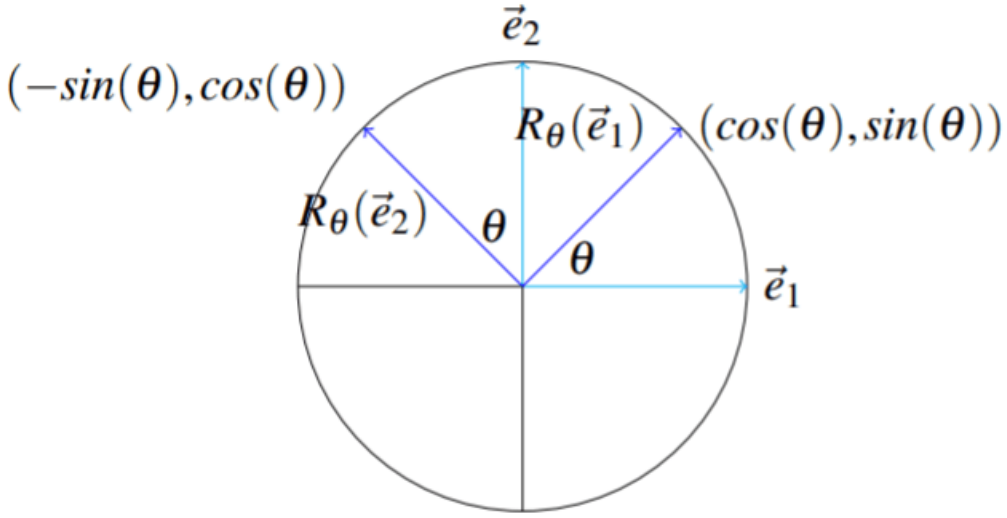


Figure 6.4.2

From Theorem 5.2.2, we need to find $R_\theta(\vec{e}_1)$ and $R_\theta(\vec{e}_2)$, and use these as the columns of the matrix A of T. We can use $\cos, \sin$ of the angle θ to find the coordinates of $R_\theta(\vec{e}_1)$ as shown in the above picture. The coordinates of $R_\theta(\vec{e}_2)$ also follow from trigonometry. Thus

$$R_\theta(\vec{e}_1) = \begin{bmatrix} \cos\theta \\ \sin\theta \end{bmatrix}, R_\theta(\vec{e}_2) = \begin{bmatrix} -\sin\theta \\ \cos\theta \end{bmatrix}$$

Therefore, from Theorem 5.2.2,

$$A = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$

We can also prove this algebraically without the use of the above picture. The definition of $[\cos[\theta], \sin[\theta]]$ is as the coordinates of the point of $R_\theta(\vec{e}_1)$. Now the point of the vector $\vec{e}_2$ is exactly $\pi/2$ further along the unit circle from the point of $\vec{e}_1$, and therefore after rotation through an angle of θ the coordinates x and y of the point of $R_\theta(\vec{e}_2)$ are given by

$$[x, y] = [\cos[\theta + \pi/2], \sin[\theta + \pi/2]] = [-\sin\theta, \cos\theta]$$

Geometric Linear Transformations in 2D GeoGebra Demo Ku, Yin Bin (Albert)

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6.5: One-to-One and Onto Transformations

Outcomes

A. Determine if a linear transformation is onto or one to one.

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation. We define the **range** or **image** of T as the set of vectors of $\mathbb{R}^m$ which are of the form $T(\vec{x})$ (equivalently, $A\vec{x}$) for some $\vec{x} \in \mathbb{R}^n$. It is common to write $T\mathbb{R}^n$, $T(\mathbb{R}^n)$, or $\mathrm{Im}(T)$ to denote these vectors.

Lemma 6.5.1: Range of a Matrix Transformation

Let A be an $m \times n$ matrix where $A_1, \cdots, A_n$ denote the columns of A. Then, for a vector $\vec{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$ in $\mathbb{R}^n$,

$$A\vec{x} = \sum_{k=1}^{n} x_k A_k$$

Therefore, $A(\mathbb{R}^n)$ is the collection of all linear combinations of these products.

Proof available at the end of this section.

This section is devoted to studying two important characterizations of linear transformations, called one to one and onto. We define them now.

Definition 6.5.1: One to One

Suppose $\vec{x}_1$ and $\vec{x}_2$ are vectors in $\mathbb{R}^n$. A linear transformation $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ is called **one to one** (often written as $1-1$) if whenever $\vec{x}_1 \neq \vec{x}_2$ it follows that :

$$T(\vec{x}_1) \neq T(\vec{x}_2)$$

Equivalently, if $T(\vec{x}_1) = T(\vec{x}_2)$, then $\vec{x}_1 = \vec{x}_2$. Thus, T is one to one if it never takes two different vectors to the same vector.

The second important characterization is called onto.

Definition 6.5.2: Onto

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation. Then T is called **onto** if whenever $\vec{x}_2 \in \mathbb{R}^m$ there exists $\vec{x}_1 \in \mathbb{R}^n$ such that $T(\vec{x}_1) = \vec{x}_2$.

We often call a linear transformation which is one-to-one an **injection**. Similarly, a linear transformation which is onto is often called a **surjection**.

The following proposition is an important result.

Proposition 6.5.1: One to One

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation. Then T is one to one if and only if $T(\vec{x}) = \vec{0}$ implies $\vec{x} = \vec{0}$.

Proof available at the end of this section.

Now assume that if $T(\vec{x}) = \vec{0}$, then it follows that $\vec{x} = \vec{0}$. If $T(\vec{v}) = T(\vec{u})$, then

$$T(\vec{v}) - T(\vec{u}) = T(\vec{v} - \vec{u}) = \vec{0}$$

which shows that $\vec{v} - \vec{u} = 0$. In other words, $\vec{v} = \vec{u}$, and T is one to one.

Note that this proposition says that if $A = \begin{bmatrix} A_1 & \cdots & A_n \end{bmatrix}$ then A is one to one if and only if whenever

$$0 = \sum_{k=1}^{n} c_k A_k$$

it follows that each scalar $c_k = 0$.

We will now take a look at an example of a one to one and onto linear transformation.

Example 6.5.1: A One to One and Onto Linear Transformation

Suppose

$$T\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix}$$

Then, $T : \mathbb{R}^2 \to \mathbb{R}^2$ is a linear transformation. Is T onto? Is it one to one?

Solution

Recall that because T can be expressed as matrix multiplication, we know that T is a linear transformation. We will start by looking at onto. So suppose $\begin{bmatrix} a \\ b \end{bmatrix} \in \mathbb{R}^2$. Does there exist $\begin{bmatrix} x \\ y \end{bmatrix} \in \mathbb{R}^2$ such that $T\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a \\ b \end{bmatrix}$? If so, then since $\begin{bmatrix} a \\ b \end{bmatrix}$ is an arbitrary vector in $\mathbb{R}^2$, it will follow that T is onto.

This question is familiar to you. It is asking whether there is a solution to the equation

$$\begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a \\ b \end{bmatrix}$$

This is the same thing as asking for a solution to the following system of equations.

$$\begin{aligned} x + y &= a \\ x + 2y &= b \end{aligned}$$

Set up the augmented matrix and row reduce.

$$\begin{bmatrix} 1 & 1 & a \\ 1 & 2 & b \end{bmatrix} \to \begin{bmatrix} 1 & 0 & 2a - b \\ 0 & 1 & b - a \end{bmatrix} \tag{6.5.1}$$

You can see from this point that the system has a solution. Therefore, we have shown that for any a, b, there is a $\begin{bmatrix} x \\ y \end{bmatrix}$ such that $T\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a \\ b \end{bmatrix}$. Thus T is onto.

Now we want to know if T is one to one. By Proposition 6.5.1 it is enough to show that $A\vec{x} = 0$ implies $\vec{x} = 0$. Consider the system $A\vec{x} = 0$ given by:

$$\begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

This is the same as the system given by

$$x + y = 0$$
$$x + 2y = 0$$

We need to show that the solution to this system is $x = 0$ and $y = 0$. By setting up the augmented matrix and row reducing, we end up with

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

This tells us that $x = 0$ and $y = 0$. Returning to the original system, this says that if

$$\begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

then

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

In other words, $A\vec{x} = 0$ implies that $\vec{x} = 0$. By Proposition 6.5.1, A is one to one, and so T is also one to one.

We also could have seen that T is one to one from our above solution for onto. By looking at the matrix given by (6.5.1), you can see that there is a **unique** solution given by $x = 2a - b$ and $y = b - a$. Therefore, there is only one vector, specifically $\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2a - b \\ b - a \end{bmatrix}$ such that $T \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a \\ b \end{bmatrix}$. Hence by Definition 6.5.1, T is one to one.

Example 6.5.2: An Onto Transformation

Let $T : \mathbb{R}^4 \mapsto \mathbb{R}^2$ be a linear transformation defined by

$$T \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} a + d \\ b + c \end{bmatrix} \text{ for all } \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \in \mathbb{R}^4$$

Prove that T is onto but not one to one.

Solution

You can prove that T is in fact linear.

To show that T is onto, let $\begin{bmatrix} x \\ y \end{bmatrix}$ be an arbitrary vector in $\mathbb{R}^2$. Taking the vector $\begin{bmatrix} x \\ y \\ 0 \\ 0 \end{bmatrix} \in \mathbb{R}^4$ we have

$$T \begin{bmatrix} x \\ y \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} x + 0 \\ y + 0 \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix}$$

This shows that T is onto.

By Proposition 6.5.1 T is one to one if and only if $T(\vec{x}) = \vec{0}$ implies that $\vec{x} = \vec{0}$. Observe that

$$T \begin{bmatrix} 1 \\ 0 \\ 0 \\ -1 \end{bmatrix} = \begin{bmatrix} 1 + -1 \\ 0 + 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

There exists a nonzero vector $\vec{x}$ in $\mathbb{R}^4$ such that $T(\vec{x}) = \vec{0}$. It follows that T is not one to one.

The above examples demonstrate a method to determine if a linear transformation T is one to one or onto. It turns out that the matrix A of T can provide this information.

Theorem 6.5.1: Matrix of a One to One or Onto Transformation

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation induced by the $m \times n$ matrix A. Then T is one to one if and only if the rank of A is n. T is onto if and only if the rank of A is m.

Consider Example 6.5.2. Above we showed that T was onto but not one to one. We can now use this theorem to determine this fact about T.

Example 6.5.3: An Onto Transformation

Let $T : \mathbb{R}^4 \mapsto \mathbb{R}^2$ be a linear transformation defined by

$$T \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} a+d \\ b+c \end{bmatrix} \text{ for all } \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \in \mathbb{R}^4$$

Prove that T is onto but not one to one.

Solution

Using Theorem 6.5.1 we can show that T is onto but not one to one from the matrix of T. Recall that to find the matrix A of T , we apply T to each of the standard basis vectors $\vec{e}_i$ of $\mathbb{R}^4$. The result is the 2×4 matrix A given by

$$A = \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix}$$

Fortunately, this matrix is already in reduced row-echelon form. The rank of A is 2. Therefore by the above theorem T is onto but not one to one.

Recall that if S and T are linear transformations, we can discuss their composite denoted $S \circ T$. The following examines what happens if both S and T are onto.

Example 6.5.4: Composite of Onto Transformations

Let $T : \mathbb{R}^k \mapsto \mathbb{R}^n$ and $S : \mathbb{R}^n \mapsto \mathbb{R}^m$ be linear transformations. If T and S are onto, then $S \circ T$ is onto.

Solution

Let $\vec{z} \in \mathbb{R}^m$. Since S is onto, there exists a vector $\vec{y} \in \mathbb{R}^n$ such that $S(\vec{y}) = \vec{z}$. Furthermore, since T is onto, there exists a vector $\vec{x} \in \mathbb{R}^k$ such that $T(\vec{x}) = \vec{y}$. Thus

$$\vec{z} = S(\vec{y}) = S(T(\vec{x})) = (ST)(\vec{x}),$$

showing that for each $\vec{z} \in \mathbb{R}^m$ there exists and $\vec{x} \in \mathbb{R}^k$ such that $(ST)(\vec{x}) = \vec{z}$. Therefore, $S \circ T$ is onto.

The next example shows the same concept with regards to one-to-one transformations.

Example 6.5.5: Composite of One to One Transformations

Let $T : \mathbb{R}^k \mapsto \mathbb{R}^n$ and $S : \mathbb{R}^n \mapsto \mathbb{R}^m$ be linear transformations. Prove that if T and S are one to one, then $S \circ T$ is one-to-one.

Solution

To prove that $S \circ T$ is one to one, we need to show that if $S(T(\vec{v})) = \vec{0}$ it follows that $\vec{v} = \vec{0}$. Suppose that $S(T(\vec{v})) = \vec{0}$. Since S is one to one, it follows that $T(\vec{v}) = \vec{0}$. Similarly, since T is one to one, it follows that $\vec{v} = \vec{0}$. Hence $S \circ T$ is one to one.

Answers

Lemma 6.5.1: Range of a Matrix Transformation

This follows from the definition of matrix multiplication.

Proposition 6.5.1: One to One

We need to prove two things here. First, we will prove that if T is one to one, then $T(\vec{x}) = \vec{0}$ implies that $\vec{x} = \vec{0}$. Second, we will show that if $T(\vec{x}) = \vec{0}$ implies that $\vec{x} = \vec{0}$, then it follows that T is one to one. Recall that a linear transformation has the property that $T(\vec{0}) = \vec{0}$.

Suppose first that T is one to one and consider $T(\vec{0})$.

$$T(\vec{0}) = T\left(\vec{0} + \vec{0}\right) = T(\vec{0}) + T(\vec{0})$$

and so, adding the additive inverse of $T(\vec{0})$ to both sides, one sees that $T(\vec{0}) = \vec{0}$. If $T(\vec{x}) = \vec{0}$ it must be the case that $\vec{x} = \vec{0}$ because it was just shown that $T(\vec{0}) = \vec{0}$ and T is assumed to be one to one.

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6.6: Isomorphisms

Outcomes

A. Determine if a linear transformation is an isomorphism.
B. Determine if two subspaces of $\mathbb{R}^n$ are isomorphic.

Recall the definition of a linear transformation. Let V and W be two subspaces of $\mathbb{R}^n$ and $\mathbb{R}^m$ respectively. A mapping $T : V \to W$ is called a **linear transformation** or **linear map** if it preserves the algebraic operations of addition and scalar multiplication. Specifically, if a, b are scalars and $\vec{x}, \vec{y}$ are vectors,

$$T\left(a\vec{x} + b\vec{y}\right) = aT(\vec{x}) + bT(\vec{y})$$

Consider the following important definition.

Definition 6.6.1: Isomorphism

A linear map T is called an **isomorphism** if the following two conditions are satisfied.

- T is one to one. That is, if $T(\vec{x}) = T(\vec{y})$, then $\vec{x} = \vec{y}$.
- T is onto. That is, if $\vec{w} \in W$, there exists $\vec{v} \in V$ such that $T(\vec{v}) = \vec{w}$.

Two such subspaces which have an isomorphism as described above are said to be **isomorphic.**

Consider the following example of an isomorphism.

Example 6.6.1: Isomorphism

Let $T : \mathbb{R}^2 \mapsto \mathbb{R}^2$ be defined by

$$T\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x+y \\ x-y \end{bmatrix}$$

Show that T is an isomorphism.

Solution

To prove that T is an isomorphism we must show

1. T is a linear transformation;
2. T is one to one;
3. T is onto.

We proceed as follows.

1. T is a linear transformation:

   Let k, p be scalars.

$$\begin{aligned} T\left(k\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} + p\begin{bmatrix} x_2 \\ y_2 \end{bmatrix}\right) &= T\left(\begin{bmatrix} kx_1 \\ ky_1 \end{bmatrix} + \begin{bmatrix} px_2 \\ py_2 \end{bmatrix}\right) \\ &= T\left(\begin{bmatrix} kx_1 + px_2 \\ ky_1 + py_2 \end{bmatrix}\right) \\ &= \begin{bmatrix} (kx_1 + px_2) + (ky_1 + py_2) \\ (kx_1 + px_2) - (ky_1 + py_2) \end{bmatrix} \\ &= \begin{bmatrix} (kx_1 + ky_1) + (px_2 + py_2) \\ (kx_1 - ky_1) + (px_2 - py_2) \end{bmatrix} \\ &= \begin{bmatrix} kx_1 + ky_1 \\ kx_1 - ky_1 \end{bmatrix} + \begin{bmatrix} px_2 + py_2 \\ px_2 - py_2 \end{bmatrix} \\ &= k\begin{bmatrix} x_1 + y_1 \\ x_1 - y_1 \end{bmatrix} + p\begin{bmatrix} x_2 + y_2 \\ x_2 - y_2 \end{bmatrix} \\ &= kT\left(\begin{bmatrix} x_1 \\ y_1 \end{bmatrix}\right) + pT\left(\begin{bmatrix} x_2 \\ y_2 \end{bmatrix}\right) \end{aligned} \tag{6.6.1}$$

Therefore T is linear.

2. T is one to one:

   We need to show that if $T(\vec{x}) = \vec{0}$ for a vector $\vec{x} \in \mathbb{R}^2$, then it follows that $\vec{x} = \vec{0}$. Let $\vec{x} = \begin{bmatrix} x \\ y \end{bmatrix}$.

   $$T\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = \begin{bmatrix} x + y \\ x - y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

   This provides a system of equations given by

   $$\begin{aligned} x + y &= 0 \\ x - y &= 0 \end{aligned} \tag{6.6.2}$$

   You can verify that the solution to this system if $x = y = 0$. Therefore

   $$\vec{x} = \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

   and T is one to one.

3. T is onto:

   Let a, b be scalars. We want to check if there is always a solution to

   $$T\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = \begin{bmatrix} x + y \\ x - y \end{bmatrix} = \begin{bmatrix} a \\ b \end{bmatrix}$$

   This can be represented as the system of equations

   $$\begin{aligned} x + y &= a \\ x - y &= b \end{aligned} \tag{6.6.3}$$

   Setting up the augmented matrix and row reducing gives

   $$\begin{bmatrix} 1 & 1 & a \\ 1 & -1 & b \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & \frac{a+b}{2} \\ 0 & 1 & \frac{a-b}{2} \end{bmatrix}$$

   This has a solution for all a, b and therefore T is onto.

Therefore T is an isomorphism.

An important property of isomorphisms is that its inverse is also an isomorphism.

Proposition 6.6.1: Inverse of an Isomorphism

Let $T : V \to W$ be an isomorphism and V, W be subspaces of $\mathbb{R}^n$. Then $T^{-1} : W \to V$ is also an isomorphism.

Proof available at the end of this section.

Another important result is that the composition of multiple isomorphisms is also an isomorphism.

Proposition 6.6.2: Composition of Isomorphisms

Let $T : V \to W$ and $S : W \to Z$ be isomorphisms where V, W, Z are subspaces of $\mathbb{R}^n$. Then $S \circ T$ defined by $(S \circ T)(\vec{v}) = S(T(\vec{v}))$ is also an isomorphism.

Proof available at the end of this section.

Consider two subspaces V and W, and suppose there exists an isomorphism mapping one to the other. In this way the two subspaces are related, which we can write as $V \sim W$. Then the previous two propositions together claim that $\sim$ is an equivalence relation. That is: $\sim$ satisfies the following conditions:

- $V \sim V$
- If $V \sim W$, it follows that $W \sim V$
- If $V \sim W$ and $W \sim Z$, then $V \sim Z$

We leave the verification of these conditions as an exercise.

Consider the following example.

Example 6.6.2: Matrix Isomorphism

Let $T : \mathbb{R}^n \to \mathbb{R}^n$ be defined by $T(\vec{x}) = A(\vec{x})$ where A is an invertible $n \times n$ matrix. Then T is an isomorphism.

Solution

The reason for this is that, since A is invertible, the only vector it sends to $\vec{0}$ is the zero vector. Hence if $A(\vec{x}) = A(\vec{y})$, then $A(\vec{x} - \vec{y}) = \vec{0}$ and so $\vec{x} = \vec{y}$. It is onto because if

$$\vec{y} \in \mathbb{R}^n, A\left(A^{-1}(\vec{y})\right) = \left(AA^{-1}\right)(\vec{y}) = \vec{y}.$$

In fact, all isomorphisms from $\mathbb{R}^n$ to $\mathbb{R}^n$ can be expressed as $T(\vec{x}) = A(\vec{x})$ where A is an invertible $n \times n$ matrix. One simply considers the matrix whose i^{th} column is $T\vec{e}_i$.

Recall that a basis of a subspace V is a set of linearly independent vectors which span V. The following fundamental lemma describes the relation between bases and isomorphisms.

Lemma 6.6.1: Mapping Bases

Let $T : V \to W$ be a linear transformation where V, W are subspaces of $\mathbb{R}^n$. If T is one to one, then it has the property that if $\{\vec{u}_1, \cdots, \vec{u}_k\}$ is linearly independent, so is $\{T(\vec{u}_1), \cdots, T(\vec{u}_k)\}$.

More generally, T is an isomorphism if and only if whenever $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a basis for V, it follows that $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ is a basis for W.

Proof available at the end of this section.

The following theorem illustrates a very useful idea for defining an isomorphism. Basically, if you know what it does to a basis, then you can construct the isomorphism.

Theorem 6.6.1: Isomorphic Subspaces

Suppose V and W are two subspaces of $\mathbb{R}^n$. Then the two subspaces are isomorphic if and only if they have the same dimension. In the case that the two subspaces have the same dimension, then for a linear map $T : V \to W$, the following are equivalent.

1. T is one to one.
2. T is onto.
3. T is an isomorphism.

Proof available at the end of this section.

Note the interesting way of defining a linear transformation in the first part of the argument by describing what it does to a basis and then "extending it linearly" to the entire subspace.

Example 6.6.4: Isomorphic Subspaces

Let $V = \mathbb{R}^3$ and let W denote

$$\text{span}\left\{\begin{bmatrix}1\\2\\1\\1\end{bmatrix}, \begin{bmatrix}0\\1\\0\\1\end{bmatrix}, \begin{bmatrix}1\\1\\2\\0\end{bmatrix}\right\}$$

Show that V and W are isomorphic.

Solution

First observe that these subspaces are both of dimension 3 and so they are isomorphic by Theorem 6.6.1. The three vectors which span W are easily seen to be linearly independent by making them the columns of a matrix and row reducing to the reduced row-echelon form.

You can exhibit an isomorphism of these two spaces as follows.

$$T(\vec{e}_1) = \begin{bmatrix}1\\2\\1\\1\end{bmatrix}, T(\vec{e}_2) = \begin{bmatrix}0\\1\\0\\1\end{bmatrix}, T(\vec{e}_3) = \begin{bmatrix}1\\1\\2\\0\end{bmatrix}$$

and extend linearly. Recall that the matrix of this linear transformation is just the matrix having these vectors as columns. Thus the matrix of this isomorphism is

$$\begin{bmatrix}1&0&1\\2&1&1\\1&0&2\\1&1&0\end{bmatrix}$$

You should check that multiplication on the left by this matrix does reproduce the claimed effect resulting from an application by T.

Consider the following example.

Example 6.6.5: Finding the Matrix of an Isomorphism

Let $V = \mathbb{R}^3$ and let W denote

$$\text{span}\left\{\begin{bmatrix}1\\2\\1\\1\end{bmatrix}, \begin{bmatrix}0\\1\\0\\1\end{bmatrix}, \begin{bmatrix}1\\1\\2\\0\end{bmatrix}\right\}$$

Let $T : V \mapsto W$ be defined as follows.

$$T\begin{bmatrix}1\\1\\0\end{bmatrix} = \begin{bmatrix}1\\2\\1\\1\end{bmatrix}, T\begin{bmatrix}0\\1\\1\end{bmatrix} = \begin{bmatrix}0\\1\\0\\1\end{bmatrix}, T\begin{bmatrix}1\\1\\1\end{bmatrix} = \begin{bmatrix}1\\1\\2\\0\end{bmatrix}$$

Find the matrix of this isomorphism T.

Solution

First note that the vectors

$$\begin{bmatrix}1\\1\\0\end{bmatrix}, \begin{bmatrix}0\\1\\1\end{bmatrix}, \begin{bmatrix}1\\1\\1\end{bmatrix}$$

are indeed a basis for $\mathbb{R}^3$ as can be seen by making them the columns of a matrix and using the reduced row-echelon form.

Now recall the matrix of T is a 4×3 matrix A which gives the same effect as T. Thus, from the way we multiply matrices,

$$A\begin{bmatrix}1&0&1\\1&1&1\\0&1&1\end{bmatrix} = \begin{bmatrix}1&0&1\\2&1&1\\1&0&2\\1&1&0\end{bmatrix}$$

Hence,

$$A = \begin{bmatrix}1&0&1\\2&1&1\\1&0&2\\1&1&0\end{bmatrix}\begin{bmatrix}1&0&1\\1&1&1\\0&1&1\end{bmatrix}^{-1} = \begin{bmatrix}1&0&0\\0&2&-1\\2&-1&1\\-1&2&-1\end{bmatrix}$$

Note how the span of the columns of this new matrix must be the same as the span of the vectors defining W.

This idea of defining a linear transformation by what it does on a basis works for linear maps which are not necessarily isomorphisms.

Example 6.6.6: Finding the Matrix of an Isomorphism

Let $V = \mathbb{R}^3$ and let W denote

$$\text{span}\left\{\begin{bmatrix}1\\0\\1\\1\end{bmatrix}, \begin{bmatrix}0\\1\\0\\1\end{bmatrix}, \begin{bmatrix}1\\1\\1\\2\end{bmatrix}\right\}$$

Let $T : V \mapsto W$ be defined as follows.

$$T\begin{bmatrix}1\\1\\0\end{bmatrix}=\begin{bmatrix}1\\0\\1\\1\end{bmatrix},T\begin{bmatrix}0\\1\\1\end{bmatrix}=\begin{bmatrix}0\\1\\0\\1\end{bmatrix},T\begin{bmatrix}1\\1\\1\end{bmatrix}=\begin{bmatrix}1\\1\\1\\2\end{bmatrix}$$

Find the matrix of this linear transformation.

Solution

Note that in this case, the three vectors which span W are not linearly independent. Nevertheless the above procedure will still work. The reasoning is the same as before. If A is this matrix, then

$$A\begin{bmatrix}1&0&1\\1&1&1\\0&1&1\end{bmatrix}=\begin{bmatrix}1&0&1\\0&1&1\\1&0&1\\1&1&2\end{bmatrix}$$

and so

$$A=\begin{bmatrix}1&0&1\\0&1&1\\1&0&1\\1&1&2\end{bmatrix}\begin{bmatrix}1&0&1\\1&1&1\\0&1&1\end{bmatrix}^{-1}=\begin{bmatrix}1&0&0\\0&0&1\\1&0&0\\1&0&1\end{bmatrix}$$

The columns of this last matrix are obviously not linearly independent.

Answers

Proposition $6.6.1$**: Inverse of an Isomorphism**

Let T be an isomorphism. Since T is onto, a typical vector in W is of the form $T(\vec{v})$ where $\vec{v}\in V$. Consider then for a,b scalars,

$$T^{-1}\left(aT(\vec{v}_1)+bT(\vec{v}_2)\right)$$

where $\vec{v}_1,\vec{v}_2\in V$. Is this equal to

$$aT^{-1}\left(T(\vec{v}_1)\right)+bT^{-1}\left(T(\vec{v}_2)\right)=a\vec{v}_1+b\vec{v}_2?$$

Since T is one to one, this will be so if

$$T\left(a\vec{v}_1+b\vec{v}_2\right)=T\left(T^{-1}\left(aT(\vec{v}_1)+bT(\vec{v}_2)\right)\right)=aT(\vec{v}_1)+bT(\vec{v}_2).$$

However, the above statement is just the condition that T is a linear map. Thus T^{-1} is indeed a linear map. If $\vec{v}\in V$ is given, then $\vec{v}=T^{-1}\left(T(\vec{v})\right)$ and so T^{-1} is onto. If $T^{-1}(\vec{v})=0$, then

$$\vec{v}=T\left(T^{-1}(\vec{v})\right)=T(\vec{0})=\vec{0}$$

and so T^{-1} is one to one.

Proposition $6.6.2$**: Composition of Isomorphisms**

Suppose $T:V\to W$ and $S:W\to Z$ are isomorphisms. Why is $S\circ T$ a linear map? For a,b scalars,

$$\begin{aligned}S\circ T\left(a\vec{v}_1+b(\vec{v}_2)\right)&=S\left(T\left(a\vec{v}_1+b\vec{v}_2\right)\right)=S\left(aT\vec{v}_1+bT\vec{v}_2\right)\\&=aS\left(T\vec{v}_1\right)+bS\left(T\vec{v}_2\right)=a\left(S\circ T\right)\left(\vec{v}_1\right)+b\left(S\circ T\right)\left(\vec{v}_2\right)\end{aligned}$$

Hence $S\circ T$ is a linear map. If $\left(S\circ T\right)\left(\vec{v}\right)=0$, then $S\left(T\left(\vec{v}\right)\right)=0$ and it follows that $T(\vec{v})=\vec{0}$ and hence by this lemma again, $\vec{v}=\vec{0}$. Thus $S\circ T$ is one to one. It remains to verify that it is onto. Let $\vec{z}\in Z$. Then since S is onto, there exists $\vec{w}\in W$ such that $S(\vec{w})=\vec{z}$. Also, since T is onto, there exists $\vec{v}\in V$ such that $T(\vec{v})=\vec{w}$. It follows that $S\left(T\left(\vec{v}\right)\right)=\vec{z}$ and so $S\circ T$ is also onto.

Lemma $6.6.1$**: Mapping Bases**

First suppose that T is a linear transformation and is one to one and $\{\vec{u}_1,\cdots,\vec{u}_k\}$ is linearly independent. It is required to show that $\{T(\vec{u}_1),\cdots,T(\vec{u}_k)\}$ is also linearly independent. Suppose then that

$$\sum_{i=1}^{k}c_iT(\vec{u}_i)=\vec{0}$$

Then, since T is linear,

$$T\left(\sum_{i=1}^{n}c_i\vec{u}_i\right)=\vec{0}$$

Since T is one to one, it follows that

$$\sum_{i=1}^{n}c_i\vec{u}_i=0$$

Now the fact that $\{\vec{u}_1, \cdots, \vec{u}_n\}$ is linearly independent implies that each $c_i = 0$. Hence $\{T(\vec{u}_1), \cdots, T(\vec{u}_n)\}$ is linearly independent.

Now suppose that T is an isomorphism and $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a basis for V. It was just shown that $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ is linearly independent. It remains to verify that $\text{span}\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\} = W$. If $\vec{w} \in W$, then since T is onto there exists $\vec{v} \in V$ such that $T(\vec{v}) = \vec{w}$. Since $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a basis, it follows that there exists scalars $\{c_i\}_{i=1}^n$ such that

$$\sum_{i=1}^n c_i \vec{v}_i = \vec{v}.$$

Hence,

$$\vec{w} = T(\vec{v}) = T\left(\sum_{i=1}^n c_i \vec{v}_i\right) = \sum_{i=1}^n c_i T(\vec{v}_i)$$

It follows that $\text{span}\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\} = W$ showing that this set of vectors is a basis for W.

Next suppose that T is a linear transformation which takes a basis to a basis. This means that if $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a basis for V, it follows $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ is a basis for W. Then if $w \in W$, there exist scalars c_i such that $w = \sum_{i=1}^n c_i T(\vec{v}_i) = T\left(\sum_{i=1}^n c_i \vec{v}_i\right)$ showing that T is onto. If $T\left(\sum_{i=1}^n c_i \vec{v}_i\right) = \vec{0}$ then $\sum_{i=1}^n c_i T(\vec{v}_i) = \vec{0}$ and since the vectors $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ are linearly independent, it follows that each $c_i = 0$. Since $\sum_{i=1}^n c_i \vec{v}_i$ is a typical vector in V, this has shown that if $T(\vec{v}) = \vec{0}$ then $\vec{v} = \vec{0}$ and so T is also one to one. Thus T is an isomorphism.

Theorem $6.6.1$**: Isomorphic Subspaces**

Suppose first that these two subspaces have the same dimension. Let a basis for V be $\{\vec{v}_1, \cdots, \vec{v}_n\}$ and let a basis for W be $\{\vec{w}_1, \cdots, \vec{w}_n\}$. Now define T as follows.

$$T(\vec{v}_i) = \vec{w}_i$$

for $\sum_{i=1}^n c_i \vec{v}_i$ an arbitrary vector of V,

$$T\left(\sum_{i=1}^n c_i \vec{v}_i\right) = \sum_{i=1}^n c_i T\vec{v}_i = \sum_{i=1}^n c_i \vec{w}_i.$$

It is necessary to verify that this is well defined. Suppose then that

$$\sum_{i=1}^n c_i \vec{v}_i = \sum_{i=1}^n \hat{c}_i \vec{v}_i$$

Then

$$\sum_{i=1}^n \left(c_i - \hat{c}_i\right) \vec{v}_i = \vec{0}$$

and since $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a basis, $c_i = \hat{c}_i$ for each i. Hence

$$\sum_{i=1}^n c_i \vec{w}_i = \sum_{i=1}^n \hat{c}_i \vec{w}_i$$

and so the mapping is well defined. Also if a, b are scalars,

$$\begin{aligned} T\left(a\sum_{i=1}^n c_i \vec{v}_i + b\sum_{i=1}^n \hat{c}_i \vec{v}_i\right) &= T\left(\sum_{i=1}^n \left(ac_i + b\hat{c}_i\right) \vec{v}_i\right) = \sum_{i=1}^n \left(ac_i + b\hat{c}_i\right) \vec{w}_i \\ &= a\sum_{i=1}^n c_i \vec{w}_i + b\sum_{i=1}^n \hat{c}_i \vec{w}_i \\ &= aT\left(\sum_{i=1}^n c_i \vec{v}_i\right) + bT\left(\sum_{i=1}^n \hat{c}_i \vec{v}_i\right) \end{aligned} \tag{6.6.4}$$

Thus T is a linear transformation.

Now if

$$T\left(\sum_{i=1}^n c_i \vec{v}_i\right) = \sum_{i=1}^n c_i \vec{w}_i = \vec{0},$$

then since the $\{\vec{w}_1, \cdots, \vec{w}_n\}$ are independent, each $c_i = 0$ and so $\sum_{i=1}^n c_i \vec{v}_i = \vec{0}$ also. Hence T is one to one. If $\sum_{i=1}^n c_i \vec{w}_i$ is a vector in W, then it equals

$$\sum_{i=1}^n c_i T(\vec{v}_i) = T\left(\sum_{i=1}^n c_i \vec{v}_i\right)$$

showing that T is also onto. Hence T is an isomorphism and so V and W are isomorphic.

Next suppose $T : V \mapsto W$ is an isomorphism, so these two subspaces are isomorphic. Then for $\{\vec{v}_1, \cdots, \vec{v}_n\}$ a basis for V, it follows that a basis for W is $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ showing that the two subspaces have the same dimension.

Now suppose the two subspaces have the same dimension. Consider the three claimed equivalences.

First consider the claim that $1.) \Rightarrow 2.)$. If T is one to one and if $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a basis for V, then $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ is linearly independent. If it is not a basis, then it must fail to span W. But then there would exist $\vec{w} \notin \text{span}\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ and it follows that $\{T(\vec{v}_1), \cdots, T(\vec{v}_n), \vec{w}\}$ would be linearly independent which is impossible because there exists a basis for W of n vectors.

Hence $\text{span}\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\} = W$ and so $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ is a basis. If $\vec{w} \in W$, there exist scalars c_i such that

$$\vec{w} = \sum_{i=1}^n c_i T(\vec{v}_i) = T\left(\sum_{i=1}^n c_i \vec{v}_i\right)$$

showing that T is onto. This shows that $1.) \Rightarrow 2.)$.

Next consider the claim that $2.) \Rightarrow 3.)$. Since $2.)$ holds, it follows that T is onto. It remains to verify that T is one to one. Since T is onto, there exists a basis of the form $\{T(\vec{v}_i), \cdots, T(\vec{v}_n)\}$. Then it follows that $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is linearly independent. Suppose

$$\sum_{i=1}^n c_i \vec{v}_i = \vec{0}$$

Then

$$\sum_{i=1}^{n} c_i T(\vec{v}_i) = \vec{0}$$

Hence each $c_i = 0$ and so, $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a basis for V. Now it follows that a typical vector in V is of the form $\sum_{i=1}^{n} c_i \vec{v}_i$. If $T\left(\sum_{i=1}^{n} c_i \vec{v}_i\right) = \vec{0}$, it follows that

$$\sum_{i=1}^{n} c_i T(\vec{v}_i) = \vec{0}$$

and so, since $\{T(\vec{v}_i), \cdots, T(\vec{v}_n)\}$ is independent, it follows each $c_i = 0$ and hence $\sum_{i=1}^{n} c_i \vec{v}_i = \vec{0}$. Thus T is one to one as well as onto and so it is an isomorphism. If T is an isomorphism, it is both one to one and onto by definition so $3.)$ implies both $1.)$ and $2.)$.

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6.7: The Kernel and Image of A Linear Map

Outcomes

A. Describe the kernel and image of a linear transformation, and find a basis for each.

In this section we will consider the case where the linear transformation is not necessarily an isomorphism. First consider the following important definition.

Definition 6.7.1: Kernel and Image

Let V and W be subspaces of $\mathbb{R}^n$ and let $T : V \mapsto W$ be a linear transformation. Then the image of T denoted as $\text{im}\,(T)$ is defined to be the set

$$\text{im}\,(T) = \{T(\vec{v}) : \vec{v} \in V\}$$

In words, it consists of all vectors in W which equal $T(\vec{v})$ for some $\vec{v} \in V$.

The kernel of T, written $\ker(T)$, consists of all $\vec{v} \in V$ such that $T(\vec{v}) = \vec{0}$. That is,

$$\ker(T) = \left\{\vec{v} \in V : T(\vec{v}) = \vec{0}\right\}$$

It follows that $\text{im}\,(T)$ and $\ker(T)$ are subspaces of W and V respectively.

Proposition 6.7.1: Kernel and Image as Subspaces

Let V, W be subspaces of $\mathbb{R}^n$ and let $T : V \to W$ be a linear transformation. Then $\ker(T)$ is a subspace of V and $\text{im}\,(T)$ is a subspace of W.

Proof available at the end of this section.

We will now examine how to find the kernel and image of a linear transformation and describe the basis of each.

Example 6.7.1: Kernel and Image of a Linear Transformation

Let $T : \mathbb{R}^4 \mapsto \mathbb{R}^2$ be defined by

$$T\begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} a-b \\ c+d \end{bmatrix}$$

Then T is a linear transformation. Find a basis for $\ker(T)$ and $\text{im}(T)$.

Solution

You can verify that T is a linear transformation.

First we will find a basis for $\ker(T)$. To do so, we want to find a way to describe all vectors $\vec{x} \in \mathbb{R}^4$ such that $T(\vec{x}) = \vec{0}$. Let $\vec{x} = \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix}$ be such a vector. Then

$$T \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} a-b \\ c+d \end{bmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

The values of a, b, c, d that make this true are given by solutions to the system

$$\begin{aligned} a - b &= 0 \\ c + d &= 0 \end{aligned} \tag{6.7.1}$$

The solution to this system is $a = s, b = s, c = t, d = -t$ where s, t are scalars. We can describe $\ker(T)$ as follows.

$$\ker(T) = \left\{ \begin{bmatrix} s \\ s \\ t \\ -t \end{bmatrix} \right\} = \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ -1 \end{bmatrix} \right\}$$

Notice that this set is linearly independent and therefore forms a basis for $\ker(T)$.

We move on to finding a basis for $\text{im}(T)$. We can write the image of T as

$$\text{im}(T) = \left\{ \begin{bmatrix} a-b \\ c+d \end{bmatrix} \right\}$$

We can write this in the form

$$\text{span} = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$$

This set is clearly not linearly independent. By removing unnecessary vectors from the set we can create a linearly independent set with the same span. This gives a basis for $\text{im}(T)$ as

$$\text{im}(T) = \text{span} \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$$

Recall that a linear transformation T is called one to one if and only if $T(\vec{x}) = \vec{0}$ implies $\vec{x} = \vec{0}$. Using the concept of kernel, we can state this theorem in another way.

Theorem 6.7.1: One to One and Kernel

Let T be a linear transformation where $\ker(T)$ is the kernel of T. Then T is one to one if and only if $\ker(T)$ consists of **only** the zero vector.

A major result is the relation between the dimension of the kernel and dimension of the image of a linear transformation. In the previous example $\ker(T)$ had dimension 2, and $\text{im}(T)$ also had dimension of 2. Is it a coincidence that the dimension of $\mathbb{M}_{22}$ is $4 = 2 + 2$? Consider the following theorem.

Theorem 6.7.2: Dimension of Kernel and Image

Let $T : V \to W$ be a linear transformation where V, W are subspaces of $\mathbb{R}^n$. Suppose the dimension of V is m. Then

$$m = \dim(\ker(T)) + \dim(\text{im}(T))$$

Proof available at the end of this section.

The above theorem leads to the next corollary.

Corollary 6.7.1

Let $T : V \to W$ be a linear transformation where V, W are subspaces of $\mathbb{R}^n$. Suppose the dimension of V is m. Then

$$\dim(\ker(T)) \leq m$$
$$\dim(\text{im}(T)) \leq m$$

This follows directly from the fact that $n = \dim(\ker(T)) + \dim(\text{im}(T))$.

Consider the following example.

Example 6.7.2

Let $T : \mathbb{R}^2 \to \mathbb{R}^3$ be defined by

$$T(\vec{x}) = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \vec{x}$$

Then $\text{im}(T) = V$ is a subspace of $\mathbb{R}^3$ and T is an isomorphism of $\mathbb{R}^2$ and V. Find a 2×3 matrix A such that the restriction of multiplication by A to $V = \text{im}(T)$ equals T^{-1}.

Solution

Since the two columns of the above matrix are linearly independent, we conclude that $\dim(\text{im}(T)) = 2$ and therefore $\dim(\ker(T)) = 2 - \dim(\text{im}(T)) = 2 - 2 = 0$ by Theorem 6.7.2. Then by Theorem 6.7.1 it follows that T is one to one.

Thus T is an isomorphism of $\mathbb{R}^2$ and the two dimensional subspace of $\mathbb{R}^3$ which is the span of the columns of the given matrix. Now in particular,

$$T(\vec{e}_1) = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \; T(\vec{e}_2) = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Thus

$$T^{-1} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = \vec{e}_1, \; T^{-1} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = \vec{e}_2$$

Extend T^{-1} to all of $\mathbb{R}^3$ by defining

$$T^{-1} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} = \vec{e}_1$$

Notice that the vectors

$$\left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right\}$$

are linearly independent so T^{-1} can be extended linearly to yield a linear transformation defined on $\mathbb{R}^3$. The matrix of T^{-1} denoted as A needs to satisfy

$$A\begin{bmatrix}1&0&0\\1&0&1\\0&1&0\end{bmatrix}=\begin{bmatrix}1&0&1\\0&1&0\end{bmatrix}$$

and so

$$A=\begin{bmatrix}1&0&1\\0&1&0\end{bmatrix}\begin{bmatrix}1&0&0\\1&0&1\\0&1&0\end{bmatrix}^{-1}=\begin{bmatrix}0&1&0\\0&0&1\end{bmatrix}$$

Note that

$$\begin{bmatrix}0&1&0\\0&0&1\end{bmatrix}\begin{bmatrix}1\\1\\0\end{bmatrix}=\begin{bmatrix}1\\0\end{bmatrix}$$

$$\begin{bmatrix}0&1&0\\0&0&1\end{bmatrix}\begin{bmatrix}0\\0\\1\end{bmatrix}=\begin{bmatrix}0\\1\end{bmatrix}$$

so the restriction to V of matrix multiplication by this matrix yields T^{-1}.

Answers

Proposition $6.7.1$**: Kernel and Image as Subspaces**

First consider $\ker(T)$. It is necessary to show that if $\vec{v}_1,\vec{v}_2$ are vectors in $\ker(T)$ and if a,b are scalars, then $a\vec{v}_1+b\vec{v}_2$ is also in $\ker(T)$. But

$$T(a\vec{v}_1+b\vec{v}_2)=aT(\vec{v}_1)+bT(\vec{v}_2)=a\vec{0}+b\vec{0}=\vec{0}$$

Thus $\ker(T)$ is a subspace of V.

Next suppose $T(\vec{v}_1),T(\vec{v}_2)$ are two vectors in $\mathrm{im}(T)$. Then if a,b are scalars,

$$aT(\vec{v}_2)+bT(\vec{v}_2)=T(a\vec{v}_1+b\vec{v}_2)$$

and this last vector is in $\mathrm{im}(T)$ by definition.

Theorem $6.7.2$**: Dimension of Kernel and Image**

From Proposition 6.7.1, $\mathrm{im}(T)$ is a subspace of W. We know that there exists a basis for $\mathrm{im}(T)$, $\{T(\vec{v}_1),\cdots,T(\vec{v}_r)\}$. Similarly, there is a basis for $\ker(T)$, $\{\vec{u}_1,\cdots,\vec{u}_s\}$. Then if $\vec{v}\in V$, there exist scalars c_i such that

$$T(\vec{v})=\sum_{i=1}^{r}c_iT(\vec{v}_i)$$

Hence $T\left(\vec{v}-\sum_{i=1}^{r}c_i\vec{v}_i\right)=0$. It follows that $\vec{v}-\sum_{i=1}^{r}c_i\vec{v}_i$ is in $\ker(T)$. Hence there are scalars a_i such that

$$\vec{v}-\sum_{i=1}^{r}c_i\vec{v}_i=\sum_{j=1}^{s}a_j\vec{u}_j$$

Hence $\vec{v}=\sum_{i=1}^{r}c_i\vec{v}_i+\sum_{j=1}^{s}a_j\vec{u}_j$. Since $\vec{v}$ is arbitrary, it follows that

$$V=\mathrm{span}\{\vec{u}_1,\cdots,\vec{u}_s,\vec{v}_1,\cdots,\vec{v}_r\}$$

If the vectors $\{\vec{u}_1,\cdots,\vec{u}_s,\vec{v}_1,\cdots,\vec{v}_r\}$ are linearly independent, then it will follow that this set is a basis. Suppose then that

$$\sum_{i=1}^{r}c_i\vec{v}_i+\sum_{j=1}^{s}a_j\vec{u}_j=0$$

Apply T to both sides to obtain

$$\sum_{i=1}^{r}c_iT(\vec{v}_i)+\sum_{j=1}^{s}a_jT(\vec{u})_j=\sum_{i=1}^{r}c_iT(\vec{v}_i)=0$$

Since $\{T(\vec{v}_1),\cdots,T(\vec{v}_r)\}$ is linearly independent, it follows that each $c_i=0$. Hence $\sum_{j=1}^{s}a_j\vec{u}_j=0$ and so, since the $\{\vec{u}_1,\cdots,\vec{u}_s\}$ are linearly independent, it follows that each $a_j=0$ also. Therefore $\{\vec{u}_1,\cdots,\vec{u}_s,\vec{v}_1,\cdots,\vec{v}_r\}$ is a basis for V and so

$$n=s+r=\dim(\ker(T))+\dim(\mathrm{im}(T))$$

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6.8: The Matrix of a Linear Transformation II

Outcomes

A. Find the matrix of a linear transformation with respect to general bases.

We begin this section with an important lemma.

Lemma 6.8.1: Mapping of a Basis

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^n$ be an isomorphism. Then T maps any basis of $\mathbb{R}^n$ to another basis for $\mathbb{R}^n$.

Conversely, if $T : \mathbb{R}^n \mapsto \mathbb{R}^n$ is a linear transformation which maps a basis of $\mathbb{R}^n$ to another basis of $\mathbb{R}^n$, then it is an isomorphism.

Proof available at the end of this section.

Consider now an important definition.

Definition 6.8.1: Coordinate Vector

Let $B = \{\vec{v}_1, \vec{v}_2, \cdots, \vec{v}_n\}$ be a basis for $\mathbb{R}^n$ and let $\vec{x}$ be an arbitrary vector in $\mathbb{R}^n$. Then $\vec{x}$ is uniquely represented as $\vec{x} = a_1\vec{v}_1 + a_2\vec{v}_2 + \cdots + a_n\vec{v}_n$ for scalars $a_1, \cdots, a_n$.

The **coordinate vector** of $\vec{x}$ with respect to the basis B, written $C_B(\vec{x})$ or $[\vec{x}]_B$, is given by

$$C_B(\vec{x}) = C_B\left(a_1\vec{v}_1 + a_2\vec{v}_2 + \cdots + a_n\vec{v}_n\right) = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$

Consider the following example.

Example 6.8.1: Coordinate Vector

Let $B = \left\{\begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \end{bmatrix}\right\}$ be a basis of $\mathbb{R}^2$ and let $\vec{x} = \begin{bmatrix} 3 \\ -1 \end{bmatrix}$ be a vector in $\mathbb{R}^2$. Find $C_B(\vec{x})$.

Solution

First, note the order of the basis is important so label the vectors in the basis B as

$$B = \left\{\begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \end{bmatrix}\right\} = \{\vec{v}_1, \vec{v}_2\}$$

Now we need to find a_1, a_2 such that $\vec{x} = a_1\vec{v}_1 + a_2\vec{v}_2$, that is:

$$\begin{bmatrix} 3 \\ -1 \end{bmatrix} = a_1\begin{bmatrix} 1 \\ 0 \end{bmatrix} + a_2\begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

Solving this system gives $a_1 = 2, a_2 = -1$. Therefore the coordinate vector of $\vec{x}$ with respect to the basis B is

$$C_B(\vec{x}) = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} 2 \\ -1 \end{bmatrix}$$

Given any basis B, one can easily verify that the coordinate function is actually an isomorphism.

Theorem 6.8.1: C_BTransformation is a Linear

For any basis B of $\mathbb{R}^n$, the coordinate function

$$C_B : \mathbb{R}^n \to \mathbb{R}^n$$

is a linear transformation, and moreover an isomorphism.

We now discuss the main result of this section, that is how to represent a linear transformation with respect to different bases.

Theorem 6.8.2: The Matrix of a Linear

Let $T : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation, and let B_1 and B_2 be bases of $\mathbb{R}^n$ and $\mathbb{R}^m$ respectively.

Then the following holds

$$C_{B_2} T = M_{B_2 B_1} C_{B_1} \tag{6.8.1}$$

where $M_{B_2 B_1}$ is a unique $m \times n$ matrix.

If the basis B_1 is given by $B_1 = \{\vec{v}_1, \cdots, \vec{v}_n\}$ in this order, then

$$M_{B_2 B_1} = \left[C_{B_2}(T(\vec{v}_1)) \; C_{B_2}(T(\vec{v}_2)) \; \cdots C_{B_2}(T(\vec{v}_n)) \right]$$

Proof available at the end of this section.

Consider the following example.

Example 6.8.2: Matrix of a Linear

Let $T : \mathbb{R}^2 \mapsto \mathbb{R}^2$ be a linear transformation defined by $T\left(\begin{bmatrix} a \\ b \end{bmatrix}\right) = \begin{bmatrix} b \\ a \end{bmatrix}$.

Consider the two bases

$$B_1 = \{\vec{v}_1, \vec{v}_2\} = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \end{bmatrix} \right\}$$

and

$$B_2 = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$$

Find the matrix M_{B_2, B_1} of T with respect to the bases B_1 and B_2.

Solution

By Theorem 6.8.2, the columns of $M_{B_2 B_1}$ are the coordinate vectors of $T(\vec{v}_1), T(\vec{v}_2)$ with respect to B_2.

Since

$$T\left(\begin{bmatrix} 1 \\ 0 \end{bmatrix}\right) = \begin{bmatrix} 0 \\ 1 \end{bmatrix},$$

a standard calculation yields

$$\begin{bmatrix} 0 \\ 1 \end{bmatrix} = \left(\frac{1}{2}\right)\begin{bmatrix} 1 \\ 1 \end{bmatrix} + \left(-\frac{1}{2}\right)\begin{bmatrix} 1 \\ -1 \end{bmatrix},$$

the first column of $M_{B_2B_1}$ is $\begin{bmatrix} \frac{1}{2} \\ -\frac{1}{2} \end{bmatrix}$.

The second column is found in a similar way. We have

$$T\left(\begin{bmatrix} -1 \\ 1 \end{bmatrix}\right) = \begin{bmatrix} 1 \\ -1 \end{bmatrix},$$

and with respect to B_2 calculate:

$$\begin{bmatrix} 1 \\ -1 \end{bmatrix} = 0\begin{bmatrix} 1 \\ 1 \end{bmatrix} + 1\begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

Hence the second column of $M_{B_2B_1}$ is given by $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$. We thus obtain

$$M_{B_2B_1} = \begin{bmatrix} \frac{1}{2} & 0 \\ -\frac{1}{2} & 1 \end{bmatrix}$$

We can verify that this is the correct matrix $M_{B_2B_1}$ on the specific example

$$\vec{v} = \begin{bmatrix} 3 \\ -1 \end{bmatrix}$$

First applying T gives

$$T(\vec{v}) = T\left(\begin{bmatrix} 3 \\ -1 \end{bmatrix}\right) = \begin{bmatrix} -1 \\ 3 \end{bmatrix}$$

and one can compute that

$$C_{B_2}\left(\begin{bmatrix} -1 \\ 3 \end{bmatrix}\right) = \begin{bmatrix} 1 \\ -2 \end{bmatrix}.$$

On the other hand, one compute $C_{B_1}(\vec{v})$ as

$$C_{B_1}\left(\begin{bmatrix} 3 \\ -1 \end{bmatrix}\right) = \begin{bmatrix} 2 \\ -1 \end{bmatrix},$$

and finally applying $M_{B_1B_2}$ gives

$$\begin{bmatrix} \frac{1}{2} & 0 \\ -\frac{1}{2} & 1 \end{bmatrix}\begin{bmatrix} 2 \\ -1 \end{bmatrix} = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$$

as above.

We see that the same vector results from either method, as suggested by Theorem 6.8.2.

If the bases B_1 and B_2 are equal, say B, then we write M_B instead of M_{BB}. The following example illustrates how to compute such a matrix. Note that this is what we did earlier when we considered only $B_1 = B_2$ to be the standard basis.

Example 6.8.3: Matrix of a Linear Transformation with respect to an Arbitrary

Consider the basis B of $\mathbb{R}^3$ given by

$$B = \{\vec{v}_1, \vec{v}_2, \vec{v}_3\} = \left\{\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix}\right\}$$

And let $T : \mathbb{R}^3 \mapsto \mathbb{R}^3$ be the linear transformation defined on B as:

$$T\begin{bmatrix}1\\0\\1\end{bmatrix} = \begin{bmatrix}1\\-1\\1\end{bmatrix}, T\begin{bmatrix}1\\1\\1\end{bmatrix} = \begin{bmatrix}1\\2\\-1\end{bmatrix}, T\begin{bmatrix}-1\\1\\0\end{bmatrix} = \begin{bmatrix}0\\1\\1\end{bmatrix}$$

1. Find the matrix M_B of T relative to the basis B.
2. Then find the usual matrix of T with respect to the standard basis of $\mathbb{R}^3$.

Solution

Equation (6.8.1) gives $C_B T = M_B C_B$, and thus $M_B = C_B T C_B^{-1}$.

Now $C_B(\vec{v}_i) = \vec{e}_i$, so the matrix of C_B^{-1} (with respect to the standard basis) is given by

$$\left[C_B^{-1}(\vec{e}_1)\ \ C_B^{-1}(\vec{e}_2)\ \ C_B^{-1}(\vec{e}_2)\right] = \begin{bmatrix}1&1&-1\\0&1&1\\1&1&0\end{bmatrix}$$

Moreover the matrix of TC_B^{-1} is given by

$$\left[TC_B^{-1}(\vec{e}_1)\ \ TC_B^{-1}(\vec{e}_2)\ \ TC_B^{-1}(\vec{e}_2)\right] = \begin{bmatrix}1&1&0\\-1&2&1\\1&-1&1\end{bmatrix}$$

Thus

$$\begin{aligned} M_B &= C_B T C_B^{-1} = [C_B^{-1}]^{-1}[TC_B^{-1}] \\ &= \begin{bmatrix}1&1&-1\\0&1&1\\1&1&0\end{bmatrix}^{-1}\begin{bmatrix}1&1&0\\-1&2&1\\1&-1&1\end{bmatrix} \\ &= \begin{bmatrix}2&-5&1\\-1&4&0\\0&-2&1\end{bmatrix} \end{aligned}$$

Consider how this works. Let $\vec{b} = \begin{bmatrix}b_1\\b_2\\b_3\end{bmatrix}$ be an arbitrary vector in $\mathbb{R}^3$.

Apply C_B^{-1} to $\vec{b}$ to get

$$b_1\begin{bmatrix}1\\0\\1\end{bmatrix} + b_2\begin{bmatrix}1\\1\\1\end{bmatrix} + b_3\begin{bmatrix}-1\\1\\0\end{bmatrix}$$

Apply T to this linear combination to obtain

$$b_1\begin{bmatrix}1\\-1\\1\end{bmatrix} + b_2\begin{bmatrix}1\\2\\-1\end{bmatrix} + b_3\begin{bmatrix}0\\1\\1\end{bmatrix} = \begin{bmatrix}b_1+b_2\\-b_1+2b_2+b_3\\b_1-b_2+b_3\end{bmatrix}$$

Now take the matrix M_B of the transformation (as found above) and multiply it by $\vec{b}$.

$$\begin{bmatrix}2&-5&1\\-1&4&0\\0&-2&1\end{bmatrix}\begin{bmatrix}b_1\\b_2\\b_3\end{bmatrix} = \begin{bmatrix}2b_1-5b_2+b_3\\-b_1+4b_2\\-2b_2+b_3\end{bmatrix}$$

Is this the coordinate vector of the above relative to the given basis? We check as follows.

$$(2b_1-5b_2+b_3)\begin{bmatrix}1\\0\\1\end{bmatrix} + (-b_1+4b_2)\begin{bmatrix}1\\1\\1\end{bmatrix} + (-2b_2+b_3)\begin{bmatrix}-1\\1\\0\end{bmatrix}$$

$$= \begin{bmatrix} b_1 + b_2 \\ -b_1 + 2b_2 + b_3 \\ b_1 - b_2 + b_3 \end{bmatrix}$$

You see it is the same thing.

Now lets find the matrix of T with respect to the standard basis. Let A be this matrix. That is, multiplication by A is the same as doing T. Thus

$$A \begin{bmatrix} 1 & 1 & -1 \\ 0 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 \\ -1 & 2 & 1 \\ 1 & -1 & 1 \end{bmatrix}$$

Hence

$$A = \begin{bmatrix} 1 & 1 & 0 \\ -1 & 2 & 1 \\ 1 & -1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & -1 \\ 0 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix}^{-1} = \begin{bmatrix} 0 & 0 & 1 \\ 2 & 3 & -3 \\ -3 & -2 & 4 \end{bmatrix}$$

Of course this is a very different matrix than the matrix of the linear transformation with respect to the non standard basis.

Answers

Lemma 6.8.1**: Mapping of a Basis**

First, suppose $T : \mathbb{R}^n \mapsto \mathbb{R}^n$ is a linear transformation which is one to one and onto. Let $\{\vec{v}_1, \cdots, \vec{v}_n\}$ be a basis for $\mathbb{R}^n$. We wish to show that $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ is also a basis for $\mathbb{R}^n$.

First consider why it is linearly independent. Suppose $\sum_{k=1}^n a_k T(\vec{v}_k) = \vec{0}$. Then by linearity we have $T\left(\sum_{k=1}^n a_k \vec{v}_k\right) = \vec{0}$ and since T is one to one, it follows that $\sum_{k=1}^n a_k \vec{v}_k = \vec{0}$. This requires that each $a_k = 0$ because $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is independent, and it follows that $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ is linearly independent.

Next take $\vec{w} \in \mathbb{R}^n$. Since T is onto, there exists $\vec{v} \in \mathbb{R}^n$ such that $T(\vec{v}) = \vec{w}$. Since $\{\vec{v}_1, \cdots, \vec{v}_n\}$ is a basis, in particular it is a spanning set and there are scalars b_k such that $T\left(\sum_{k=1}^n b_k \vec{v}_k\right) = T(\vec{v}) = \vec{w}$. Therefore $\vec{w} = \sum_{k=1}^n b_k T(\vec{v}_k)$ which is in the $\operatorname{span}\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$. Therefore, $\{T(\vec{v}_1), \cdots, T(\vec{v}_n)\}$ is a basis as claimed.

Suppose now that $T : \mathbb{R}^n \mapsto \mathbb{R}^n$ is a linear transformation such that $T(\vec{v}_i) = \vec{w}_i$ where $\{\vec{v}_1, \cdots, \vec{v}_n\}$ and $\{\vec{w}_1, \cdots, \vec{w}_n\}$ are two bases for $\mathbb{R}^n$.

To show that T is one to one, let $T\left(\sum_{k=1}^n c_k \vec{v}_k\right) = \vec{0}$. Then $\sum_{k=1}^n c_k T(\vec{v}_k) = \sum_{k=1}^n c_k \vec{w}_k = \vec{0}$. It follows that each $c_k = 0$ because it is given that $\{\vec{w}_1, \cdots, \vec{w}_n\}$ is linearly independent. Hence $T\left(\sum_{k=1}^n c_k \vec{v}_k\right) = \vec{0}$ implies that $\sum_{k=1}^n c_k \vec{v}_k = \vec{0}$ and so T is one to one.

To show that T is onto, let $\vec{w}$ be an arbitrary vector in $\mathbb{R}^n$. This vector can be written as $\vec{w} = \sum_{k=1}^n d_k \vec{w}_k = \sum_{k=1}^n d_k T(\vec{v}_k) = T\left(\sum_{k=1}^n d_k \vec{v}_k\right)$. Therefore, T is also onto.

Theorem 6.8.2**: The Matrix of a Linear**

The above equation (6.8.1) can be represented by the following diagram.

$$\begin{array}{ccc} & T & \\ \mathbb{R}^n & \rightarrow & \mathbb{R}^m \\ C_{B_1} \downarrow & \circ & \downarrow C_{B_2} \\ \mathbb{R}^n & \rightarrow & \mathbb{R}^m \\ & M_{B_2 B_1} & \end{array}$$

Since C_{B_1} is an isomorphism, then the matrix we are looking for is the matrix of the linear transformation

$$C_{B_2} T C_{B_1}^{-1} : \mathbb{R}^n \mapsto \mathbb{R}^m.$$

By Theorem 5.2.2, the columns are given by the image of the standard basis $\{\vec{e}_1, \vec{e}_2, \cdots, \vec{e}_n\}$. But since $C_{B_1}^{-1}(\vec{e}_i) = \vec{v}_i$, we readily obtain that

$$\begin{aligned} M_{B_2 B_1} &= \left[C_{B_2} T C_{B_1}^{-1}(\vec{e}_1) \;\; C_{B_2} T C_{B_1}^{-1}(\vec{2}_2) \;\; \cdots \;\; C_{B_2} T C_{B_1}^{-1}(\vec{e}_n)\right] \\ &= \left[C_{B_2}(T(\vec{v}_1)) \;\; C_{B_2}(T(\vec{v}_2)) \;\; \cdots \;\; C_{B_2}(T(\vec{v}_n))\right] \end{aligned}$$

and this completes the proof.

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6.9: The General Solution of a Linear System

Outcomes

A. Use linear transformations to determine the particular solution and general solution to a system of equations.
B. Find the kernel of a linear transformation.

Recall the definition of a linear transformation discussed above. T is a **linear transformation** if whenever $\vec{x}, \vec{y}$ are vectors and k, p are scalars,

$$T\left(k\vec{x}+p\vec{y}\right)=kT\left(\vec{x}\right)+pT\left(\vec{y}\right)$$

Thus linear transformations distribute across addition and pass scalars to the outside.

It turns out that we can use linear transformations to solve linear systems of equations. Indeed given a system of linear equations of the form $A\vec{x}=\vec{b}$, one may rephrase this as $T(\vec{x})=\vec{b}$ where T is the linear transformation T_A induced by the coefficient matrix A. With this in mind consider the following definition.

Definition 6.9.1: Particular Solution of a System of Equations

Suppose a linear system of equations can be written in the form

$$T\left(\vec{x}\right)=\vec{b}$$

If $T\left(\vec{x}_p\right)=\vec{b}$, then $\vec{x}_p$ is called a **particular solution** of the linear system.

Recall that a system is called homogeneous if every equation in the system is equal to 0. Suppose we represent a homogeneous system of equations by $T\left(\vec{x}\right)=0$. It turns out that the $\vec{x}$ for which $T\left(\vec{x}\right)=0$ are part of a special set called the **null space** of T. We may also refer to the null space as the **kernel** of T, and we write $ker\left(T\right)$.

Consider the following definition.

Definition 6.9.2: Null Space or Kernel of a Linear Transformation

Let T be a linear transformation. Define

$$\ker\left(T\right)=\left\{\vec{x}:T\left(\vec{x}\right)=\vec{0}\right\}$$

The kernel, $\ker\left(T\right)$ consists of the set of all vectors $\vec{x}$ for which $T(\vec{x})=\vec{0}$. This is also called the **null space** of T.

We may also refer to the kernel of T as the **solution space** of the equation $T\left(\vec{x}\right)=\vec{0}$.

Consider the following example.

Example 6.9.1: The Kernel of the Derivative

Let $\frac{d}{dx}$ denote the linear transformation defined on f, the functions which are defined on $\mathbb{R}$ and have a continuous derivative. Find $\ker\left(\frac{d}{dx}\right)$.

Solution

The example asks for functions f which the property that $\frac{df}{dx} = 0$. As you may know from calculus, these functions are the constant functions. Thus $\ker\left(\frac{d}{dx}\right)$ is the set of constant functions.

Definition 6.9.2 states that $\ker(T)$ is the set of solutions to the equation,

$$T(\vec{x}) = \vec{0}$$

Since we can write $T(\vec{x})$ as $A\vec{x}$, you have been solving such equations for quite some time.

We have spent a lot of time finding solutions to systems of equations in general, as well as homogeneous systems. Suppose we look at a system given by $A\vec{x} = \vec{b}$, and consider the related homogeneous system. By this, we mean that we replace $\vec{b}$ by $\vec{0}$ and look at $A\vec{x} = \vec{0}$. It turns out that there is a very important relationship between the solutions of the original system and the solutions of the associated homogeneous system. In the following theorem, we use linear transformations to denote a system of equations. Remember that $T(\vec{x}) = A\vec{x}$.

Theorem 6.9.1: Particular Solution and General Solution

Suppose $\vec{x}_p$ is a solution to the linear system given by ,

$$T(\vec{x}) = \vec{b}$$

Then if $\vec{y}$ is any other solution to $T(\vec{x}) = \vec{b}$, there exists $\vec{x}_0 \in \ker(T)$ such that

$$\vec{y} = \vec{x}_p + \vec{x}_0$$

Hence, every solution to the linear system can be written as a sum of a particular solution, $\vec{x}_p$, and a solution $\vec{x}_0$ to the associated homogeneous system given by $T(\vec{x}) = \vec{0}$.

Proof available at the end of this section.

Sometimes people remember the above theorem in the following form. The solutions to the system $T(\vec{x}) = \vec{b}$ are given by $\vec{x}_p + \ker(T)$ where $\vec{x}_p$ is a particular solution to $T(\vec{x}) = \vec{b}$.

For now, we have been speaking about the kernel or null space of a linear transformation T. However, we know that every linear transformation T is determined by some matrix A. Therefore, we can also speak about the null space of a matrix. Consider the following example.

Example 6.9.2: The Null Space of a Matrix

Let

$$A = \begin{bmatrix} 1 & 2 & 3 & 0 \\ 2 & 1 & 1 & 2 \\ 4 & 5 & 7 & 2 \end{bmatrix}$$

Find $\text{null}(A)$. Equivalently, find the solutions to the system of equations $A\vec{x} = \vec{0}$.

Solution

We are asked to find $\left\{\vec{x} : A\vec{x} = \vec{0}\right\}$. In other words we want to solve the system, $A\vec{x} = \vec{0}$. Let $\vec{x} = \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix}$. Then this amounts to solving

$$\begin{bmatrix} 1 & 2 & 3 & 0 \\ 2 & 1 & 1 & 2 \\ 4 & 5 & 7 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

This is the linear system

$$\begin{aligned} x + 2y + 3z &= 0 \\ 2x + y + z + 2w &= 0 \\ 4x + 5y + 7z + 2w &= 0 \end{aligned}$$

To solve, set up the augmented matrix and row reduce to find the reduced row-echelon form.

$$\begin{bmatrix} 1 & 2 & 3 & 0 & 0 \\ 2 & 1 & 1 & 2 & 0 \\ 4 & 5 & 7 & 2 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & -\frac{1}{3} & \frac{4}{3} & 0 \\ 0 & 1 & \frac{5}{3} & -\frac{2}{3} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

This yields $x = \frac{1}{3}z - \frac{4}{3}w$ and $y = \frac{2}{3}w - \frac{5}{3}z$. Since $\text{null}\,(A)$ consists of the solutions to this system, it consists vectors of the form,

$$\begin{bmatrix} \frac{1}{3}z - \frac{4}{3}w \\ \frac{2}{3}w - \frac{5}{3}z \\ z \\ w \end{bmatrix} = z \begin{bmatrix} \frac{1}{3} \\ -\frac{5}{3} \\ 1 \\ 0 \end{bmatrix} + w \begin{bmatrix} -\frac{4}{3} \\ \frac{2}{3} \\ 0 \\ 1 \end{bmatrix}$$

Consider the following example.

Example 6.9.3: A General Solution

The **general solution** of a linear system of equations is the set of all possible solutions. Find the general solution to the linear system,

$$\begin{bmatrix} 1 & 2 & 3 & 0 \\ 2 & 1 & 1 & 2 \\ 4 & 5 & 7 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 9 \\ 7 \\ 25 \end{bmatrix}$$

given that $\begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 2 \\ 1 \end{bmatrix}$ is one solution.

Solution

Note the matrix of this system is the same as the matrix in Example 6.9.2. Therefore, from Theorem 6.9.1, you will obtain all solutions to the above linear system by adding a particular solution $\vec{x}_p$ to the solutions of the associated homogeneous system, $\vec{x}$. One particular solution is given above by

$$\vec{x}_p = \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 2 \\ 1 \end{bmatrix}$$

Using this particular solution along with the solutions found in Example 6.9.2, we obtain the following solutions,

$$z\begin{bmatrix} \frac{1}{3} \\ -\frac{5}{3} \\ 1 \\ 0 \end{bmatrix} + w\begin{bmatrix} -\frac{4}{3} \\ \frac{2}{3} \\ 0 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ 2 \\ 1 \end{bmatrix}$$

Hence, any solution to the above linear system is of this form.

Answers

Theorem $6.9.1$**: Particular Solution and General Solution**

Consider $\vec{y} - \vec{x}_p = \vec{y} + (-1)\vec{x}_p$. Then $T(\vec{y} - \vec{x}_p) = T(\vec{y}) - T(\vec{x}_p)$. Since $\vec{y}$ and $\vec{x}_p$ are both solutions to the system, it follows that $T(\vec{y}) = \vec{b}$ and $T(\vec{x}_p) = \vec{b}$. Hence, $T(\vec{y}) - T(\vec{x}_p) = \vec{b} - \vec{b} = \vec{0}$. Let $\vec{x}_0 = \vec{y} - \vec{x}_p$. Then, $T(\vec{x}_0) = \vec{0}$ so $\vec{x}_0$ is a solution to the associated homogeneous system and so is in $\ker(T)$.

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6.10: SUPPLEMENTARY NOTES - MORE ON LINEAR TRANSFORMATIONS

Linear Transformations can be fun! The image on the title page of this text represents two linear transformations in the plane. The two linear transformations together created the artwork.

The differential and integral operators of calculus can be regarded as linear transformations!

6.10.1: Examples and Elementary Properties

6.10.1E: Examples and Elementary Properties Exercises

6.10.2: Kernel and Image of a Linear Transformation

6.10.2E: Kernel and Image of a Linear Transformation Exercises

6.10.3: Isomorphisms and Composition

6.10.3E: Isomorphisms and Composition Exercises

6.10.4: A Theorem about Differential Equations

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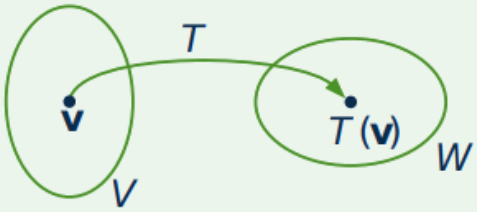
6.10.1: EXAMPLES AND ELEMENTARY PROPERTIES

Definition: Linear Transformations of Vector Spaces

If V and W are two vector spaces, a function $T : V \to W$ is called a **linear transformation** if it satisfies the following axioms.

$$\begin{array}{lll} \text{T1.} & T(\mathbf{v} + \mathbf{v}_1) = T(\mathbf{v}) + T(\mathbf{v}_1) & \text{for all } \mathbf{v} \text{ and } \mathbf{v}_1 \text{ in } V. \\ \text{T2.} & T(r\mathbf{v}) = rT(\mathbf{v}) & \text{for all } \mathbf{v} \text{ in } V \text{ and } r \text{ in } \mathbb{R}. \end{array}$$

A linear transformation $T : V \to V$ is called a **linear operator** on V. The situation can be visualized as in the diagram.



Axiom T1 is just the requirement that T *preserves* vector addition. It asserts that the result $T(\mathbf{v} + \mathbf{v}_1)$ of adding $\mathbf{v}$ and $\mathbf{v}_1$ first and then applying T is the same as applying T first to get $T(\mathbf{v})$ and $T(\mathbf{v}_1)$ and then adding. Similarly, axiom T2 means that T *preserves* scalar multiplication. Note that, even though the additions in axiom T1 are both denoted by the same symbol $+$, the addition on the left forming $\mathbf{v} + \mathbf{v}_1$ is carried out in V, whereas the addition $T(\mathbf{v}) + T(\mathbf{v}_1)$ is done in W. Similarly, the scalar multiplications $r\mathbf{v}$ and $rT(\mathbf{v})$ in axiom T2 refer to the spaces V and W, respectively.

We have already seen many examples of linear transformations $T : \mathbb{R}^n \to \mathbb{R}^m$. In fact, writing vectors in $\mathbb{R}^n$ as columns, Theorem2.6.2 shows that, for each such T, there is an $m \times n$ matrix A such that $T(\mathbf{x}) = A\mathbf{x}$ for every $\mathbf{x}$ in $\mathbb{R}^n$. Moreover, the matrix A is given by $A = \left[\begin{array}{cccc} T(\mathbf{e}_1) & T(\mathbf{e}_2) & \cdots & T(\mathbf{e}_n) \end{array} \right]$ where $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ is the standard basis of $\mathbb{R}^n$. We denote this transformation by $T_A : \mathbb{R}^n \to \mathbb{R}^m$, defined by

$$T_A(\mathbf{x}) = A\mathbf{x} \quad \text{for all } \mathbf{x} \text{ in } \mathbb{R}^n$$

Example 6.10.1.1 lists three important linear transformations that will be referred to later. The verification of axioms T1 and T2 is left to the reader.

Example 6.10.1.1

If V and W are vector spaces, the following are linear transformations:

Identify operator $V \to V$ $\quad 1_V : V \to V$ $\quad$ where $1_V(\mathbf{v}) = \mathbf{v}$ for all $\mathbf{v}$ in V Zero transformation $V \to W$ $\quad 0 : V \to W$ $\quad$ where $0(\mathbf{v}) = \mathbf{0}$ for all $\mathbf{v}$ in V Scalar operator $V \to V$ $\quad a : V \to V$ $\quad$ where $a(\mathbf{v}) = a\mathbf{v}$ for all $\mathbf{v}$ in V (Here a is any real number.)

The symbol 0 will be used to denote the zero transformation from V to W for *any* spaces V and W. It was also used earlier to denote the zero function $[a, b] \to \mathbb{R}$.

The next example gives two important transformations of matrices. Recall that the trace $tr\mathbf{A}$ of an $n \times n$ matrix A is the sum of the entries on the main diagonal.

Example 6.10.1.2

Show that the transposition and trace are linear transformations. More precisely,

$$\begin{array}{ll} R : \mathbf{M}_{mn} \to \mathbf{M}_{nm} & \text{where } R(A) = A^T \text{ for all } A \text{ in } \mathbf{M}_{mn} \\ S : \mathbf{M}_{mn} \to \mathbb{R} & \text{where } S(A) = tr\mathbf{A} \text{ for all } A \text{ in } \mathbf{M}_{nn} \end{array}$$

are both linear transformations.

Solution

Axioms T1 and T2 for transposition are $(A+B)^T = A^T + B^T$ and $(rA)^T = r(A^T)$, respectively (using Theorem 2.1.2). The verifications for the trace are left to the reader.

Example 6.10.1.3

If a is a scalar, define $E_a : \mathbf{P}_n \to \mathbb{R}$ by $E_a(p) = p(a)$ for each polynomial p in $\mathbf{P}_n$. Show that E_a is a linear transformation (called **evaluation** at a).

Solution

If p and q are polynomials and r is in $\mathbb{R}$, we use the fact that the sum $p+q$ and scalar product rp are defined as for functions:

$$(p+q)(x) = p(x) + q(x) \quad \text{and} \quad (rp)(x) = rp(x)$$

for all x. Hence, for all p and q in $\mathbf{P}_n$ and all r in $\mathbb{R}$:

$$\begin{array}{l} E_a(p+q) = (p+q)(a) = p(a) + q(a) = E_a(p) + E_a(q), \quad \text{and} \\ E_a(rp) = (rp)(a) = rp(a) = rE_a(p). \end{array}$$

Hence E_a is a linear transformation.

The next example involves some calculus.

Example 6.10.1.4

Show that the differentiation and integration operations on $\mathbf{P}_n$ are linear transformations. More precisely,

$$\begin{array}{ll} D : \mathbf{P}_n \to \mathbf{P}_{n-1} & \text{where } D[p(x)] = p'(x) \text{ for all } p(x) \text{ in } \mathbf{P}_n \\ I : \mathbf{P}_n \to \mathbf{P}_{n+1} & \text{where } I[p(x)] = \displaystyle\int_0^x p(t)dt \text{ for all } p(x) \text{ in } \mathbf{P}_n \end{array}$$

are linear transformations.

Solution

These restate the following fundamental properties of differentiation and integration.

$$[p(x)+q(x)]' = p'(x) + q'(x) \quad \text{and} \quad [rp(x)]' = (rp)'(x)$$

$$\int_0^x [p(t)+q(t)]\,dt = \int_0^x p(t)dt + \int_0^x q(t)dt \quad \text{and} \quad \int_0^x rp(t)dt = r\int_0^x p(t)dt$$

The next theorem collects three useful properties of *all* linear transformations. They can be described by saying that, in addition to preserving addition and scalar multiplication (these are the axioms), linear transformations preserve the zero vector, negatives, and linear combinations.

Theorem 7.1.1

Let $T : V \to W$ be a linear transformation.

1. $T(\mathbf{0}) = \mathbf{0}$.
2. $T(-\mathbf{v}) = -T(\mathbf{v})$ for all $\mathbf{v}$ in V.
3. $T(r_1\mathbf{v}_1 + r_2\mathbf{v}_2 + \cdots + r_k\mathbf{v}_k) = r_1T(\mathbf{v}_1) + r_2T(\mathbf{v}_2) + \cdots + r_kT(\mathbf{v}_k)$ for all $\mathbf{v}_i$ in V and all r_i in $\mathbb{R}$.

Proof

$T(\mathbf{0}) = T(0\mathbf{v}) = 0T(\mathbf{v}) = \mathbf{0}$ for any $\mathbf{v}$ in V.

$T(-\mathbf{v}) = T[(-1)\mathbf{v}] = (-1)T(\mathbf{v}) = -T(\mathbf{v})$ for any $\mathbf{v}$ in V.

The proof of Theorem 2.6.1 goes through.

□

The ability to use the last part of Theorem 7.1.1 effectively is vital to obtaining the benefits of linear transformations. Example 7.1.5 and Theorem 7.1.2 provide illustrations.

Example 7.1.5

Let $T : V \to W$ be a linear transformation. If $T(\mathbf{v} - 3\mathbf{v}_1) = \mathbf{w}$ and $T(2\mathbf{v} - \mathbf{v}_1) = \mathbf{w}_1$, find $T(\mathbf{v})$ and $T(\mathbf{v}_1)$ in terms of $\mathbf{w}$ and $\mathbf{w}_1$.

Solution

The given relations imply that

$$T(\mathbf{v}) - 3T(\mathbf{v}_1) = \mathbf{w}$$
$$2T(\mathbf{v}) - T(\mathbf{v}_1) = \mathbf{w}_1$$

by Theorem 7.1.1. Subtracting twice the first from the second gives $T(\mathbf{v}_1) = \frac{1}{5}(\mathbf{w}_1 - 2\mathbf{w})$. Then substitution gives $T(\mathbf{v}) = \frac{1}{5}(3\mathbf{w}_1 - \mathbf{w})$.

The full effect of property (3) in Theorem 7.1.1 is this: If $T : V \to W$ is a linear transformation and $T(\mathbf{v}_1), T(\mathbf{v}_2), \ldots, T(\mathbf{v}_n)$ are known, then $T(\mathbf{v})$ can be computed for *every* vector $\mathbf{v}$ in $span\{\mathbf{v_1}, \mathbf{v_2}, \ldots, \mathbf{v_n}\}$. In particular, if $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$ spans V, then $T(\mathbf{v})$ is determined for all $\mathbf{v}$ in V by the choice of $T(\mathbf{v}_1), T(\mathbf{v}_2), \ldots, T(\mathbf{v}_n)$. The next theorem states this somewhat differently. As for functions in general, two linear transformations $T : V \to W$ and $S : V \to W$ are called **equal** (written $T = S$) if they have the same **action**; that is, if $T(\mathbf{v}) = S(\mathbf{v})$ for all $\mathbf{v}$ in V.

Theorem 7.1.2

Let $T : V \to W$ and $S : V \to W$ be two linear transformations. Suppose that $V = span\{\mathbf{v_1}, \mathbf{v_2}, \ldots, \mathbf{v_n}\}$. If T$(\mathbf{v}_i) = S(\mathbf{v}_i)$ for each i, then $T = S$.

Proof

If $\mathbf{v}$ is any vector in $V = pan\{\mathbf{v_1}, \mathbf{v_2}, \ldots, \mathbf{v_n}\}$, write $\mathbf{v} = a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + \cdots + a_n\mathbf{v}_n$ where each a_i is in $\mathbb{R}$. Since $T(\mathbf{v}_i) = S(\mathbf{v}_i)$ for each i, Theorem 7.1.1 gives

$$\begin{aligned} T(\mathbf{v}) &= T(a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + \cdots + a_n\mathbf{v}_n) \\ &= a_1T(\mathbf{v}_1) + a_2T(\mathbf{v}_2) + \cdots + a_nT(\mathbf{v}_n) \\ &= a_1S(\mathbf{v}_1) + a_2S(\mathbf{v}_2) + \cdots + a_nS(\mathbf{v}_n) \\ &= S(a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + \cdots + a_n\mathbf{v}_n) \\ &= S(\mathbf{v}) \end{aligned}$$

Since $\mathbf{v}$ was arbitrary in V, this shows that $T = S$.

Example 6.10.1.6

Let $V = span\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$. Let $T : V \to W$ be a linear transformation. If $T(\mathbf{v}_1) = \cdots = T(\mathbf{v}_n) = \mathbf{0}$, show that $T = 0$, the zero transformation from V to W.

Solution

The zero transformation $0 : V \to W$ is defined by $0(\mathbf{v}) = \mathbf{0}$ for all $\mathbf{v}$ in V (Example 7.1.1), so $T(\mathbf{v}_i) = 0(\mathbf{v}_i)$ holds for each i. Hence $T = 0$ by Theorem 7.1.2.

Theorem 7.1.2 can be expressed as follows: If we know what a linear transformation $T : V \to W$ does to each vector in a spanning set for V, then we know what T does to *every* vector in V. If the spanning set is a basis, we can say much more.

Theorem 6.10.1.3

Let V and W be vector spaces and let $\{\mathbf{b}_1, \mathbf{b}_2, \ldots, \mathbf{b}_n\}$ be a basis of V. Given any vectors $\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_n$ in W (they need not be distinct), there exists a unique linear transformation $T : V \to W$ satisfying $T(\mathbf{b}_i) = \mathbf{w}_i$ for each $i = 1, 2, \ldots, n$. In fact, the action of T is as follows:

Given $\mathbf{v} = v_1\mathbf{b}_1 + v_2\mathbf{b}_2 + \cdots + v_n\mathbf{b}_n$ in V, v_i in $\mathbb{R}$, then

$$T(\mathbf{v}) = T(v_1\mathbf{b}_1 + v_2\mathbf{b}_2 + \cdots + v_n\mathbf{b}_n) = v_1\mathbf{w}_1 + v_2\mathbf{w}_2 + \cdots + v_n\mathbf{w}_n.$$

Proof

If a transformation T *does* exist with $T(\mathbf{b}_i) = \mathbf{w}_i$ for each i, and if S is any other such transformation, then $T(\mathbf{b}_i) = \mathbf{w}_i = S(\mathbf{b}_i)$ holds for each i, so $S = T$ by Theorem 7.1.2. Hence T is unique if it exists, and it remains to show that there really is such a linear transformation. Given $\mathbf{v}$ in V, we must specify $T(\mathbf{v})$ in W. Because $\{\mathbf{b}_1, \ldots, \mathbf{b}_n\}$ is a basis of V, we have $\mathbf{v} = v_1\mathbf{b}_1 + \cdots + v_n\mathbf{b}_n$, where $v_1, \ldots, v_n$ are *uniquely* determined by $\mathbf{v}$ (this is Theorem 6.3.1). Hence we may define $T : V \to W$ by

$$T(\mathbf{v}) = T(v_1\mathbf{b}_1 + v_2\mathbf{b}_2 + \cdots + v_n\mathbf{b}_n) = v_1\mathbf{w}_1 + v_2\mathbf{w}_2 + \cdots + v_n\mathbf{w}_n$$

for all $\mathbf{v} = v_1\mathbf{b}_1 + \cdots + v_n\mathbf{b}_n$ in V. This satisfies $T(\mathbf{b}_i) = \mathbf{w}_i$ for each i; the verification that T is linear is left to the reader.

□

This theorem shows that linear transformations can be defined almost at will: Simply specify where the basis vectors go, and the rest of the action is dictated by the linearity. Moreover, Theorem 7.1.2 shows that deciding whether two linear transformations are equal comes down to determining whether they have the same effect on the basis vectors. So, given a basis $\{\mathbf{b}_1, \ldots, \mathbf{b}_n\}$ of a vector space V, there is a different linear transformation $V \to W$ for every ordered selection $\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_n$ of vectors in W (not necessarily distinct).

Example 6.10.1.7

Find a linear transformation $T : \mathbf{P}_2 \to \mathbf{M}_{22}$ such that

$$T(1+x)=\begin{bmatrix}1&0\\0&0\end{bmatrix},\quad T(x+x^2)=\begin{bmatrix}0&1\\1&0\end{bmatrix},\quad \text{and}\quad T(1+x^2)=\begin{bmatrix}0&0\\0&1\end{bmatrix}.$$

Solution

The set $\{1+x, x+x^2, 1+x^2\}$ is a basis of $\mathbf{P}_2$, so every vector $p=a+bx+cx^2$ in $\mathbf{P}_2$ is a linear combination of these vectors. In fact

$$p(x)=\frac{1}{2}(a+b-c)(1+x)+\frac{1}{2}(-a+b+c)(x+x^2)+\frac{1}{2}(a-b+c)(1+x^2)$$

Hence Theorem 7.1.3 gives

$$\begin{aligned}T\left[p(x)\right]&=\frac{1}{2}(a+b-c)\begin{bmatrix}1&0\\0&0\end{bmatrix}+\frac{1}{2}(-a+b+c)\begin{bmatrix}0&1\\1&0\end{bmatrix}+\frac{1}{2}(a-b+c)\begin{bmatrix}0&0\\0&1\end{bmatrix}\\&=\frac{1}{2}\begin{bmatrix}a+b-c&-a+b+c\\-a+b+c&a-b+c\end{bmatrix}\end{aligned}$$

6.10.1E: Examples and Elementary Properties Exercises

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6.10.1E: Examples and Elementary Properties Exercises

Exercise 6.10.1E.1

Show that each of the following functions is a linear transformation. $T : \mathbb{R}^2 \to \mathbb{R}^2$; $T(x, y) = (x, -y)$ (reflection in the x axis)

a. $T : \mathbb{R}^2 \to \mathbb{R}^2; T(x, y) = (x, -y)$ (reflection in the x axis)
b. $T : \mathbb{R}^3 \to \mathbb{R}^3; T(x, y, z) = (x, y, -z)$ (reflection in the $x - y$ plane)
c. $T : \mathbb{C} \to \mathbb{C}; T(z) = \bar{z}$ (conjugation)
d. $T : \mathbf{M}_{mn} \to \mathbf{M}_{kl}; T(A) = PAQ, P$ a $k \times m$ matrix, Q an $n \times l$ matrix, both fixed
e. $T : \mathbf{M}_{nn} \to \mathbf{M}_{nn}; T(A) = A^T + A$
f. $T : \mathbf{P}_n \to \mathbb{R}; T[p(x)] = p(0)$
g. $T : \mathbf{P}_n \to \mathbb{R}; T\left(r_0 + r_1 x + \ldots + r_n x^n\right) = r_n$
h. $T : \mathbb{R}^n \to \mathbb{R}; T(\mathbf{x}) = \mathbf{x} \cdot \mathbf{z}, \mathbf{z}$ a fixed vector in $\mathbb{R}^n$
i. $T : \mathbf{P}_n \to \mathbf{P}_n; T[p(x)] = p(x + 1)$
j. $T : \mathbb{R}^n \to V; T\left(r_1, \ldots, r_n\right) = r_1 \mathbf{e}_1 + \ldots + r_n \mathbf{e}_n$ where $\{\mathbf{e}_1, \ldots, \mathbf{e}_n\}$ is a fixed basis of V.
k. $T : V \to \mathbb{R}; T\left(r_1 \mathbf{e}_1 + \ldots + r_n \mathbf{e}_n\right) = r_1$, where $\{\mathbf{e}_1, \ldots, \mathbf{e}_n\}$ is a fixed basis of V

Answer available at the end of this section.

Exercise 6.10.1E.2

In each case, show that T is *not* a linear transformation.

a. $T : \mathbf{M}_{nn} \to \mathbb{R}$; $T(A) = \det A$
b. $T : \mathbf{M}_{nm} \to \mathbb{R}$; $T(A) = rank\mathbf{A}$
c. $T : \mathbb{R} \to \mathbb{R}$; $T(x) = x^2$
d. $T : V \to V$; $T(\mathbf{v}) = \mathbf{v} + \mathbf{u}$ where $\mathbf{u} \neq \mathbf{0}$ is a fixed vector in V (T is called the **translation** by $\mathbf{u}$)

Answer available at the end of this section.

Exercise 6.10.1E.3

In each case, assume that T is a linear transformation.

a. If $T : V \to \mathbb{R}$ and $T(\mathbf{v}_1) = 1, T(\mathbf{v}_2) = -1$, find $T(3\mathbf{v}_1 - 5\mathbf{v}_2)$.
b. If $T : V \to \mathbb{R}$ and $T(\mathbf{v}_1) = 2, T(\mathbf{v}_2) = -3$, find $T(3\mathbf{v}_1 + 2\mathbf{v}_2)$.
c. If $T : \mathbb{R}^2 \to \mathbb{R}^2$ and $T \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, T \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$, find $T \begin{bmatrix} -1 \\ 3 \end{bmatrix}$.
d. If $T : \mathbb{R}^2 \to \mathbb{R}^2$ and $T \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, T \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$, find $T \begin{bmatrix} 1 \\ -7 \end{bmatrix}$.
e. If $T : \mathbf{P}_2 \to \mathbf{P}_2$ and $T(x + 1) = x, T(x - 1) = 1, T(x^2) = 0$, find $T(2 + 3x - x^2)$.
f. If $T : \mathbf{P}_2 \to \mathbb{R}$ and $T(x + 2) = 1, T(1) = 5, T(x^2 + x) = 0$, find $T(2 - x + 3x^2)$.

Answer available at the end of this section.

Exercise 6.10.1E.4

In each case, find a linear transformation with the given properties and compute $T(\mathbf{v})$.

a. $T : \mathbb{R}^2 \to \mathbb{R}^3$; $T(1, 2) = (1, 0, 1), T(-1, 0) = (0, 1, 1)$; $\mathbf{v} = (2, 1)$

b. $T : \mathbb{R}^2 \to \mathbb{R}^3$; $T(2,-1) = (1,-1,1)$, $T(1,1) = (0,1,0)$; $\mathbf{v} = (-1,2)$
c. $T : \mathbf{P}_2 \to \mathbf{P}_3$; $T(x^2) = x^3$, $T(x+1) = 0$, $T(x-1) = x$; $\mathbf{v} = x^2 + x + 1$
d. $T : \mathbf{M}_{22} \to \mathbb{R}$; $T\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} = 3$, $T\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = -1$, $T\begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} = 0 = T\begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$; $\mathbf{v} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$

Answer available at the end of this section.

Exercise $6.10.1E.5$

If $T : V \to V$ is a linear transformation, find $T(\mathbf{v})$ and $T(\mathbf{w})$ if:

a. $T(\mathbf{v} + \mathbf{w}) = \mathbf{v} - 2\mathbf{w}$ and $T(2\mathbf{v} - \mathbf{w}) = 2\mathbf{v}$
b. $T(\mathbf{v} + 2\mathbf{w}) = 3\mathbf{v} - \mathbf{w}$ and $T(\mathbf{v} - \mathbf{w}) = 2\mathbf{v} - 4\mathbf{w}$

Answer available at the end of this section.

Example $6.10.1E.6$

If $T : V \to W$ is a linear transformation, show that $T(\mathbf{v} - \mathbf{v}_1) = T(\mathbf{v}) - T(\mathbf{v}_1)$ for all $\mathbf{v}$ and $\mathbf{v}_1$ in V.

Example $6.10.1E.7$

Let $\{\mathbf{e}_1, \mathbf{e}_2\}$ be the standard basis of $\mathbb{R}^2$. Is it possible to have a linear transformation T such that $T(\mathbf{e}_1)$ lies in $\mathbb{R}$ while $T(\mathbf{e}_2)$ lies in $\mathbb{R}^2$? Explain your answer.

Exercise $6.10.1E.8$

Let $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ be a basis of V and let $T : V \to V$ be a linear transformation.

a. If $T(\mathbf{v}_i) = \mathbf{v}_i$ for each i, show that $T = 1_V$.
b. If $T(\mathbf{v}_i) = -\mathbf{v}_i$ for each i, show that $T = -1$ is the scalar operator (see Example 7.1.1).

Answer available at the end of this section.

Example $6.10.1E.9$

If A is an $m \times n$ matrix, let $C_k(A)$ denote column k of A. Show that $C_k : \mathbf{M}_{mn} \to \mathbb{R}^m$ is a linear transformation for each $k = 1, \dots, n$.

Example $6.10.1E.10$

Let $\{\mathbf{e}_1, \dots, \mathbf{e}_n\}$ be a basis of $\mathbb{R}^n$. Given k, $1 \le k \le n$, define $P_k : \mathbb{R}^n \to \mathbb{R}^n$ by $P_k(r_1\mathbf{e}_1 + \cdots + r_n\mathbf{e}_n) = r_k\mathbf{e}_k$. Show that P_k a linear transformation for each k.

Example $6.10.1E.11$

Let $S : V \to W$ and $T : V \to W$ be linear transformations. Given a in $\mathbb{R}$, define functions $(S + T) : V \to W$ and $(aT) : V \to W$ by $(S + T)(\mathbf{v}) = S(\mathbf{v}) + T(\mathbf{v})$ and $(aT)(\mathbf{v}) = aT(\mathbf{v})$ for all $\mathbf{v}$ in V. Show that $S + T$ and aT are linear transformations.

Exercise $6.10.1E.12$

Describe all linear transformations $T : \mathbb{R} \to V$.

Answer available at the end of this section.

Example $6.10.1E.13$

Let V and W be vector spaces, let V be finite dimensional, and let $\mathbf{v} \neq \mathbf{0}$ in V. Given any $\mathbf{w}$ in W, show that there exists a linear transformation $T : V \to W$ with $T(\mathbf{v}) = \mathbf{w}$. [Hint: Theorem 7.1.3 and Theorem 6.4.1.]

Example $6.10.1E.14$

Given $\mathbf{y}$ in $\mathbb{R}^n$, define $S_{\mathbf{y}} : \mathbb{R}^n \to \mathbb{R}$ by $S_{\mathbf{y}}(\mathbf{x}) = \mathbf{x} \cdot \mathbf{y}$ for all $\mathbf{x}$ in $\mathbb{R}^n$ (where $\cdot$ is the dot product introduced in Section 5.3).

a. Show that $S_{\mathbf{y}} : \mathbb{R}^n \to \mathbb{R}$ is a linear transformation for any $\mathbf{y}$ in $\mathbb{R}^n$.
b. Show that every linear transformation $T : \mathbb{R}^n \to \mathbb{R}$ arises in this way; that is, $T = S_{\mathbf{y}}$ for some $\mathbf{y}$ in $\mathbb{R}^n$. [*Hint*: If $\{\mathbf{e}_1, \dots, \mathbf{e}_n\}$ is the standard basis of $\mathbb{R}^n$, write $S_{\mathbf{y}}(\mathbf{e}_i) = y_i$ for each i. Use Theorem 7.1.1.]

Exercise $6.10.1E.15$

Let $T : V \to W$ be a linear transformation.

a. If U is a subspace of V, show that $T(U) = \{T(\mathbf{u}) \mid \mathbf{u} \text{ in } U\}$ is a subspace of W (called the **image** of U under T).
b. If P is a subspace of W, show that $\{\mathbf{v} \text{ in } V \mid T(\mathbf{v}) \text{ in } P\}$ is a subspace of V (called the **preimage** of P under T).

Answer available at the end of this section.

Example $6.10.1E.16$

Show that differentiation is the only linear transformation $\mathbf{P}_n \to \mathbf{P}_n$ that satisfies $T(x^k) = kx^{k-1}$ for each $k = 0, 1, 2, \dots, n$.

Example $6.10.1E.17$

Let $T : V \to W$ be a linear transformation and let $\mathbf{v}_1, \dots, \mathbf{v}_n$ denote vectors in V.

a. If $\{T(\mathbf{v}_1), \dots, T(\mathbf{v}_n)\}$ is linearly independent, show that $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ is also independent.
b. Find $T : \mathbb{R}^2 \to \mathbb{R}^2$ for which the converse of part (a) is false.

Exercise $6.10.1E.18$

Suppose $T : V \to V$ is a linear operator with the property that $T[T(\mathbf{v})] = \mathbf{v}$ for all $\mathbf{v}$ in V. (For example, transposition in $\mathbf{M}_{nn}$ or conjugation in $\mathbb{C}$.) If $\mathbf{v} \neq \mathbf{0}$ in V, show that $\{\mathbf{v}, T(\mathbf{v})\}$ is linearly independent if and only if $T(\mathbf{v}) \neq \mathbf{v}$ and $T(\mathbf{v}) \neq -\mathbf{v}$.

Answer available at the end of this section.

Example 6.10.1E.19

If a and b are real numbers, define $T_{a,b} : \mathbb{C} \to \mathbb{C}$ by $T_{a,b}(r + si) = ra + sbi$ for all $r + si$ in $\mathbb{C}$.

a. Show that $T_{a,b}$ is linear and $T_{a,b}(\overline{z}) = \overline{T_{a,b}(z)}$ for all z in $\mathbb{C}$. (Here $\overline{z}$ denotes the conjugate of z.)
b. If $T : \mathbb{C} \to \mathbb{C}$ is linear and $T(\overline{z}) = \overline{T(z)}$ for all z in $\mathbb{C}$, show that $T = T_{a,b}$ for some real a and b.

Example 6.10.1E.20

Show that the following conditions are equivalent for a linear transformation $T : \mathbf{M}_{22} \to \mathbf{M}_{22}$.

a. $tr[\mathbf{T(A)}] = tr\mathbf{A}$ for all A in $\mathbf{M}_{22}$.
b. $T \begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} = r_{11}B_{11} + r_{12}B_{12} + r_{21}B_{21} + r_{22}B_{22}$ for matrices B_{ij} such that $tr\mathbf{B_{11}} = 1 = tr\mathbf{B_{22}}$ and $tr\mathbf{B_{12}} = 0 = tr\mathbf{B_{21}}$.

Exercise 6.10.1E.21

Given a in $\mathbb{R}$, consider the **evaluation** map $E_a : \mathbf{P}_n \to \mathbb{R}$ defined in Example 7.1.3.

a. Show that E_a is a linear transformation satisfying the additional condition that $E_a(x^k) = [E_a(x)]^k$ holds for all $k = 0, 1, 2, \ldots$. [*Note*: $x^0 = 1$.]
b. If $T : \mathbf{P}_n \to \mathbb{R}$ is a linear transformation satisfying $T(x^k) = [T(x)]^k$ for all $k = 0, 1, 2, \ldots$, show that $T = E_a$ for some a in R.

Answer available at the end of this section.

Example 6.10.1E.22

If $T : \mathbf{M}_{nn} \to \mathbb{R}$ is any linear transformation satisfying $T(AB) = T(BA)$ for all A and B in $\mathbf{M}_{nn}$, show that there exists a number k such that $T(A) = ktr\mathbf{A}$ for all A. (See Lemma 5.5.1.) [*Hint*: Let E_{ij} denote the $n \times n$ matrix with 1 in the (i, j) position and zeros elsewhere.

Exercise 6.10.1E.23

Show that $E_{ik}E_{lj} = \begin{cases} 0 & \text{if } k \neq l \\ E_{ij} & \text{if } k = l \end{cases}$. Use this to show that $T(E_{ij}) = 0$ if $i \neq j$ and $T(E_{11}) = T(E_{22}) = \cdots = T(E_{nn})$. Put $k = T(E_{11})$ and use the fact that $\{E_{ij} \mid 1 \leq i, j \leq n\}$ is a basis of $\mathbf{M}_{nn}$.]

Exercise 6.10.1E.24

Let $T : \mathbb{C} \to \mathbb{C}$ be a linear transformation of the real vector space $\mathbb{C}$ and assume that $T(a) = a$ for every real number a. Show that the following are equivalent:

a. $T(zw) = T(z)T(w)$ for all z and w in $\mathbb{C}$.
b. Either $T = 1_{\mathbb{C}}$ or $T(z) = \overline{z}$ for each z in $\mathbb{C}$ (where $\overline{z}$ denotes the conjugate).

Answers

Exercise 6.10.1E.1

b. $T(\vec{v}) = \vec{v}A$ where $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{bmatrix}$

d. $T(A+B) = P(A+B)Q = PAQ + PBQ = T(A) + T(B); T(rA) = P(rA)Q = rPAQ = rT(A)$

f. $$T[(p+q)(x)] = (p+q)(0) = p(0) + q(0) = T[p(x)] + T[q(x)]$$
$$T[(rp)(x)] = (rp)(0) = r(p(0)) = rT[p(x)]$$

h. $T(X+Y) = (X+Y) \cdot Z = X \cdot Z + Y \cdot Z = T(X) + T(Y)$, and $T(rX) = (rX) \cdot Z = r(X \cdot Z) = rT(X)$

j. If $\vec{v} = (v_1, \ldots, v_n)$ and $\vec{w} = (w_1, \ldots, w_n)$, then $T(\vec{v} + \vec{w}) = (v_1 + w_1)\vec{e}_1 + \cdots + (v_n + w_n)\vec{e}_n = (v_1\vec{e}_1 + \cdots + v_n\vec{e}_n) + (w_1\vec{e}_1 + \cdots + w_n\vec{e}_n) = T(\vec{v}) + T(\vec{w})$ $T(a\vec{v}) = (av_1)\vec{e} + \cdots + (av_n)\vec{e}_n = a(v\vec{e} + \cdots + v_n\vec{e}_n) = aT(\vec{v})$

Exercise 6.10.1E.2

b. $\text{rank}(A+B) \neq \text{rank } A + \text{rank } B$ in general. For example, $A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ and $B = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$

d. $T(\vec{0}) = \vec{0} + \vec{u} = \vec{u} \neq \vec{0}$, so T is not linear by Theorem 7.1.1.

Exercise 6.10.1E.3

b. $T(3\vec{v}_1 + 2\vec{v}_2) = 0$

d. $T\begin{bmatrix} 1 \\ -7 \end{bmatrix} = \begin{bmatrix} -3 \\ 4 \end{bmatrix}$

f. $T(2 - x + 3x^2) = 46$

Exercise 6.10.1E.4

b. $T(x,y) = \frac{1}{3}(x-y, 3y, x-y); T(-1,2) = (-1,2,-1)$

d. $T\begin{bmatrix} a & b \\ c & d \end{bmatrix} = 3a - 3c + 2b$

Exercise 6.10.1E.5

b. $T(\mathbf{v}) = \frac{1}{3}(7\mathbf{v} - 9\mathbf{w})$, $T(\mathbf{w}) = \frac{1}{3}(\mathbf{v} + 3\mathbf{w})$

Exercise 6.10.1E.8

b. $T(\vec{v}) = (-1)\vec{v}$ for all $\vec{v}$ in V, so T is the scalar operator -1.

Exercise 6.10.1E.12

If $T(1) = \vec{v}$, then $T(r) = T(r \cdot 1) = rT(1) = r\vec{v}$ for all r in $\mathbb{R}$.

Exercise 6.10.1E.15

b. $\mathbf{0}$ is in $U = \{\mathbf{v} \in V \mid T(\mathbf{v}) \in P\}$ because $T(\mathbf{0}) = \mathbf{0}$ is in P. If $\mathbf{v}$ and $\mathbf{w}$ are in U, then $T(\mathbf{v})$ and $T(\mathbf{w})$ are in P. Hence $T(\mathbf{v} + \mathbf{w}) = T(\mathbf{v}) + T(\mathbf{w})$ is in P and $T(r\mathbf{v}) = rT(\mathbf{v})$ is in P, so $\mathbf{v} + \mathbf{w}$ and $r\mathbf{v}$ are in U.

Exercise 6.10.1E.18

Suppose $r\vec{v} + sT(\vec{v}) = \vec{0}$. If $s = 0$, then $r = 0$ (because $\vec{v} \neq \vec{0}$). If $s \neq 0$, then $T(\vec{v}) = a\vec{v}$ where $a = -s^{-1}r$. Thus $\vec{v} = T^2(\vec{v}) = T(a\vec{v}) = a^2\vec{v}$, so $a^2 = 1$, again because $\vec{v} \neq \vec{0}$. Hence $a = \pm 1$. Conversely, if $T(\vec{v}) = \pm\vec{v}$, then $\{\vec{v}, T(\vec{v})\}$ is certainly not independent.

Exercise 6.10.1E.21

b. Given such a T, write $T(x) = a$. If $p = p(x) = \sum_{i=0}^{n} a_i x^i$, then $T(p) = \sum a_i T(x^i) = \sum a_i [T(x)]^i = \sum a_i a^i = p(a) = E_a(p)$. Hence $T = E_a$

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6.10.2: KERNEL AND IMAGE OF A LINEAR TRANSFORMATION

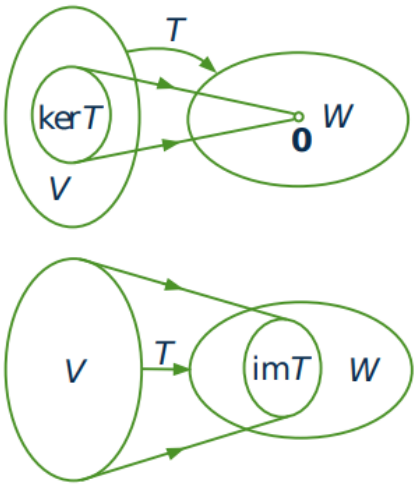
This section is devoted to two important subspaces associated with a linear transformation $T : V \to W$.

Definition: 6.10.2.1: Kernel and Image of a Linear Transformation

The **kernel** of T (denoted $\ker\ T$) and the **image** of T (denoted $im\ T$ or $T(V)$) are defined by

$$\ker\ T = \{\mathbf{v} \text{ in } V \mid T(\mathbf{v}) = \mathbf{0}\}$$
$$im\ T = \{T(\mathbf{v}) \mid \mathbf{v} \text{ in } V\} = T(V)$$

The kernel of T is often called the **nullspace** of T because it consists of all vectors $\mathbf{v}$ in V satisfying the *condition* that $T(\mathbf{v}) = \mathbf{0}$. The image of T is often called the **range** of T and consists of all vectors $\mathbf{w}$ in W of the *form* $\mathbf{w} = T(\mathbf{v})$ for some $\mathbf{v}$ in V. These subspaces are depicted in the diagrams.



Example 7.2.1

Let $T_A : \mathbb{R}^n \to \mathbb{R}^m$ be the linear transformation induced by the $m \times n$ matrix A, that is $T_A(\mathbf{x}) = A\mathbf{x}$ for all columns $\mathbf{x}$ in $\mathbb{R}^n$. Then

$$\ker\ T_A = \{\mathbf{x} \mid A\mathbf{x} = \mathbf{0}\} = null\ A \quad \text{and}$$
$$im\ T_A = \{A\mathbf{x} \mid \mathbf{x} \text{ in } \mathbb{R}^n\} = im\ A$$

Hence the following theorem extends Example 5.1.2.

Theorem 6.10.2.1

Let $T : V \to W$ be a linear transformation.

1. $\ker\ T$ *is a subspace of* V.
2. $im\ T$ *is a subspace of* W.

Proof

The fact that $T(\mathbf{0}) = \mathbf{0}$ shows that $\ker\ T$ and $im\ \ T$ contain the zero vector of V and W respectively.

1. If $\mathbf{v}$ and $\mathbf{v}_1$ lie in $\ker\ T$, then $T(\mathbf{v}) = \mathbf{0} = T(\mathbf{v}_1)$, so
$$T(\mathbf{v} + \mathbf{v}_1) = T(\mathbf{v}) + T(\mathbf{v}_1) = \mathbf{0} + \mathbf{0} = \mathbf{0}$$
$$T(r\mathbf{v}) = rT(\mathbf{v}) = r\mathbf{0} = \mathbf{0} \quad \text{for all } r \text{ in } \mathbb{R}$$
2. If $\mathbf{w}$ and $\mathbf{w}_1$ lie in $im\ \ T$, write $\mathbf{w} = T(\mathbf{v})$ and $\mathbf{w}_1 = T(\mathbf{v}_1)$ where $\mathbf{v}, \mathbf{v}_1 \in V$. Then
$$\mathbf{w} + \mathbf{w}_1 = T(\mathbf{v}) + T(\mathbf{v}_1) = T(\mathbf{v} + \mathbf{v}_1)$$
$$r\mathbf{w} = rT(\mathbf{v}) = T(r\mathbf{v}) \quad \text{for all } r \text{ in } \mathbb{R}$$

□

Given a linear transformation $T : V \to W$:

- $dim\ \ (\ker\ T)$ is called the **nullity** of T and denoted as $nullity\ \ (T)$
- $dim\ \ (im\ \ T)$ is called the **rank** of T and denoted as $rank\ \ (T)$

The $rank$ of a matrix A was defined earlier to be the dimension of $col\ \ A$, the column space of A. The two usages of the word $rank$ are consistent in the following sense. Recall the definition of T_A in Example 7.2.1.

Example 6.10.2.2

Given an $m \times n$ matrix A, show that $im\ \ T_A = col\ \ A$, so $rank\ \ T_A = rank\ \ A$.

Solution

Write $A = \begin{bmatrix} \mathbf{c}_1 & \cdots & \mathbf{c}_n \end{bmatrix}$ in terms of its columns. Then

$$im\ T_A = \{A\mathbf{x} \mid \mathbf{x} \text{ in } \mathbb{R}^n\} = \{x_1\mathbf{c}_1 + \cdots + x_n\mathbf{c}_n \mid x_i \text{ in } \mathbb{R}\}$$

using Definition 2.5. Hence $im\ \ T_A$ is the column space of A; the rest follows.

Often, a useful way to study a subspace of a vector space is to exhibit it as the kernel or image of a linear transformation. Here is an example.

Example 6.10.2.3

Define a transformation $P : \|M_{nn} \to \|M_{nn}$ by $P(A) = A - A^T$ for all A in $\mathbf{M}_{nn}$. Show that P is linear and that:

a. $\ker\ P$ consists of all symmetric matrices.
b. $im\ \ P$ consists of all skew-symmetric matrices.

Solution

The verification that P is linear is left to the reader. To prove part (a), note that a matrix A lies in $\ker\ P$ just when $0 = P(A) = A - A^T$, and this occurs if and only if $A = A^T$—that is, A is symmetric. Turning to part (b), the space $im\ \ P$ consists of all matrices $P(A)$, A in $\mathbf{M}_{nn}$. Every such matrix is skew-symmetric because

$$P(A)^T = (A - A^T)^T = A^T - A = -P(A)$$

On the other hand, if S is skew-symmetric (that is, $S^T = -S$), then S lies in $im\ \ P$. In fact,

$$P\left[\frac{1}{2}S\right] = \frac{1}{2}S - \left[\frac{1}{2}S\right]^T = \frac{1}{2}(S - S^T) = \frac{1}{2}(S + S) = S$$

One-to-One and Onto Transformations

Definition: 6.10.2.2: One-to-one and Onto Linear Transformations

Let $T : V \to W$ be a linear transformation.

1. T is said to be **onto** if $im\ T = W$.
2. T is said to be **one-to-one** if $T(\mathbf{v}) = T(\mathbf{v}_1)$ implies $\mathbf{v} = \mathbf{v}_1$.

A vector $\mathbf{w}$ in W is said to be **hit** by T if $\mathbf{w} = T(\mathbf{v})$ for some $\mathbf{v}$ in V. Then T is onto if every vector in W is hit at least once, and T is one-to-one if no element of W gets hit twice. Clearly the onto transformations T are those for which $im\ T = W$ is as large a subspace of W as possible. By contrast, Theorem 6.10.2.2 shows that the one-to-one transformations T are the ones with $\ker T$ as *small* a subspace of V as possible.

Theorem 6.10.2.2

If $T : V \to W$ is a linear transformation, then T is one-to-one if and only if $\ker T = \{\mathbf{0}\}$.

Proof

If T is one-to-one, let $\mathbf{v}$ be any vector in $\ker T$. Then $T(\mathbf{v}) = \mathbf{0}$, so $T(\mathbf{v}) = T(\mathbf{0})$. Hence $\mathbf{v} = \mathbf{0}$ because T is one-to-one. Hence $\ker T = \{\mathbf{0}\}$.

Conversely, assume that $\ker T = \{\mathbf{0}\}$ and let $T(\mathbf{v}) = T(\mathbf{v}_1)$ with $\mathbf{v}$ and $\mathbf{v}_1$ in V. Then $T(\mathbf{v} - \mathbf{v}_1) = T(\mathbf{v}) - T(\mathbf{v}_1) = \mathbf{0}$, so $\mathbf{v} - \mathbf{v}_1$ lies in $\ker T = \{\mathbf{0}\}$. This means that $\mathbf{v} - \mathbf{v}_1 = \mathbf{0}$, so $\mathbf{v} = \mathbf{v}_1$, proving that T is one-to-one.

□

Example 6.10.2.4

The identity transformation $1_V : V \to V$ is both one-to-one and onto for any vector space V.

Example 6.10.2.5

Consider the linear transformations

$$\begin{aligned} S &: \mathbb{R}^3 \to \mathbb{R}^2 \quad \text{given by } S(x, y, z) = (x + y, x - y) \\ T &: \mathbb{R}^2 \to \mathbb{R}^3 \quad \text{given by } T(x, y) = (x + y, x - y, x) \end{aligned}$$

Show that T is one-to-one but not onto, whereas S is onto but not one-to-one.

Solution

The verification that they are linear is omitted. T is one-to-one because

$$\ker T = \{(x, y) \mid x + y = x - y = x = 0\} = \{(0, 0)\}$$

However, it is not onto. For example $(0,0,1)$ does not lie in $im\ T$ because if $(0,0,1)=(x+y,x-y,x)$ for some x and y, then $x+y=0=x-y$ and $x=1$, an impossibility. Turning to S, it is not one-to-one by Theorem 7.2.2 because $(0,0,1)$ lies in $\ker S$. But every element (s,t) in $\mathbb{R}^2$ lies in $im\ S$ because $(s,t)=(x+y,x-y)=S(x,y,z)$ for some x, y, and z (in fact, $x=\frac{1}{2}(s+t)$, $y=\frac{1}{2}(s-t)$, and $z=0$). Hence S is onto.

Example 6.10.2.6

Let U be an invertible $m\times m$ matrix and define

$$T:\|M_{mn}\to\|M_{mn}\quad\text{by}\quad T(X)=UX\text{ for all }X\text{ in }\|M_{mn}$$

Show that T is a linear transformation that is both one-to-one and onto.

Solution

The verification that T is linear is left to the reader. To see that T is one-to-one, let $T(X)=0$. Then $UX=0$, so left-multiplication by U^{-1} gives $X=0$. Hence $\ker T=\{\mathbf{0}\}$, so T is one-to-one. Finally, if Y is any member of $\mathbf{M}_{mn}$, then $U^{-1}Y$ lies in $\mathbf{M}_{mn}$ too, and $T(U^{-1}Y)=U(U^{-1}Y)=Y$. This shows that T is onto.

The linear transformations $\mathbb{R}^n\to\mathbb{R}^m$ all have the form T_A for some $m\times n$ matrix A (Theorem 2.6.2). The next theorem gives conditions under which they are onto or one-to-one. Note the connection with Theorem 5.4.3 and Theorem 5.4.4.

Theorem 6.10.2.3

Let A be an $m\times n$ matrix, and let $T_A:\mathbb{R}^n\to\mathbb{R}^m$ be the linear transformation induced by A, that is $T_A(\mathbf{x})=A\mathbf{x}$ for all columns $\mathbf{x}$ in $\mathbb{R}^n$.

1. T_A is onto if and only if $rank\ A=m$.
2. T_A is one-to-one if and only if $rank\ A=n$.

Proof

1. We have that $im\ T_A$ is the column space of A (see Example 7.2.2), so T_A is onto if and only if the column space of A is $\mathbb{R}^m$. Because the $rank$ of A is the dimension of the column space, this holds if and only if $rank\ A=m$.
2. $\ker T_A=\{\mathbf{x}\text{ in }\mathbb{R}^n\mid A\mathbf{x}=\mathbf{0}\}$, so (using Theorem 7.2.2) T_A is one-to-one if and only if $A\mathbf{x}=\mathbf{0}$ implies $\mathbf{x}=\mathbf{0}$. This is equivalent to $rank\ A=n$ by Theorem 5.4.3.

□

The Dimension Theorem

Let A denote an $m\times n$ matrix of $rank\ r$ and let $T_A:\mathbb{R}^n\to\mathbb{R}^m$ denote the corresponding matrix transformation given by $T_A(\mathbf{x})=A\mathbf{x}$ for all columns $\mathbf{x}$ in $\mathbb{R}^n$. It follows from Example 7.2.1 and Example 7.2.2 that $im\ T_A=col\ A$, so $dim\ (im\ T_A)=dim\ col\ A)=r$. On the other hand Theorem 5.4.2 shows that $dim\ (\ker T_A)=dim\ (null\ A)=n-r$. Combining these we see that

$$dim\ (im\ T_A)+dim\ (\ker T_A)=n\quad\text{for every }m\times n\text{ matrix }A$$

The main result of this section is a deep generalization of this observation.

Theorem 6.10.2.4: Dimension Theorem

Let $T : V \to W$ be any linear transormation and assume that $\ker\ T$ and $im\ \ T$ are both finite dimensional. Then V is also finite dimensional and

$$dim\ V = dim\ (\ker\ T) + dim\ (im\ T)$$

In other words, $dim\ \ V = nullity\ \ (T) + rank\ \ (T)$.

Proof

Every vector in $im\ \ T = T(V)$ has the form $T(\mathbf{v})$ for some $\mathbf{v}$ in V. Hence let $\{T(\mathbf{e}_1), T(\mathbf{e}_2), \ldots, T(\mathbf{e}_r)\}$ be a basis of $im\ \ T$, where the $\mathbf{e}_i$ lie in V. Let $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_k\}$ be any basis of $\ker\ T$. Then $dim\ \ (im\ \ T) = r$ and $dim\ \ (\ker\ T) = k$, so it suffices to show that $B = \{\mathbf{e}_1, \ldots, \mathbf{e}_r, \mathbf{f}_1, \ldots, \mathbf{f}_k\}$ is a basis of V.

1. B *spans* V. If $\mathbf{v}$ lies in V, then $T(\mathbf{v})$ lies in $im\ \ V$, so

$$T(\mathbf{v}) = t_1T(\mathbf{e}_1) + t_2T(\mathbf{e}_2) + \cdots + t_rT(\mathbf{e}_r) \quad t_i \text{ in } \mathbb{R}$$

2. B is *linearly independent*. Suppose that t_i and s_j in $\mathbb{R}$ satisfy

$$t_1\mathbf{e}_1 + \cdots + t_r\mathbf{e}_r + s_1\mathbf{f}_1 + \cdots + s_k\mathbf{f}_k = \mathbf{0} \tag{6.10.2.1}$$

$$s_1\mathbf{f}_1 + \cdots + s_k\mathbf{f}_k = \mathbf{0}$$

so $s_1 = \cdots = s_k = 0$ by the independence of $\{\mathbf{f}_1, \ldots, \mathbf{f}_k\}$. This proves that B is linearly independent.

□

Note that the vector space V is not assumed to be finite dimensional in Theorem 7.2.4. In fact, verifying that $\ker\ T$ and $im\ \ T$ are both finite dimensional is often an important way to *prove* that V is finite dimensional.

Note further that $r + k = n$ in the proof so, after relabelling, we end up with a basis

$$B = \{\mathbf{e}_1,\ \mathbf{e}_2,\ \ \ldots,\ \mathbf{e}_r,\ \mathbf{e}_{r+1},\ \ \ldots,\ \mathbf{e}_n\}$$

of V with the property that $\{\mathbf{e}_{r+1}, \ldots, \mathbf{e}_n\}$ is a basis of $\ker\ T$ and $\{T(\mathbf{e}_1), \ldots, T(\mathbf{e}_r)\}$ is a basis of $im\ \ T$. In fact, if V is known in advance to be finite dimensional, then *any* basis $\{\mathbf{e}_{r+1}, \ldots, \mathbf{e}_n\}$ of $\ker\ T$ can be extended to a basis $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_r, \mathbf{e}_{r+1}, \ldots, \mathbf{e}_n\}$ of V by Theorem 6.4.1. Moreover, it turns out that, no matter how this is done, the vectors $\{T(\mathbf{e}_1), \ldots, T(\mathbf{e}_r)\}$ will be a basis of $im\ \ T$. This result is useful, and we record it for reference. The proof is much like that of Theorem 6.10.2.4 and is left as Exercise 6.10.2.26 .

Theorem 6.10.2.5

Let $T : V \to W$ be a linear transformation, and let $\{\mathbf{e}_1, \ldots, \mathbf{e}_r, \mathbf{e}_{r+1}, \ldots, \mathbf{e}_n\}$ be a basis of V such that $\{\mathbf{e}_{r+1}, \ldots, \mathbf{e}_n\}$ is a basis of $\ker\ T$. Then $\{T(\mathbf{e}_1), \ldots, T(\mathbf{e}_r)\}$ is a basis of $im\ \ T$, and hence $r = rank\ \ T$.

The dimension theorem is one of the most useful results in all of linear algebra. It shows that if either $dim\ \ (\ker\ T)$ or $dim\ \ (im\ \ T)$ can be found, then the other is automatically known. In many cases it is easier to compute one than the other, so the theorem is a real asset. The rest of this section is devoted to illustrations of this fact. The next example uses the dimension theorem to give a different proof of the first part of Theorem 5.4.2.

Example 6.10.2.7

Let A be an $m \times n$ matrix of $rank\ r$. Show that the space $null\ A$ of all solutions of the system $A\mathbf{x} = \mathbf{0}$ of m homogeneous equations in n variables has dimension $n - r$.

Solution

The space in question is just $\ker T_A$, where $T_A : \mathbb{R}^n \to \mathbb{R}^m$ is defined by $T_A(\mathbf{x}) = A\mathbf{x}$ for all columns $\mathbf{x}$ in $\mathbb{R}^n$. But $dim\ (im\ T_A) = rank\ T_A = rank\ A = r$ by Example 7.2.2, so $dim\ (\ker T_A) = n - r$ by the dimension theorem.

Example 6.10.2.8

If $T : V \to W$ is a linear transformation where V is finite dimensional, then

$$dim\ (\ker T) \leq dim\ V \quad \text{and} \quad dim\ (im\ T) \leq dim\ V$$

Indeed, $dim\ V = dim\ (\ker T) + dim\ (im\ T)$ by Theorem 6.10.2.4. Of course, the first inequality also follows because $\ker T$ is a subspace of V.

Example 6.10.2.9

Let $D : \|P_n \to \|P_{n-1}$ be the differentiation map defined by $D[p(x)] = p'(x)$. Compute $\ker D$ and hence conclude that D is onto.

Solution

Because $p'(x) = 0$ means $p(x)$ is constant, we have $dim\ (\ker D) = 1$. Since $dim\ \mathbf{P}_n = n + 1$, the dimension theorem gives

$$dim\ (im\ D) = (n + 1) - dim\ (\ker D) = n = dim\ (\mathbf{P}_{n-1})$$

This implies that $im\ D = \|P_{n-1}$, so D is onto.

Of course it is not difficult to verify directly that each polynomial $q(x)$ in $\mathbf{P}_{n-1}$ is the derivative of some polynomial in $\mathbf{P}_n$ (simply integrate $q(x)$!), so the dimension theorem is not needed in this case. However, in some situations it is difficult to see directly that a linear transformation is onto, and the method used in Example 7.2.9 may be by far the easiest way to prove it. Here is another illustration.

Example 6.10.2.10

Given a in $\mathbb{R}$, the evaluation map $E_a : \|P_n \to \mathbb{R}$ is given by $E_a[p(x)] = p(a)$. Show that E_a is linear and onto, and hence conclude that $\{(x - a), (x - a)^2, \ldots, (x - a)^n\}$ is a basis of $\ker E_a$, the subspace of all polynomials $p(x)$ for which $p(a) = 0$.

Solution

E_a is linear by Example 7.1.3; the verification that it is onto is left to the reader. Hence $dim\ (im\ E_a) = dim\ (\mathbb{R}) = 1$, so $dim\ (\ker E_a) = (n + 1) - 1 = n$ by the dimension theorem. Now each of the n polynomials $(x - a), (x - a)^2, \ldots, (x - a)^n$ clearly lies in $\ker E_a$, and they are linearly independent (they have distinct degrees). Hence they are a basis because $dim\ (\ker E_a) = n$.

We conclude by applying the dimension theorem to the $rank$ of a matrix.

Example 6.10.2.11

If A is any $m \times n$ matrix, show that $rank\ A = rank\ A^TA = rank\ AA^T$.

Solution

It suffices to show that $rank\ \ A = rank\ \ A^TA$ (the rest follows by replacing A with A^T). Write $B = A^TA$, and consider the associated matrix transformations

$$T_A : \mathbb{R}^n \to \mathbb{R}^m \quad \text{and} \quad T_B : \mathbb{R}^n \to \mathbb{R}^n$$

The dimension theorem and Example 7.2.2 give

$$rank\ A = rank\ T_A = dim\ (im\ T_A) = n - dim\ (\ker\ T_A)$$
$$rank\ B = rank\ T_B = dim\ (im\ T_B) = n - dim\ (\ker\ T_B)$$

so it suffices to show that $\ker\ T_A = \ker\ T_B$. Now $A\mathbf{x} = \mathbf{0}$ implies that $B\mathbf{x} = A^TA\mathbf{x} = \mathbf{0}$, so $\ker\ T_A$ is contained in $\ker\ T_B$. On the other hand, if $B\mathbf{x} = \mathbf{0}$, then $A^TA\mathbf{x} = \mathbf{0}$, so

$$\|A\mathbf{x}\|^2 = (A\mathbf{x})^T(A\mathbf{x}) = \mathbf{x}^TA^TA\mathbf{x} = \mathbf{x}^T\mathbf{0} = 0$$

This implies that $A\mathbf{x} = \mathbf{0}$, so $\ker\ T_B$ is contained in $\ker\ T_A$.

6.10.2E: Kernel and Image of a Linear Transformation Exercises

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6.10.2E: Kernel and Image of a Linear Transformation Exercises

Exercise $6.10.2E.1$

For each matrix A, find a basis for the kernel and image of T_A, and find the $rank$ and $nullity$ of T_A.

a. $\begin{bmatrix} 1 & 2 & -1 & 1 \\ 3 & 1 & 0 & 2 \\ 1 & -3 & 2 & 0 \end{bmatrix}$

b. $\begin{bmatrix} 2 & 1 & -1 & 3 \\ 1 & 0 & 3 & 1 \\ 1 & 1 & -4 & 2 \end{bmatrix}$

c. $\begin{bmatrix} 1 & 2 & -1 \\ 3 & 1 & 2 \\ 4 & -1 & 5 \\ 0 & 2 & -2 \end{bmatrix}$

d. $\begin{bmatrix} 2 & 1 & 0 \\ 1 & -1 & 3 \\ 1 & 2 & -3 \\ 0 & 3 & -6 \end{bmatrix}$

Answer available at the end of this section.

Exercise $6.10.2E.2$

In each case, (i) find a basis of $\ker\ T$, and (ii) find a basis of $im\ \ T$. You may assume that T is linear.

a. $T : P_2 \to \mathbb{R}^2$; $T(a + bx + cx^2) = (a, b)$
b. $T : P_2 \to \mathbb{R}^2$; $T(p(x)) = (p(0), p(1))$
c. $T : \mathbb{R}^3 \to \mathbb{R}^3$; $T(x, y, z) = (x + y, x + y, 0)$
d. $T : \mathbb{R}^3 \to \mathbb{R}^4$; $T(x, y, z) = (x, x, y, y)$
e. $T : M_{22} \to \|M_{22}$; $T \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} a+b & b+c \\ c+d & d+a \end{bmatrix}$
f. $T : M_{22} \to \mathbb{R}$; $T \begin{bmatrix} a & b \\ c & d \end{bmatrix} = a + d$
g. $T : P_n \to \mathbb{R}$; $T(r_0 + r_1x + \cdots + r_nx^n) = r_n$
h. $T : \mathbb{R}^n \to \mathbb{R}$; $T(r_1, r_2, \ldots, r_n) = r_1 + r_2 + \cdots + r_n$
i. $T : M_{22} \to \|M_{22}$; $T(X) = XA - AX$, where
j. $A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$

Answer available at the end of this section.

Exercise $6.10.2E.1$

Let $P : V \to \mathbb{R}$ and $Q : V \to \mathbb{R}$ be linear transformations, where V is a vector space. Define $T : V \to \mathbb{R}^2$ by $T(\mathbf{v}) = (P(\mathbf{v}), Q(\mathbf{v}))$.

a. Show that T is a linear transformation.
b. Show that $\ker\ T = \ker\ P \cap \ker\ Q$, the set of vectors in both $\ker\ P$ and $\ker\ Q$.

Answer available at the end of this section.

Exercise $6.10.2E.4$

In each case, find a basis
$B = \{\mathbf{e}_1, \dots, \mathbf{e}_r, \mathbf{e}_{r+1}, \dots, \mathbf{e}_n\}$ of V such that $\{\mathbf{e}_{r+1}, \dots, \mathbf{e}_n\}$ is a basis of $\ker T$, and verify Theorem 7.2.5.

a. $T : \mathbb{R}^3 \to \mathbb{R}^4$; $T(x, y, z) = (x - y + 2z, x + y - z, 2x + z, 2y - 3z)$
b. $T : \mathbb{R}^3 \to \mathbb{R}^4$; $T(x, y, z) = (x + y + z, 2x - y + 3z, z - 3y, 3x + 4z)$

Answer available at the end of this section.

Exercise $6.10.2E.5$

Show that every matrix X in $\mathbf{M}_{nn}$ has the form $X = A^T - 2A$ for some matrix A in $\mathbf{M}_{nn}$. [*Hint*: The dimension theorem.]

Exercise $6.10.2E.6$

In each case either prove the statement or give an example in which it is false. Throughout, let $T : V \to W$ be a linear transformation where V and W are finite dimensional.

a. If $V = W$, then $\ker T \subseteq im\ T$.
b. If $dim\ V = 5$, $dim\ W = 3$, and $dim\ (\ker T) = 2$, then T is onto.
c. If $dim\ V = 5$ and $dim\ W = 4$, then $\ker T \neq \{\mathbf{0}\}$.
d. If $\ker T = V$, then $W = \{\mathbf{0}\}$.
e. If $W = \{\mathbf{0}\}$, then $\ker T = V$.
f. If $W = V$, and $im\ T \subseteq \ker T$, then $T = 0$.
g. If $\{\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3\}$ is a basis of V and $T(\mathbf{e}_1) = \mathbf{0} = T(\mathbf{e}_2)$, then $dim\ (im\ T) \leq 1$.
h. If $dim\ (\ker T) \leq dim\ W$, then $dim\ W \geq \frac{1}{2} dim\ V$.
i. If T is one-to-one, then $dim\ V \leq dim\ W$.
j. If $dim\ V \leq dim\ W$, then T is one-to-one.
k. If T is onto, then $dim\ V \geq dim\ W$.
l. If $dim\ V \geq dim\ W$, then T is onto.
m. If $\{T(\mathbf{v}_1), \dots, T(\mathbf{v}_k)\}$ is independent, then $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ is independent.
n. If $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ spans V, then $\{T(\mathbf{v}_1), \dots, T(\mathbf{v}_k)\}$ spans W.

Answer available at the end of this section.

Exercise $6.10.2E.7$

Show that linear independence is preserved by one-to-one transformations and that spanning sets are preserved by onto transformations. More precisely, if $T : V \to W$ is a linear transformation, show that:

a. If T is one-to-one and $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ is independent in V, then $\{T(\mathbf{v}_1), \dots, T(\mathbf{v}_n)\}$ is independent in W.
b. If T is onto and $V = span\ \{\mathbf{v}_1, \dots, \mathbf{v}_n\}$, then $W = span\ \{T(\mathbf{v}_1), \dots, T(\mathbf{v}_n)\}$.

Answer available at the end of this section.

Exercise $6.10.2E.8$

Given $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ in a vector space V, define $T : \mathbb{R}^n \to V$ by $T(r_1, \dots, r_n) = r_1\mathbf{v}_1 + \cdots + r_n\mathbf{v}_n$. Show that T is linear, and that:

a. T is one-to-one if and only if $\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ is independent.
b. T is onto if and only if $V = span\ \{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$.

Answer available at the end of this section.

Exercise $6.10.2E.9$

Let $T : V \to V$ be a linear transformation where V is finite dimensional. Show that exactly one of (i) and (ii) holds:

i. $T(\mathbf{v}) = \mathbf{0}$ for some $\mathbf{v} \neq \mathbf{0}$ in V;
ii. $T(\mathbf{x}) = \mathbf{v}$ has a solution $\mathbf{x}$ in V for every $\mathbf{v}$ in V.

Exercise $6.10.2E.10$

Let $T : \|M_{nn} \to \mathbb{R}$ denote the trace map: $T(A) = tr\ \ A$ for all A in $\mathbf{M}_{nn}$. Show that $dim\ \ (\ker\ T) = n^2 - 1$.

Answer available at the end of this section.

Exercise $6.10.2E.11$

Show that the following are equivalent for a linear transformation $T : V \to W$.

a. $\ker\ T = V$
b. $im\ \ T = \{\mathbf{0}\}$
c. $T = 0$

Exercise $6.10.2E.12$

Let A and B be $m \times n$ and $k \times n$ matrices, respectively. Assume that $A\mathbf{x} = \mathbf{0}$ implies $B\mathbf{x} = \mathbf{0}$ for every n-column $\mathbf{x}$. Show that $rank\ \ A \geq rank\ \ B$. [Hint: Theorem 7.2.4.]

Answer available at the end of this section.

Exercise $6.10.2E.13$

Let A be an $m \times n$ matrix of $rank\ \ r$. Thinking of $\mathbb{R}^n$ as rows, define $V = \{\mathbf{x} \text{ in } \mathbb{R}^m \mid \mathbf{x}A = \mathbf{0}\}$. Show that $dim\ \ V = m - r$.

Exercise $6.10.2E.14$

Consider

$$V = \left\{ \left[\begin{array}{cc} a & b \\ c & d \end{array} \right] \middle| \, a + c = b + d \right\}$$

a. Consider $S : \|M_{22} \to \mathbb{R}$ with $S \left[\begin{array}{cc} a & b \\ c & d \end{array} \right] = a + c - b - d$. Show that S is linear and onto and that V is a subspace of $\mathbf{M}_{22}$. Compute $dim\ \ V$.
b. Consider $T : V \to \mathbb{R}$ with $T \left[\begin{array}{cc} a & b \\ c & d \end{array} \right] = a + c$. Show that T is linear and onto, and use this information to compute $dim\ \ (\ker\ T)$.

Exercise 6.10.2E.15

Define $T : \|P_n \to \mathbb{R}$ by $T[p(x)] =$ the sum of all the coefficients of $p(x)$.

a. Use the dimension theorem to show that $dim\ (\ker T) = n$.
b. Conclude that $\{x - 1, x^2 - 1, \ldots, x^n - 1\}$ is a basis of $\ker T$.

Answer available at the end of this section.

Exercise 6.10.2E.16

Use the dimension theorem to prove Theorem 1.3.1: If A is an $m \times n$ matrix with $m < n$, the system $A\mathbf{x} = \mathbf{0}$ of m homogeneous equations in n variables always has a nontrivial solution.

Exercise 6.10.2E.17

Let B be an $n \times n$ matrix, and consider the subspaces $U = \{A \mid A \text{ in } \|M_{mn}, AB = 0\}$ and $V = \{AB \mid A \text{ in } \|M_{mn}\}$. Show that $dim\ U + dim\ V = mn$.

Exercise 6.10.2E.18

Let U and V denote, respectively, the spaces of even and odd polynomials in $\mathbf{P}_n$. Show that $dim\ U + dim\ V = n + 1$. [*Hint*: Consider $T : \|P_n \to \|P_n$ where $T[p(x)] = p(x) - p(-x)$.]

Exercise 6.10.2E.19

Show that every polynomial $f(x)$ in $\mathbf{P}_{n-1}$ can be written as $f(x) = p(x + 1) - p(x)$ for some polynomial $p(x)$ in $\mathbf{P}_n$. [*Hint*: Define $T : \|P_n \to \|P_{n-1}$ by $T[p(x)] = p(x + 1) - p(x)$.]

Exercise 6.10.2E.20

Let U and V denote the spaces of symmetric and skew-symmetric $n \times n$ matrices. Show that $dim\ U + dim\ V = n^2$.

Answer available at the end of this section.

Exercise 6.10.2E.21

Assume that B in $\mathbf{M}_{nn}$ satisfies $B^k = 0$ for some $k \geq 1$. Show that every matrix in $\mathbf{M}_{nn}$ has the form $BA - A$ for some A in $\mathbf{M}_{nn}$. [*Hint*: Show that $T : M_{nn} \to M_{nn}$ is linear and one-to-one where $T(A) = BA - A$ for each A.]

Exercise 6.10.2E.22

Fix a column $\mathbf{y} \neq \mathbf{0}$ in $\mathbb{R}^n$ and let $U = \{A \text{ in } \mathbf{M}_{nn} \mid A\mathbf{y} = \mathbf{0}\}$. Show that $dim\ U = n(n - 1)$.

Answer available at the end of this section.

Exercise $6.10.2E.23$

If B in $\mathbf{M}_{mn}$ has $rank\ r$, let $U = \{A \text{ in } \mathbf{M}_{nn} \mid BA = 0\}$ and $W = \{BA \mid A \text{ in } \mathbf{M}_{nn}\}$. Show that $dim\ U = n(n-r)$ and $dim\ W = nr$. [*Hint*: Show that U consists of all matrices A whose columns are in the $null$ space of B. Use Example $6.10.2E.7$.]

Exercise $6.10.2E.24$

Let $T : V \to V$ be a linear transformation where $dim\ V = n$. If $\ker T \cap im\ T = \{\mathbf{0}\}$, show that every vector $\mathbf{v}$ in V can be written $\mathbf{v} = \mathbf{u} + \mathbf{w}$ for some $\mathbf{u}$ in $\ker T$ and $\mathbf{w}$ in $im\ T$. [*Hint*: Choose bases $B \subseteq \ker T$ and $D \subseteq im\ T$, and use Exercise 6.3.33.]

Exercise $6.10.2E.25$

Let $T : \mathbb{R}^n \to \mathbb{R}^n$ be a linear operator of $rank\ 1$, where $\mathbb{R}^n$ is written as rows. Show that there exist numbers $a_1, a_2, \dots, a_n$ and $b_1, b_2, \dots, b_n$ such that $T(X) = XA$ for all rows X in $\mathbb{R}^n$, where

$$A = \begin{bmatrix} a_1b_1 & a_1b_2 & \cdots & a_1b_n \\ a_2b_1 & a_2b_2 & \cdots & a_2b_n \\ \vdots & \vdots & & \vdots \\ a_nb_1 & a_nb_2 & \cdots & a_nb_n \end{bmatrix}$$

[*Hint*: $im\ T = \mathbb{R}\mathbf{w}$ for $\mathbf{w} = (b_1, \dots, b_n)$ in $\mathbb{R}^n$.]

Exercise $6.10.2E.26$

Prove Theorem 7.2.5.

Exercise $6.10.2E.27$

Let $T : V \to \mathbb{R}$ be a nonzero linear transformation, where $dim\ V = n$. Show that there is a basis $\{\mathbf{e}_1, \dots, \mathbf{e}_n\}$ of V so that $T(r_1\mathbf{e}_1 + r_2\mathbf{e}_2 + \cdots + r_n\mathbf{e}_n) = r_1$.

Exercise $6.10.2E.28$

Let $f \neq 0$ be a fixed polynomial of degree $m \geq 1$. If p is any polynomial, recall that $(p \circ f)(x) = p[f(x)]$. Define $T_f : P_n \to P_{n+m}$ by $T_f(p) = p \circ f$.

a. Show that T_f is linear.
b. Show that T_f is one-to-one.

Exercise $6.10.2E.29$

Let U be a subspace of a finite dimensional vector space V.

a. Show that $U = \ker T$ for some linear operator $T : V \to V$.
b. Show that $U = im\ S$ for some linear operator $S : V \to V$. [*Hint*: Theorem 6.4.1 and Theorem 7.1.3.]

Answer available at the end of this section.

Exercise $6.10.2E.30$

Let V and W be finite dimensional vector spaces.

a. Show that $dim\ W \leq dim\ V$ if and only if there exists an onto linear transformation $T : V \to W$. [*Hint*: Theorem 6.4.1 and Theorem 7.1.3.]
b. Show that $dim\ W \geq dim\ V$ if and only if there exists a one-to-one linear transformation $T : V \to W$. [*Hint*: Theorem 6.4.1 and Theorem 7.1.3.]

Answers

Exercise $6.10.2E.1$

b. $\left\{\begin{bmatrix} -3 \\ 7 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 0 \\ -1 \end{bmatrix}\right\}; \left\{\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix}\right\}; 2, 2$

d. $\left\{\begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix}\right\}; \left\{\begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ -1 \\ -2 \end{bmatrix}\right\}; 2, 1$

Exercise $6.10.2E.2$

b. $\{x^2 - x\}; \{(1, 0), (0, 1)\}$
d. $\{(0, 0, 1)\}; \{(1, 1, 0, 0), (0, 0, 1, 1)\}$
f. $\left\{\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}\right\}; \{1\}$
h. $\{(1, 0, 0, \ldots, 0, -1), (0, 1, 0, \ldots, 0, -1), \ldots, (0, 0, 0, \ldots, 1, -1)\}; \{1\}$
j. $\left\{\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}\right\}$
$\left\{\begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix}\right\}$

Exercise $6.10.2E.1$

b. $T(\mathbf{v}) = \mathbf{0} = (0, 0)$ if and only if $P(\mathbf{v}) = 0$ and $Q(\mathbf{v}) = 0$; that is, if and only if $\mathbf{v}$ is in $\ker P \cap \ker Q$.

Exercise $6.10.2E.4$

b. $\ker T = span\ \{(-4, 1, 3)\}$; $B = \{(1, 0, 0), (0, 1, 0), (-4, 1, 3)\}$, $im\ T = span\ \{(1, 2, 0, 3), (1, -1, -3, 0)\}$

Exercise $6.10.2E.6$

b. Yes. $dim\ (im\ T) = 5 - dim\ (\ker T) = 3$, so $im\ T = W$ as $dim\ W = 3$.
d. No. $T = 0 : \mathbb{R}^2 \to \mathbb{R}^2$
f. No. $T : \mathbb{R}^2 \to \mathbb{R}^2$, $T(x, y) = (y, 0)$. Then $\ker T = im\ T$
h. Yes. $dim\ V = dim\ (\ker T) + dim\ (im\ T) \leq dim\ W + dim\ W = 2dim\ W$
j. No. Consider $T : \mathbb{R}^2 \to \mathbb{R}^2$ with $T(x, y) = (y, 0)$.
l. No. Same example as **(j)**.
n. No. Define $T : \mathbb{R}^2 \to \mathbb{R}^2$ by $T(x, y) = (x, 0)$. If $\mathbf{v}_1 = (1, 0)$ and $\mathbf{v}_2 = (0, 1)$, then $\mathbb{R}^2 = span\ \{\mathbf{v}_1, \mathbf{v}_2\}$ but $\mathbb{R}^2 \neq span\ \{T(\mathbf{v}_1), T(\mathbf{v}_2)\}$.

Exercise $6.10.2E.7$

b. Given $\mathbf{w}$ in W, let $\mathbf{w} = T(\mathbf{v})$, $\mathbf{v}$ in V, and write $\mathbf{v} = r_1\mathbf{v}_1 + \cdots + r_n\mathbf{v}_n$. Then $\mathbf{w} = T(\mathbf{v}) = r_1T(\mathbf{v}_1) + \cdots + r_nT(\mathbf{v}_n)$.

Exercise $6.10.2E.8$

b. $im\ T = \{\sum_i r_i\mathbf{v}_i \mid r_i \text{ in } \mathbb{R}\} = span\ \{\mathbf{v}_i\}$.

Exercise $6.10.2E.10$

T is linear and onto. Hence $1 = dim\ \mathbb{R} = dim\ (im\ T) = dim\ (\mathbf{M}_{nn}) - dim\ (\ker T) = n^2 - dim\ (\ker T)$

Exercise $6.10.2E.12$

The condition means $\ker (T_A) \subseteq \ker(T_B)$, so $dim\ [\ker(T_A)] \leq dim\ [\ker(T_B)]$. Then Theorem 7.2.4 gives $dim\ [im\ (T_A)] \geq dim\ [im\ (T_B)]$; that is, $rank\ A \geq rank\ B$.

Exercise $6.10.2E.15$

b. $B = \{x - 1, \ldots, x^n - 1\}$ is independent (distinct degrees) and contained in $\ker T$. Hence B is a basis of $\ker T$ by **(a)**.

Exercise $6.10.2E.20$

Define $T : M_{nn} \to M_{nn}$ by $T(A) = A - A^T$ for all A in $\mathbf{M}_{nn}$. Then $\ker T = U$ and $im\ T = V$ by Example 7.2.3, so the dimension theorem gives $n^2 = dim\ \mathbf{M}_{nn} = dim\ (U) + dim\ (V)$.

Exercise $6.10.2E.22$

Define $T : \|M_{nn} \to \mathbb{R}^n$ by $T(A) = A\mathbf{y}$ for all A in $\mathbf{M}_{nn}$. Then T is linear with $\ker T = U$, so it is enough to show that T is onto (then $dim\ U = n^2 - dim\ (im\ T) = n^2 - n$). We have $T(0) = \mathbf{0}$. Let $\mathbf{y} = \begin{bmatrix} y_1 & y_2 & \cdots & y_n \end{bmatrix}^T \neq \mathbf{0}$ in $\mathbb{R}^n$. If $y_k \neq 0$ let $\mathbf{c}_k = y_k^{-1}\mathbf{y}$, and let $\mathbf{c}_j = \mathbf{0}$ if $j \neq k$. If $A = \begin{bmatrix} \mathbf{c}_1 & \mathbf{c}_2 & \cdots & \mathbf{c}_n \end{bmatrix}$, then $T(A) = A\mathbf{y} = y_1\mathbf{c}_1 + \cdots + y_k\mathbf{c}_k + \cdots + y_n\mathbf{c}_n = \mathbf{y}$. This shows that T is onto, as required.

Exercise $6.10.2E.29$

b. By Lemma 6.4.2, let $\{\mathbf{u}_1, \ldots, \mathbf{u}_m, \ldots, \mathbf{u}_n\}$ be a basis of V where $\{\mathbf{u}_1, \ldots, \mathbf{u}_m\}$ is a basis of U. By Theorem 7.1.3 there is a linear transformation $S : V \to V$ such that $S(\mathbf{u}_i) = \mathbf{u}_i$ for $1 \leq i \leq m$, and $S(\mathbf{u}_i) = \mathbf{0}$ if $i > m$. Because each $\mathbf{u}_i$ is in $im\ S$, $U \subseteq im\ S$. But if $S(\mathbf{v})$ is in $im\ S$, write $\mathbf{v} = r_1\mathbf{u}_1 + \cdots + r_m\mathbf{u}_m + \cdots + r_n\mathbf{u}_n$. Then $S(\mathbf{v}) = r_1S(\mathbf{u}_1) + \cdots + r_mS(\mathbf{u}_m) = r_1\mathbf{u}_1 + \cdots + r_m\mathbf{u}_m$ is in U. So $im\ S \subseteq U$.

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6.10.3: ISOMORPHISMS AND COMPOSITION

Often two vector spaces can consist of quite different types of vectors but, on closer examination, turn out to be the same underlying space displayed in different symbols. For example, consider the spaces

$$\mathbb{R}^2 = \{(a, b) \mid a, b \in \mathbb{R}\} \quad \text{and} \quad \mathbf{P}_1 = \{a + bx \mid a, b \in \mathbb{R}\}$$

Compare the addition and scalar multiplication in these spaces:

$$\begin{array}{cc} 2(a,b) + (a_1, b_1) = (a + a_1, b + b_1) & (a + bx) + (a_1 + b_1x) = (a + a_1) + (b + b_1)x \\ r(a, b) = (ra, rb) & r(a + bx) = (ra) + (rb)x \end{array}$$

Clearly these are the *same* vector space expressed in different notation: if we change each (a, b) in $\mathbb{R}^2$ to $a + bx$, then $\mathbb{R}^2$ *becomes* $\mathbf{P}_1$, complete with addition and scalar multiplication. This can be expressed by noting that the map $(a, b) \mapsto a + bx$ is a linear transformation $\mathbb{R}^2 \to \mathbf{P}_1$ that is both one-to-one and onto. In this form, we can describe the general situation.

Definition 6.10.3.1: Isomorphic Vector Spaces

A linear transformation $T : V \to W$ is called an **isomorphism** if it is both onto and one-to-one. The vector spaces V and W are said to be **isomorphic** if there exists an isomorphism $T : V \to W$, and we write $V \cong W$ when this is the case.

Example 6.10.3.1

The identity transformation $1_V : V \to V$ is an isomorphism for any vector space V.

Example 6.10.3.2

If $T : \mathbf{M}_{mn} \to \mathbf{M}_{nm}$ is defined by $T(A) = A^T$ for all A in $\mathbf{M}_{mn}$, then T is an isomorphism (verify). Hence $\mathbf{M}_{mn} \cong \mathbf{M}_{nm}$.

Example 6.10.3.3

Isomorphic spaces can "look" quite different. For example, $\mathbf{M}_{22} \cong \mathbf{P}_3$ because the map $T : \mathbf{M}_{22} \to \mathbf{P}_3$ given by $T \begin{bmatrix} a & b \\ c & d \end{bmatrix} = a + bx + cx^2 + dx^3$ is an isomorphism (verify).

Isomorphic spaces can "look" quite different. For example, $\mathbf{M}_{22} \cong P_3$ because the map $T : M_{22} \to P_3$ given by $T \begin{bmatrix} a & b \\ c & d \end{bmatrix} = a + bx + cx^2 + dx^3$ is an isomorphism (verify).

The word *isomorphism* comes from two Greek roots: *iso*, meaning "same," and *morphos*, meaning "form." An isomorphism $T : V \to W$ induces a pairing

$$\mathbf{v} \leftrightarrow T(\mathbf{v})$$

between vectors $\mathbf{v}$ in V and vectors $T(\mathbf{v})$ in W that preserves vector addition and scalar multiplication. Hence, *as far as their vector space properties are concerned*, the spaces V and W are identical except for notation. Because addition and scalar multiplication in either space are completely determined by the same operations in the other space, all *vector space* properties of either space are completely determined by those of the other.

One of the most important examples of isomorphic spaces was considered in Chapter 4]. Let A denote the set of all "arrows" with tail at the origin in space, and make A into a vector space using the parallelogram law and the scalar multiple law (see Section 4.1). Then define a transformation $T : \mathbb{R}^3 \to A$ by taking

$$T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \text{ the arrow } \mathbf{v} \text{ from the origin to the point } P(x,y,z).$$

In Section 4.1 matrix addition and scalar multiplication were shown to correspond to the parallelogram law and the scalar multiplication law for these arrows, so the map T is a linear transformation. Moreover T is an isomorphism: it is one-to-one by Theorem 4.1.2, and it is onto because, given an arrow $\mathbf{v}$ in A with tip $P(x,y,z)$, we have $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \mathbf{v}$. This justifies the identification $\mathbf{v} = \begin{bmatrix} x \\ y \\ z \end{bmatrix}$ in Chapter 4 of the geometric arrows with the algebraic matrices. This identification is very useful. The arrows give a "picture" of the matrices and so bring geometric intuition into $\mathbb{R}^3$; the matrices are useful for detailed calculations and so bring analytic precision into geometry. This is one of the best examples of the power of an isomorphism to shed light on both spaces being considered.

The following theorem gives a very useful characterization of isomorphisms: They are the linear transformations that preserve bases.

Theorem 6.10.3.1

If V and W are finite dimensional spaces, the following conditions are equivalent for a linear transformation $T: V \to W$.

1. T is an isomorphism.
2. If $\{\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n\}$ is any basis of V, then $\{T(\mathbf{e}_1), T(\mathbf{e}_2), \dots, T(\mathbf{e}_n)\}$ is a basis of W.
3. There exists a basis $\{\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n\}$ of V such that $\{T(\mathbf{e}_1), T(\mathbf{e}_2), \dots, T(\mathbf{e}_n)\}$ is a basis of W.

Proof

(1) $\Rightarrow$ (2). Let $\{\mathbf{e}_1, \dots, \mathbf{e}_n\}$ be a basis of V. If $t_1T(\mathbf{e}_1) + \cdots + t_nT(\mathbf{e}_n) = \mathbf{0}$ with t_i in $\mathbb{R}$, then $T(t_1\mathbf{e}_1 + \cdots + t_n\mathbf{e}_n) = \mathbf{0}$, so $t_1\mathbf{e}_1 + \cdots + t_n\mathbf{e}_n = \mathbf{0}$ (because $\ker T = \{\mathbf{0}\}$). But then each $t_i = 0$ by the independence of the $\mathbf{e}_i$, so $\{T(\mathbf{e}_1), \dots, T(\mathbf{e}_n)\}$ is independent. To show that it spans W, choose $\mathbf{w}$ in W. Because T is onto, $\mathbf{w} = T(\mathbf{v})$ for some $\mathbf{v}$ in V, so write $\mathbf{v} = t_1\mathbf{e}_1 + \cdots + t_n\mathbf{e}_n$. Hence we obtain $\mathbf{w} = T(\mathbf{v}) = t_1T(\mathbf{e}_1) + \cdots + t_nT(\mathbf{e}_n)$, proving that $\{T(\mathbf{e}_1), \dots, T(\mathbf{e}_n)\}$ spans W.

(2) $\Rightarrow$ (3). This is because V has a basis.

(3) $\Rightarrow$ (1). If $T(\mathbf{v}) = \mathbf{0}$, write $\mathbf{v} = v_1\mathbf{e}_1 + \cdots + v_n\mathbf{e}_n$ where each v_i is in $\mathbb{R}$. Then

$$\mathbf{0} = T(\mathbf{v}) = v_1T(\mathbf{e}_1) + \cdots + v_nT(\mathbf{e}_n)$$

so $v_1 = \cdots = v_n = 0$ by (3). Hence $\mathbf{v} = \mathbf{0}$, so $\ker T = \{\mathbf{0}\}$ and T is one-to-one. To show that T is onto, let $\mathbf{w}$ be any vector in W. By (3) there exist $w_1, \dots, w_n$ in $\mathbb{R}$ such that

$$\mathbf{w} = w_1T(\mathbf{e}_1) + \cdots + w_nT(\mathbf{e}_n) = T(w_1\mathbf{e}_1 + \cdots + w_n\mathbf{e}_n)$$

Thus T is onto.

□

Theorem 6.10.3.1 dovetails nicely with Theorem 7.1.3 as follows. Let V and W be vector spaces of dimension n, and suppose that $\{\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n\}$ and $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_n\}$ are bases of V and W, respectively. Theorem 7.1.3 asserts that there exists a linear transformation $T: V \to W$ such that

$$T(\mathbf{e}_i) = \mathbf{f}_i \quad \text{for each } i = 1, 2, \dots, n$$

Then $\{T(\mathbf{e}_1), \dots, T(\mathbf{e}_n)\}$ is evidently a basis of W, so T is an isomorphism by Theorem 7.3.1. Furthermore, the action of T is prescribed by

$$T(r_1\mathbf{e}_1 + \cdots + r_n\mathbf{e}_n) = r_1\mathbf{f}_1 + \cdots + r_n\mathbf{f}_n$$

so isomorphisms between spaces of equal dimension can be easily defined as soon as bases are known. In particular this shows that if two vector spaces V and W have the same dimension then they are isomorphic, that is $V \cong W$. This is half of the following theorem.

Theorem 6.10.3.2

If V and W are finite dimensional vector spaces, then $V \cong W$ if and only if $dim\ V = dim\ W$.

Proof

It remains to show that if $V \cong W$ then $dim\ V = dim\ W$. But if $V \cong W$, then there exists an isomorphism $T : V \to W$. Since V is finite dimensional, let $\{\mathbf{e}_1, \ldots, \mathbf{e}_n\}$ be a basis of V. Then $\{T(\mathbf{e}_1), \ldots, T(\mathbf{e}_n)\}$ is a basis of W by Theorem 7.3.1, so $dim\ W = n = dim\ V$.

Corollary6.10.3.1

Let U, V, and W denote vector spaces. Then:

1. $V \cong V$ for every vector space V.
2. If $V \cong W$ then $W \cong V$.
3. If $U \cong V$ and $V \cong W$, then $U \cong W$.

The proof is left to the reader. By virtue of these properties, the relation $\cong$ is called an *equivalence relation* on the class of finite dimensional vector spaces. Since $dim\ (\mathbb{R}^n) = n$ it follows that

Corollary 6.10.3.2

If V is a vector space and $dim\ V = n$, then V is isomorphic to $\mathbb{R}^n$.

If V is a vector space of dimension n, note that there are important explicit isomorphisms $V \to \mathbb{R}^n$. Fix a basis $B = \{\mathbf{b}_1, \mathbf{b}_2, \ldots, \mathbf{b}_n\}$ of V and write $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$ for the standard basis of $\mathbb{R}^n$. By Theorem 7.1.3 there is a unique linear transformation $C_B : V \to \mathbb{R}^n$ given by

$$C_B(v_1\mathbf{b}_1 + v_2\mathbf{b}_2 + \cdots + v_n\mathbf{b}_n) = v_1\mathbf{e}_1 + v_2\mathbf{e}_2 + \cdots + v_n\mathbf{e}_n = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}$$

where each v_i is in $\mathbb{R}$. Moreover, $C_B(\mathbf{b}_i) = \mathbf{e}_i$ for each i so C_B is an isomorphism by Theorem 7.3.1, called the **coordinate isomorphism** corresponding to the basis B. These isomorphisms will play a central role in Chapter 9.

The conclusion in the above corollary can be phrased as follows: As far as vector space properties are concerned, every n -dimensional vector space V is essentially the same as $\mathbb{R}^n$; they are the "same" vector space except for a change of symbols. This appears to make the process of abstraction seem less important—just study $\mathbb{R}^n$ and be done with it! But consider the different "feel" of the spaces $\mathbf{P}_8$ and $\mathbf{M}_{33}$ even though they are both the "same" as $\mathbb{R}^9$: For example, vectors in $\mathbf{P}_8$ can have roots, while vectors in $\mathbf{M}_{33}$ can be multiplied. So the merit in the abstraction process lies in identifying *common* properties of the vector spaces in the various examples. This is important even for finite dimensional spaces. However, the payoff from abstraction is much greater in the infinite dimensional case, particularly for spaces of functions.

Example 6.10.3.4

Let V denote the space of all 2×2 symmetric matrices. Find an isomorphism $T : \mathbf{P}_2 \to V$ such that $T(1) = I$, where I is the 2×2 identity matrix.

Solution

$\{1, x, x^2\}$ is a basis of $\mathbf{P}_2$, and we want a basis of V containing I. The set $\left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}$ is independent in V, so it is a basis because $dim\ V = 3$ (by Example 6.3.11). Hence define $T : \mathbf{P}_2 \to V$ by taking $T(1) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $T(x) = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$, $T(x^2) = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$, and extending linearly as in Theorem 6.10.3.1. Then T is an isomorphism by Theorem 7.3.1, and its action is given by

$$T(a + bx + cx^2) = aT(1) + bT(x) + cT(x^2) = \begin{bmatrix} a & b \\ b & a + c \end{bmatrix}$$

The dimension theorem (Theorem 7.2.4) gives the following useful fact about isomorphisms.

Theorem 6.10.3.3

If V and W have the same dimension n, a linear transformation $T : V \to W$ is an isomorphism if it is either one-to-one or onto.

Proof

The dimension theorem asserts that $dim\ (\ker T) + dim\ (im\ T) = n$, so $dim\ (\ker T) = 0$ if and only if $dim\ (im\ T) = n$. Thus T is one-to-one if and only if T is onto, and the result follows.

□

Composition

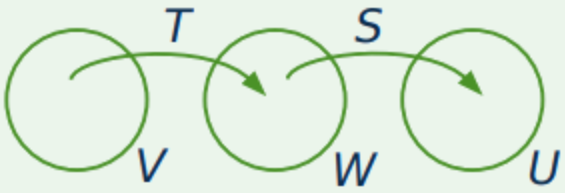
Suppose that $T : V \to W$ and $S : W \to U$ are linear transformations. They link together as in the diagram so, as in Section 2.3, it is possible to define a new function $V \to U$ by first applying T and then S.

Definition: Composition of LinearTransformations

Given linear transformations $V \xrightarrow{T} W \xrightarrow{S} U$, the **composite** $ST : V \to U$ of T and S is defined by

$$ST(\mathbf{v}) = S\left[T(\mathbf{v})\right] \quad \text{for all } \mathbf{v} \text{ in } V$$

The operation of forming the new function ST is called **composition**.[1]



The action of ST can be described compactly as follows: ST means first T then S.

Not all pairs of linear transformations can be composed. For example, if $T : V \to W$ and $S : W \to U$ are linear transformations then $ST : V \to U$ is defined, but TS *cannot* be formed unless $U = V$ because $S : W \to U$ and $T : V \to W$ do not "link" in that order.[2]

Moreover, even if ST and TS can both be formed, they may not be equal. In fact, if $S : \mathbb{R}^m \to \mathbb{R}^n$ and $T : \mathbb{R}^n \to \mathbb{R}^m$ are induced by matrices A and B respectively, then ST and TS can both be formed (they are induced by AB and BA respectively), but the matrix products AB and BA may not be equal (they may not even be the same size). Here is another example.

Example 6.10.3.5

Define: $S : \mathbf{M}_{22} \to \mathbf{M}_{22}$ and $T : \mathbf{M}_{22} \to \mathbf{M}_{22}$ by $S\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} c & d \\ a & b \end{bmatrix}$ and $T(A) = A^T$ for $A \in M_{22}$. Describe the action of ST and TS, and show that $ST \neq TS$.

Solution

$$ST\begin{bmatrix} a & b \\ c & d \end{bmatrix} = S\begin{bmatrix} a & c \\ b & d \end{bmatrix} = \begin{bmatrix} b & d \\ a & c \end{bmatrix},$$

whereas $TS\begin{bmatrix} a & b \\ c & d \end{bmatrix} = T\begin{bmatrix} c & d \\ a & b \end{bmatrix} = \begin{bmatrix} c & a \\ d & b \end{bmatrix}$.

It is clear that $TS\begin{bmatrix} a & b \\ c & d \end{bmatrix}$ need not equal $ST\begin{bmatrix} a & b \\ c & d \end{bmatrix}$, so $TS \neq ST$.

The next theorem collects some basic properties of the composition operation.

Theorem 6.10.3.4[3]

Let $V \xrightarrow{T} W \xrightarrow{S} U \xrightarrow{R} Z$ be linear transformations.

1. The composite ST is again a linear transformation.
2. $T1_V = T$ and $1_W T = T$.
3. $(RS)T = R(ST)$.

Proof

The proofs of (1) and (2) are left as Exercise 7.3.25. To prove (3), observe that, for all $\mathbf{v}$ in V:

$$\{(RS)T\}(\mathbf{v}) = (RS)\,[T(\mathbf{v})] = R\{S\,[T(\mathbf{v})]\} = R\{(ST)(\mathbf{v})\} = \{R(ST)\}(\mathbf{v})$$

Up to this point, composition seems to have no connection with isomorphisms. In fact, the two notions are closely related.

Theorem 7.3.5

Let V and W be finite dimensional vector spaces. The following conditions are equivalent for a linear transformation $T : V \to W$.

1. T is an isomorphism.
2. There exists a linear transformation $S : W \to V$ such that $ST = 1_V$ and $TS = 1_W$.

Moreover, in this case S is also an isomorphism and is uniquely determined by T:

$$\text{If } \mathbf{w} \text{ in } W \text{ is written as } \mathbf{w} = T(\mathbf{v}), \text{ then } S(\mathbf{w}) = \mathbf{v}.$$

Proof

(1) $\Rightarrow$ (2). If $B = \{\mathbf{e}_1, \dots, \mathbf{e}_n\}$ is a basis of V, then $D = \{T(\mathbf{e}_1), \dots, T(\mathbf{e}_n)\}$ is a basis of W by Theorem 7.3.1. Hence (using Theorem 7.1.3), define a linear transformation $S : W \to V$ by

$$S[T(\mathbf{e}_i)] = \mathbf{e}_i \quad \text{for each } i \tag{6.10.3.1}$$

Since $\mathbf{e}_i = 1_V(\mathbf{e}_i)$, this gives $ST = 1_V$ by Theorem 7.1.2. But applying T gives $T[S[T(\mathbf{e}_i)]] = T(\mathbf{e}_i)$ for each i, so $TS = 1_W$ (again by Theorem 7.1.2, using the basis D of W).

(2) $\Rightarrow$ (1). If $T(\mathbf{v}) = T(\mathbf{v}_1)$, then $S[T(\mathbf{v})] = S[T(\mathbf{v}_1)]$. Because $ST = 1_V$ by (2), this reads $\mathbf{v} = \mathbf{v}_1$; that is, T is one-to-one. Given $\mathbf{w}$ in W, the fact that $TS = 1_W$ means that $\mathbf{w} = T[S(\mathbf{w})]$, so T is onto.

Finally, S is uniquely determined by the condition $ST = 1_V$ because this condition implies (6.10.3.1). S is an isomorphism because it carries the basis D to B. As to the last assertion, given $\mathbf{w}$ in W, write $\mathbf{w} = r_1T(\mathbf{e}_1) + \cdots + r_nT(\mathbf{e}_n)$. Then $\mathbf{w} = T(\mathbf{v})$, where $\mathbf{v} = r_1\mathbf{e}_1 + \cdots + r_n\mathbf{e}_n$. Then $S(\mathbf{w}) = \mathbf{v}$ by (6.10.3.1).

Given an isomorphism $T : V \to W$, the unique isomorphism $S : W \to V$ satisfying condition (2) of Theorem 7.3.5 is called the **inverse** of T and is denoted by T^{-1}. Hence $T : V \to W$ and $T^{-1} : W \to V$ are related by the **fundamental identities**:

$$T^{-1}[T(\mathbf{v})] = \mathbf{v} \text{ for all } \mathbf{v} \text{ in } V \quad \text{and} \quad T\left[T^{-1}(\mathbf{w})\right] = \mathbf{w} \text{ for all } \mathbf{w} \text{ in } W$$

In other words, each of T and T^{-1} reverses the action of the other. In particular, equation (6.10.3.1) in the proof of Theorem 7.3.5 shows how to define T^{-1} using the image of a basis under the isomorphism T. Here is an example.

Example 6.10.3.6

Define $T : \mathbf{P}_1 \to \mathbf{P}_1$ by $T(a + bx) = (a - b) + ax$. Show that T has an inverse, and find the action of T^{-1}.

Solution

The transformation T is linear (verify). Because $T(1) = 1 + x$ and $T(x) = -1$, T carries the basis $B = \{1, x\}$ to the basis $D = \{1 + x, -1\}$. Hence T is an isomorphism, and T^{-1} carries D back to B, that is,

$$T^{-1}(1 + x) = 1 \quad \text{and} \quad T^{-1}(-1) = x$$

Because $a + bx = b(1 + x) + (b - a)(-1)$, we obtain

$$T^{-1}(a + bx) = bT^{-1}(1 + x) + (b - a)T^{-1}(-1) = b + (b - a)x$$

Sometimes the action of the inverse of a transformation is apparent.

Example 6.10.3.7

If $B = \{\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_n\}$ is a basis of a vector space V, the coordinate transformation $C_B : V \to \mathbb{R}^n$ is an isomorphism defined by

$$C_B(v_1\mathbf{b}_1 + v_2\mathbf{b}_2 + \cdots + v_n\mathbf{b}_n) = (v_1, v_2, \dots, v_n)^T$$

The way to reverse the action of C_B is clear: $C_B^{-1} : \mathbb{R}^n \to V$ is given by

$$C_B^{-1}(v_1, v_2, \dots, v_n) = v_1\mathbf{b}_1 + v_2\mathbf{b}_2 + \cdots + v_n\mathbf{b}_n \quad \text{for all } v_i \text{ in } V$$

Condition (2) in Theorem 7.3.5 characterizes the inverse of a linear transformation $T : V \to W$ as the (unique) transformation $S : W \to V$ that satisfies $ST = 1_V$ and $TS = 1_W$. This often determines the inverse.

Example 6.10.3.8

Define $T : \mathbb{R}^3 \to \mathbb{R}^3$ by $T(x, y, z) = (z, x, y)$. Show that $T^3 = 1_{\mathbb{R}^3}$, and hence find T^{-1}.

Solution

$T^2(x, y, z) = T[T(x, y, z)] = T(z, x, y) = (y, z, x)$. Hence

$$T^3(x, y, z) = T\left[T^2(x, y, z)\right] = T(y, z, x) = (x, y, z)$$

Since this holds for all (x, y, z), it shows that $T^3 = 1_{\mathbb{R}^3}$, so $T(T^2) = 1_{\mathbb{R}^3} = (T^2)T$. Thus $T^{-1} = T^2$ by (2) of Theorem 7.3.5.

Example 6.10.3.9

Define $T : \mathbf{P}_n \to \mathbb{R}^{n+1}$ by $T(p) = (p(0), p(1), \dots, p(n))$ for all p in $\mathbf{P}_n$. Show that T^{-1} exists.

Solution

The verification that T is linear is left to the reader. If $T(p) = 0$, then $p(k) = 0$ for $k = 0, 1, \dots, n$, so p has $n + 1$ distinct roots. Because p has degree at most n, this implies that $p = 0$ is the zero polynomial (Theorem

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1. Note: In Section 2.3 we denoted the composite as $S \circ T$. However, it is more convenient to use the simpler notation ST.
2. Actually, all that is required is $U \subseteq V$.
3. Theorem 7.3.4 can be expressed by saying that vector spaces and linear transformations are an example of a category. In general a category consists of certain objects and, for any two objects X and Y, a set $\mathrm{mor}(\mathrm{X}, \mathrm{Y})$. The elements α of mor(X, Y) are called morphisms from X to Y and are written $\alpha : \mathrm{X} \to \mathrm{Y}$. It is assumed that identity morphisms and composition are defined in such a way that Theorem 7.3.4 holds. Hence, in the category of vector spaces the objects are the vector spaces themselves and the morphisms are the linear transformations. Another example is the category of metric spaces, in which the objects are sets equipped with a distance function (called a metric), and the morphisms are continuous functions (with respect to the metric). The category of sets and functions is a very basic example.

6.10.3E: Isomorphisms and Composition Exercises

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6.10.3E: Isomorphisms and Composition Exercises

Exercise 6.10.3E.1

Verify that each of the following is an isomorphism (Theorem 7.3.3 is useful).

a. $T : \mathbb{R}^3 \to \mathbb{R}^3$; $T(x, y, z) = (x + y, y + z, z + x)$
b. $T : \mathbb{R}^3 \to \mathbb{R}^3$; $T(x, y, z) = (x, x + y, x + y + z)$
c. $T : \mathbb{C} \to \mathbb{C}$; $T(z) = \overline{z}$
d. $T : \mathbf{M}_{mn} \to \mathbf{M}_{mn}$; $T(X) = UXV$, U and V invertible
e. $T : \mathbf{P}_1 \to \mathbb{R}^2$; $T[p(x)] = [p(0), p(1)]$
f. $T : V \to V$; $T(\mathbf{v}) = k\mathbf{v}$, $k \neq 0$ a fixed number, V any vector space
g. $T : \mathbf{M}_{22} \to \mathbb{R}^4$; $T \begin{bmatrix} a & b \\ c & d \end{bmatrix} = (a + b, d, c, a - b)$
h. $T : \mathbf{M}_{mn} \to \mathbf{M}_{nm}$; $T(A) = A^T$

Answer available at the end of this section.

Exercise 6.10.3E.2

Show that

$$\{a + bx + cx^2, a_1 + b_1x + c_1x^2, a_2 + b_2x + c_2x^2\}$$

is a basis of $\mathbf{P}_2$ if and only if $\{(a, b, c), (a_1, b_1, c_1), (a_2, b_2, c_2)\}$ is a basis of $\mathbb{R}^3$.

Exercise 6.10.3E.3

If V is any vector space, let V^n denote the space of all n-tuples $(\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n)$, where each $\mathbf{v}_i$ lies in V. (This is a vector space with component-wise operations; see Exercise 6.1.17.) If $C_j(A)$ denotes the jth column of the $m \times n$ matrix A, show that $T : \mathbf{M}_{mn} \to (\mathbb{R}^m)^n$ is an isomorphism if
$T(A) = \begin{bmatrix} C_1(A) & C_2(A) & \cdots & C_n(A) \end{bmatrix}$. (Here $\mathbb{R}^m$ consists of columns.)

Exercise 6.10.3E.4

In each case, compute the action of ST and TS, and show that $ST \neq TS$.

a. $S : \mathbb{R}^2 \to \mathbb{R}^2$ with $S(x, y) = (y, x)$; $T : \mathbb{R}^2 \to \mathbb{R}^2$ with $T(x, y) = (x, 0)$
b. $S : \mathbb{R}^3 \to \mathbb{R}^3$ with $S(x, y, z) = (x, 0, z)$; $T : \mathbb{R}^3 \to \mathbb{R}^3$ with $T(x, y, z) = (x + y, 0, y + z)$
c. $S : \mathbf{P}_2 \to \mathbf{P}_2$ with $S(p) = p(0) + p(1)x + p(2)x^2$; $T : \mathbf{P}_2 \to \mathbf{P}_2$ with $T(a + bx + cx^2) = b + cx + ax^2$
d. $S : \mathbf{M}_{22} \to \mathbf{M}_{22}$ with $S \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} a & 0 \\ 0 & d \end{bmatrix}$; $T : \mathbf{M}_{22} \to \mathbf{M}_{22}$ with $T \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} c & a \\ d & b \end{bmatrix}$

Answer available at the end of this section.

Exercise 6.10.3E.5

In each case, show that the linear transformation T satisfies $T^2 = T$.

a. $T:\mathbb{R}^4\to\mathbb{R}^4$; $T(x,y,z,w)=(x,0,z,0)$
b. $T:\mathbb{R}^2\to\mathbb{R}^2$; $T(x,y)=(x+y,0)$
c. $T:\mathbf{P}_2\to\mathbf{P}_2$;$T(a+bx+cx^2)=(a+b-c)+cx+cx^2$
d. $T:\mathbf{M}_{22}\to\mathbf{M}_{22}$; $T\begin{bmatrix} a & b \\ c & d \end{bmatrix}=\frac{1}{2}\begin{bmatrix} a+c & b+d \\ a+c & b+d \end{bmatrix}$

Answer available at the end of this section.

Exercise $6.10.3E.6$

Determine whether each of the following transformations T has an inverse and, if so, determine the action of T^{-1}.

a. $T:\mathbb{R}^3\to\mathbb{R}^3$; $T(x,y,z)=(x+y,y+z,z+x)$
b. $T:\mathbb{R}^4\to\mathbb{R}^4$; $T(x,y,z,t)=(x+y,y+z,z+t,t+x)$
c. $T:\mathbf{M}_{22}\to\mathbf{M}_{22}$; $T\begin{bmatrix} a & b \\ c & d \end{bmatrix}=\begin{bmatrix} a-c & b-d \\ 2a-c & 2b-d \end{bmatrix}$
d. $T:\mathbf{M}_{22}\to\mathbf{M}_{22}$; $T\begin{bmatrix} a & b \\ c & d \end{bmatrix}=\begin{bmatrix} a+2c & b+2d \\ 3c-a & 3d-b \end{bmatrix}$
e. $T:\mathbf{P}_2\to\mathbb{R}^3$; $T(a+bx+cx^2)=(a-c,2b,a+c)$
f. $T:\mathbf{P}_2\to\mathbb{R}^3$; $T(p)=[p(0),p(1),p(-1)]$

Answer available at the end of this section.

Exercise $6.10.3E.7$

In each case, show that T is self-inverse, that is: $T^{-1}=T$.

a. $T:\mathbb{R}^4\to\mathbb{R}^4$; $T(x,y,z,w)=(x,-y,-z,w)$
b. $T:\mathbb{R}^2\to\mathbb{R}^2$; $T(x,y)=(ky-x,y)$, k any fixed number
c. $T:\mathbf{P}_n\to\mathbf{P}_n$; $T(p(x))=p(3-x)$
d. $T:\mathbf{M}_{22}\to\mathbf{M}_{22}$; $T(X)=AX$ where $A=\frac{1}{4}\begin{bmatrix} 5 & -3 \\ 3 & -5 \end{bmatrix}$

Answer available at the end of this section.

Exercise $6.10.3E.8$

In each case, show that $T^6=1_{R^4}$ and so determine T^{-1}.

a. $T:\mathbb{R}^4\to\mathbb{R}^4$; $T(x,y,z,w)=(-x,z,w,y)$
b. $T:\mathbb{R}^4\to\mathbb{R}^4$; $T(x,y,z,w)=(-y,x-y,z,-w)$

Answer available at the end of this section.

Exercise $6.10.3E.9$

In each case, show that T is an isomorphism by defining T^{-1} explicitly.

a. $T:\mathbf{P}_n\to\mathbf{P}_n$ is given by $T[p(x)]=p(x+1)$.
b. $T:\mathbf{M}_{nn}\to\mathbf{M}_{nn}$ is given by $T(A)=UA$ where U is invertible in $\mathbf{M}_{nn}$.

Answer available at the end of this section.

Exercise $6.10.3E.10$

Given linear transformations $V \xrightarrow{T} W \xrightarrow{S} U$:

a. If S and T are both one-to-one, show that ST is one-to-one.
b. If S and T are both onto, show that ST is onto.

Answer available at the end of this section.

Exercise $6.10.3E.11$

Let $T : V \to W$ be a linear transformation.

a. If T is one-to-one and $TR = TR_1$ for transformations R and $R_1 : U \to V$, show that $R = R_1$.
b. If T is onto and $ST = S_1T$ for transformations S and $S_1 : W \to U$, show that $S = S_1$.

Exercise $6.10.3E.12$

Consider the linear transformations $V \xrightarrow{T} W \xrightarrow{R} U$.

a. Show that $\ker\ T \subseteq \ker\ RT$.
b. Show that $im\ \ RT \subseteq im\ \ R$.

Answer available at the end of this section.

Exercise $6.10.3E.13$

Let $V \xrightarrow{T} U \xrightarrow{S} W$ be linear transformations.

a. If ST is one-to-one, show that T is one-to-one and that $dim\ \ V \leq dim\ \ U$.
b. If ST is onto, show that S is onto and that $dim\ \ W \leq dim\ \ U$.

Answer available at the end of this section.

Exercise $6.10.3E.14$

Let $T : V \to V$ be a linear transformation. Show that $T^2 = 1_V$ if and only if T is invertible and $T = T^{-1}$

Exercise $6.10.3E.15$

Let N be a nilpotent $n \times n$ matrix (that is, $N^k = 0$ for some k). Show that $T : \mathbf{M}_{nm} \to \mathbf{M}_{nm}$ is an isomorphism if $T(X) = X - NX$. [*Hint*: If X is in $\ker\ T$, show that $X = NX = N^2X = \cdots$. Then use Theorem $6.10.3E.3$.]

Exercise $6.10.3E.16$

Let $T : V \to W$ be a linear transformation, and let $\{\mathbf{e}_1, \ldots, \mathbf{e}_r, \mathbf{e}_{r+1}, \ldots, \mathbf{e}_n\}$ be any basis of V such that $\{\mathbf{e}_{r+1}, \ldots, \mathbf{e}_n\}$ is a basis of $\ker\ T$. Show that $im\ \ T \cong span\ \ \{\mathbf{e}_1, \ldots, \mathbf{e}_r\}$. [Hint: See Theorem $6.10.3E.3$.]

Answer available at the end of this section.

Exercise $6.10.3E.17$

Is every isomorphism $T : \mathbf{M}_{22} \to \mathbf{M}_{22}$ given by an invertible matrix U such that $T(X) = UX$ for all X in $\mathbf{M}_{22}$? Prove your answer.

Exercise $6.10.3E.18$

Let $\mathbf{D}_n$ denote the space of all functions f from $\{1, 2, \dots, n\}$ to $\mathbb{R}$ (see Exercise 6.3.35). If $T : \mathbf{D}_n \to \mathbb{R}^n$ is defined by

$$T(f) = (f(1), f(2), \dots, f(n)),$$

show that T is an isomorphism

Exercise $6.10.3E.19$

a. Let V be the vector space of Exercise6.1.3. Find an isomorphism $T : V \to \mathbb{R}^1$.
b. Let V be the vector space of Exercise 6.1.4. Find an isomorphism $T : V \to \mathbb{R}^2$.

Answer available at the end of this section.

Exercise $6.10.3E.20$

Let $V \xrightarrow{T} W \xrightarrow{S} V$ be linear transformations such that $ST = 1_V$. If $dim\ V = dim\ W = n$, show that $S = T^{-1}$ and $T = S^{-1}$. [Hint: Exercise 7.3.13 and Theorem 7.3.3, Theorem 7.3.4, and Theorem 7.3.5.]

Exercise $6.10.3E.21$

Let $V \xrightarrow{T} W \xrightarrow{S} V$ be functions such that $TS = 1_W$ and $ST = 1_V$. If T is linear, show that S is also linear

Exercise $6.10.3E.22$

Let A and B be matrices of size $p \times m$ and $n \times q$. Assume that $mn = pq$. Define $R : \mathbf{M}_{mn} \to \mathbf{M}_{pq}$ by $R(X) = AXB$.

a. Show that $\mathbf{M}_{mn} \cong \mathbf{M}_{pq}$ by comparing dimensions.
b. Show that R is a linear transformation.
c. Show that if R is an isomorphism, then $m = p$ and $n = q$. [*Hint*: Show that $T : \mathbf{M}_{mn} \to \mathbf{M}_{pn}$ given by $T(X) = AX$ and $S : \mathbf{M}_{mn} \to \mathbf{M}_{mq}$ given by $S(X) = XB$ are both one-to-one, and use the dimension theorem.]

Exercise $6.10.3E.23$

Let $T : V \to V$ be a linear transformation such that $T^2 = 0$ is the zero transformation.

a. If $V \neq \{\mathbf{0}\}$, show that T cannot be invertible.
b. If $R : V \to V$ is defined by $R(\mathbf{v}) = \mathbf{v} + T(\mathbf{v})$ for all $\mathbf{v}$ in V, show that R is linear and invertible.

Exercise $6.10.3E.24$

Let V consist of all sequences $[x_0, x_1, x_2, \dots)$ of numbers, and define vector operations

$$[x_o, x_1, ...) + [y_0, y_1, ...) = [x_0 + y_0, x_1 + y_1, ...)$$
$$r[x_0, x_1, ...) = [rx_0, rx_1, ...)$$

a. Show that V is a vector space of infinite dimension.
b. Define $T : V \to V$ and $S : V \to V$ by $T[x_0, x_1, ...) = [x_1, x_2, ...)$ and $S[x_0, x_1, ...) = [0, x_0, x_1, ...)$. Show that $TS = 1_V$, so TS is one-to-one and onto, but that T is not one-to-one and S is not onto.

Answer available at the end of this section.

Exercise $6.10.3E.25$

Prove (1) and (2) of Theorem $6.10.3E.4$

Exercise $6.10.3E.26$

Define $T : \mathbf{P}_n \to \mathbf{P}_n$ by
$T(p) = p(x) + xp'(x)$ for all p in $\mathbf{P}_n$.

a. Show that T is linear.
b. Show that $\ker T = \{\mathbf{0}\}$ and conclude that T is an isomorphism. [*Hint*: Write $p(x) = a_0 + a_1x + \cdots + a_nx^n$ and compare coefficients if $p(x) = -xp'(x)$.]
c. Conclude that each $q(x)$ in $\mathbf{P}_n$ has the form $q(x) = p(x) + xp'(x)$ for some unique polynomial $p(x)$.
d. Does this remain valid if T is defined by $T[p(x)] = p(x) - xp'(x)$? Explain.

Answer available at the end of this section.

Exercise $6.10.3E.27$

Let $T : V \to W$ be a linear transformation, where V and W are finite dimensional.

a. Show that T is one-to-one if and only if there exists a linear transformation $S : W \to V$ with $ST = 1_V$. [*Hint*: If $\{\mathbf{e}_1, ..., \mathbf{e}_n\}$ is a basis of V and T is one-to-one, show that W has a basis $\{T(\mathbf{e}_1), ..., T(\mathbf{e}_n), \mathbf{f}_{n+1}, ..., \mathbf{f}_{n+k}\}$ and use Theorem 7.1.2 and Theorem 7.1.3.]
b. Show that T is onto if and only if there exists a linear transformation $S : W \to V$ with $TS = 1_W$. [Hint: Let $\{\mathbf{e}_1, ..., \mathbf{e}_r, ..., \mathbf{e}_n\}$ be a basis of V such that $\{\mathbf{e}_{r+1}, ..., \mathbf{e}_n\}$ is a basis of $\ker T$. Use Theorem 7.2.5, Theorem \7.1.2 and Theorem 7.1.3.]

Answer available at the end of this section.

Exercise $6.10.3E.28$

Let S and T be linear transformations $V \to W$, where $dim\ V = n$ and $dim\ W = m$.

a. Show that $\ker S = \ker T$ if and only if $T = RS$ for some isomorphism $R : W \to W$. [*Hint*: Let $\{\mathbf{e}_1, ..., \mathbf{e}_r, ..., \mathbf{e}_n\}$ be a basis of V such that $\{\mathbf{e}_{r+1}, ..., \mathbf{e}_n\}$ is a basis of $\ker S = \ker T$. Use Theorem 7.2.5 to extend $\{S(\mathbf{e}_1), ..., S(\mathbf{e}_r)\}$ and $\{T(\mathbf{e}_1), ..., T(\mathbf{e}_r)\}$ to bases of W.]
b. Show that $im\ S = im\ T$ if and only if $T = SR$ for some isomorphism $R : V \to V$. [*Hint*: Show that $dim\ (\ker S) = dim\ (\ker T)$ and choose bases $\{\mathbf{e}_1, ..., \mathbf{e}_r, ..., \mathbf{e}_n\}$ and $\{\mathbf{f}_1, ..., \mathbf{f}_r, ..., \mathbf{f}_n\}$ of V where $\{\mathbf{e}_{r+1}, ..., \mathbf{e}_n\}$ and $\{\mathbf{f}_{r+1}, ..., \mathbf{f}_n\}$ are bases of $\ker S$ and $\ker T$, respectively. If $1 \le i \le r$, show that $S(\mathbf{e}_i) = T(\mathbf{g}_i)$ for some $\mathbf{g}_i$ in V, and prove that $\{\mathbf{g}_1, ..., \mathbf{g}_r, \mathbf{f}_{r+1}, ..., \mathbf{f}_n\}$ is a basis of V.]

Answer available at the end of this section.

Exercise $6.10.3E.29$

If $T : V \to V$ is a linear transformation where $dim\ \ V = n$, show that $TST = T$ for some isomorphism $S : V \to V$. [Hint: Let $\{\mathbf{e}_1, \ldots, \mathbf{e}_r, \mathbf{e}_{r+1}, \ldots, \mathbf{e}_n\}$ be as in Theorem 7.2.5. Extend $\{T(\mathbf{e}_1), \ldots, T(\mathbf{e}_r)\}$ to a basis of V, and use Theorem 7.3.1, Theorem 7.1.2, and Theorem 7.1.3.]

Answer available at the end of this section.

Exercise $6.10.3E.30$

Let A and B denote $m \times n$ matrices. In each case show that (1) and (2) are equivalent.

a. (1) A and B have the same null space. (2) $B = PA$ for some invertible $m \times m$ matrix P.
b. (1) A and B have the same range. (2) $B = AQ$ for some invertible $n \times n$ matrix Q.

[*Hint*: Use Exercise 7.3.28.]

Answers

Exercise $6.10.3E.1$

b. T is onto because $T(1,-1,0) = (1,0,0)$, $T(0,1,-1) = (0,1,0)$, and $T(0,0,1) = (0,0,1)$. Use Theorem 7.3.3.
d. T is one-to-one because $0 = T(X) = UXV$ implies that $X = 0$ (U and V are invertible). Use Theorem 7.3.3.
f. T is one-to-one because $\mathbf{0} = T(\mathbf{v}) = k\mathbf{v}$ implies that $\mathbf{v} = \mathbf{0}$ (because $k \neq 0$).
h. T is onto because $T\left(\frac{1}{k}\mathbf{v}\right) = \mathbf{v}$ for all $\mathbf{v}$. [Here Theorem 7.3.3 does not apply if $dim\ \ V$ is not finite.]
j. T is one-to-one because $T(A) = 0$ implies $A^T = 0$, whence $A = 0$. Use Theorem 7.3.3.

Exercise $6.10.3E.4$

b. $ST(x,y,z) = (x+y, 0, y+z)$, $TS(x,y,z) = (x,0,z)$
d. $ST\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} c & 0 \\ 0 & d \end{bmatrix}$, $TS\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} 0 & a \\ d & 0 \end{bmatrix}$

Exercise $6.10.3E.5$

b. $T^2(x,y) = T(x+y,0) = (x+y,0) = T(x,y)$. Hence $T^2 = T$.
d. $T^2\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \frac{1}{2}T\begin{bmatrix} a+c & b+d \\ a+c & b+d \end{bmatrix} = \frac{1}{2}\begin{bmatrix} a+c & b+d \\ a+c & b+d \end{bmatrix}$

Exercise $6.10.3E.6$

b. No inverse; $(1,-1,1,-1)$ is in $\ker T$.
d. $T^{-1}\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \frac{1}{5}\begin{bmatrix} 3a-2c & 3b-2d \\ a+c & b+d \end{bmatrix}$
f. $T^{-1}(a,b,c) = \frac{1}{2}\left[2a + (b-c)x - (2a-b-c)x^2\right]$

Exercise $6.10.3E.7$

b. $T^2(x,y) = T(ky-x, y) = (ky-(ky-x), y) = (x,y)$
d. $T^2(X) = A^2X = IX = X$

Exercise $6.10.3E.8$

b. $T^3(x,y,z,w) = (x,y,z,-w)$ so $T^6(x,y,z,w) = T^3\left[T^3(x,y,z,w)\right] = (x,y,z,w)$. Hence $T^{-1} = T^5$. So $T^{-1}(x,y,z,w) = (y-x,-x,z,-w)$.

Exercise $6.10.3E.9$

b. $T^{-1}(A) = U^{-1}A$.

Exercise $6.10.3E.10$

b. Given $\mathbf{u}$ in U, write $\mathbf{u} = S(\mathbf{w})$, $\mathbf{w}$ in W (because S is onto). Then write $\mathbf{w} = T(\mathbf{v})$, $\mathbf{v}$ in V (T is onto). Hence $\mathbf{u} = ST(\mathbf{v})$, so ST is onto.

Exercise $6.10.3E.12$

b. For all $\mathbf{v}$ in V, $(RT)(\mathbf{v}) = R\left[T(\mathbf{v})\right]$ is in $im\ \ (R)$.

Exercise $6.10.3E.13$

b. Given $\mathbf{w}$ in W, write $\mathbf{w} = ST(\mathbf{v})$, $\mathbf{v}$ in V (ST is onto). Then $\mathbf{w} = S\left[T(\mathbf{v})\right]$, $T(\mathbf{v})$ in U, so S is onto. But then $im\ \ S = W$, so $dim\ \ U = dim\ \ (\ker S) + dim\ \ (im\ \ S) \geq dim\ \ (im\ \ S) = dim\ \ W$.

Exercise $6.10.3E.16$

$\{T(\mathbf{e}_1), T(\mathbf{e}_2), \ldots, T(\mathbf{e}_r)\}$ is a basis of $im\ \ T$ by Theorem 7.2.5. So $T : span\ \ \{\mathbf{e}_1, \ldots, \mathbf{e}_r\} \to im\ \ T$ is an isomorphism by Theorem $6.10.3E.3$.

Exercise $6.10.3E.19$

b. $T(x,y) = (x, y+1)$

Exercise $6.10.3E.24$

b. $TS[x_0, x_1, \ldots) = T[0, x_0, x_1, \ldots) = [x_0, x_1, \ldots)$, so $TS = 1_V$. Hence TS is both onto and one-to-one, so T is onto and S is one-to-one by Exercise 7.3.13. But $[1,0,0,\ldots)$

is in $\ker\ T$ while $[1,0,0,\ldots)$ is not in $im\ \ S$.

Exercise $6.10.3E.26$

b. If $T(p)=0$, then $p(x)=-xp'(x)$. We write $p(x)=a_0+a_1x+a_2x^2+\cdots+a_nx^n$, and this becomes $a_0+a_1x+a_2x^2+\cdots+a_nx^n=-a_1x-2a_2x^2-\cdots-na_nx^n$. Equating coefficients yields $a_0=0, 2a_1=0, 3a_2=0,\ldots,(n+1)a_n=0$, whence $p(x)=0$.

c. This means that $\ker\ T=0$, so T is one-to-one. But then T is an isomorphism .

Exercise $6.10.3E.27$

b. If $ST=1_V$ for some S, then T is onto by Exercise 7.3.13. If T is onto, let $\{\mathbf{e}_1,\ldots,\mathbf{e}_r,\ldots,\mathbf{e}_n\}$ be a basis of V such that $\{\mathbf{e}_{r+1},\ldots,\mathbf{e}_n\}$ is a basis of $\ker\ T$. Since T is onto, $\{T(\mathbf{e}_1),\ldots,T(\mathbf{e}_r)\}$ is a basis of $im\ \ T=W$ by Theorem 7.2.5. Thus $S:W\to V$ is an isomorphism where by $S\{T(\mathbf{e}_i)]=\mathbf{e}_i$ for $i=1,2,\ldots,r$. Hence $TS[T(\mathbf{e}_i)]=T(\mathbf{e}_i)$ for each i, that is $TS[T(\mathbf{e}_i)]=1_W[T(\mathbf{e}_i)]$. This means that $TS=1_W$ because they agree on the basis $\{T(\mathbf{e}_1),\ldots,T(\mathbf{e}_r)\}$ of W.

Exercise $6.10.3E.28$

b. Conversely, assume that $im\ \ S=im\ \ T$. Then $dim\ \ (\ker\ S)=dim\ \ (\ker\ T)$ by the dimension theorem. Let $\{\mathbf{e}_1,\ldots,\mathbf{e}_r,\mathbf{e}_{r+1},\ldots,\mathbf{e}_n\}$ and $\{\mathbf{f}_1,\ldots,\mathbf{f}_r,\mathbf{f}_{r+1},\ldots,\mathbf{f}_n\}$ be bases of V such that $\{\mathbf{e}_{r+1},\ldots,\mathbf{e}_n\}$ and $\{\mathbf{f}_{r+1},\ldots,\mathbf{f}_n\}$ are bases of $\ker\ S$ and $\ker\ T$, respectively. By Theorem 7.2.5, $\{S(\mathbf{e}_1),\ldots,S(\mathbf{e}_r)\}$ and $\{T(\mathbf{f}_1),\ldots,T(\mathbf{f}_r)\}$ are both bases of $im\ \ S=im\ \ T$. So let $\mathbf{g}_1,\ldots,\mathbf{g}_r$ in V be such that $S(\mathbf{e}_i)=T(\mathbf{g}_i)$ for each $i=1,2,\ldots,r$. Show that

$$B=\{\mathbf{g}_1,\ldots,\mathbf{g}_r,\mathbf{f}_{r+1},\ldots,\mathbf{f}_n\}\text{ is a basis of }V.$$

Then define $R:V\to V$ by $R(\mathbf{g}_i)=\mathbf{e}_i$ for $i=1,2,\ldots,r$, and $R(\mathbf{f}_j)=\mathbf{e}_j$ for $j=r+1,\ldots,n$. Then R is an isomorphism by Theorem $6.10.3E.25$. Finally $SR=T$ since they have the same effect on the basis B.

Exercise $6.10.3E.29$

Let $B=\{\mathbf{e}_1,\ldots,\mathbf{e}_r,\mathbf{e}_{r+1},\ldots,\mathbf{e}_n\}$ be a basis of V with $\{\mathbf{e}_{r+1},\ldots,\mathbf{e}_n\}$ a basis of $\ker\ T$. If $\{T(\mathbf{e}_1),\ldots,T(\mathbf{e}_r),\mathbf{w}_{r+1},\ldots,\mathbf{w}_n\}$ is a basis of V, define S by $S[T(\mathbf{e}_i)]=\mathbf{e}_i$ for $1\le i\le r$, and $S(\mathbf{w}_j)=\mathbf{e}_j$ for $r+1\le j\le n$. Then S is an isomorphism by Theorem $6.10.3E.25$, and $TST(\mathbf{e}_i)=T(\mathbf{e}_i)$ clearly holds for $1\le i\le r$. But if $i\ge r+1$, then $T(\mathbf{e}_i)=\mathbf{0}=TST(\mathbf{e}_i)$, so $T=TST$ by Theorem $6.10.3E.25$.

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6.10.4: A Theorem about Differential Equations

A Theorem about Differential Equations

Differential equations are instrumental in solving a variety of problems throughout science, social science, and engineering. In this brief section, we will see that the set of solutions of a linear differential equation (with constant coefficients) is a vector space and we will calculate its dimension. The proof is pure linear algebra, although the applications are primarily in analysis. However, a key result (Lemma 7.4.3 below) can be applied much more widely.

We denote the derivative of a function $f : \mathbb{R} \to \mathbb{R}$ by f', and f will be called **differentiable** if it can be differentiated any number of times. If f is a differentiable function, the nth derivative $f^{(n)}$ of f is the result of differentiating n times. Thus $f^{(0)} = f, f^{(1)} = f', f^{(2)} = f^{(1)\prime}$, ..., and in general $f^{(n+1)} = f^{(n)\prime}$ for each $n \geq 0$. For small values of n these are often written as $f, f', f'', f''', \ldots$.

If a, b, and c are numbers, the differential equations

$$f'' - af' - bf = 0 \quad \text{or} \quad f''' - af'' - bf' - cf = 0$$

are said to be of **second order** and **third-order**, respectively. In general, an equation

$$f^{(n)} - a_{n-1}f^{(n-1)} - a_{n-2}f^{(n-2)} - \cdots - a_2 f^{(2)} - a_1 f^{(1)} - a_0 f^{(0)} = 0, a_i \text{ in } \mathbb{R} \tag{6.10.4.1}$$

is called a **differential equation of order** n. We want to describe all solutions of this equation. Of course a knowledge of calculus is required.

The set $\mathbf{F}$ of all functions $\mathbb{R} \to \mathbb{R}$ is a vector space with operations as described in Example 6.1.7. If f and g are differentiable, we have $(f + g)' = f' + g'$ and $(af)' = af'$ for all a in $\mathbb{R}$. With this it is a routine matter to verify that the following set is a subspace of $\mathbf{F}$:

$$\mathbf{D}_n = f : \mathbb{R} \to \mathbb{R} | f \text{ is differentiable and is a solution to equation } 6.10.4.1$$

Our sole objective in this section is to prove

Theorem 6.10.4.1

The space $\mathbf{D}_n$ has dimension n.

We have already used this theorem in Section 3.5

As will be clear later, the proof of Theorem $6.10.4.1$ requires that we enlarge $\mathbf{D}_n$ somewhat and allow our differentiable functions to take values in the set $\mathbb{C}$ of complex numbers. To do this, we must clarify what it means for a function $f : \mathbb{R} \to \mathbb{C}$ to be differentiable. For each real number x write $f(x)$ in terms of its real and imaginary parts $f_r(x)$ and $f_i(x)$:

$$f(x) = f_r(x) + if_i(x)$$

This produces new functions $f_r : \mathbb{R} \to \mathbb{R}$ and $f_i : \mathbb{R} \to \mathbb{R}$, called the **real** and **imaginary parts** of f, respectively. We say that f is **differentiable** if both f_r and f_i are differentiable (as real functions), and we define the **derivative** f' of f by

$$f' = f_r' + if_i'$$

We refer to this frequently in what follows.

Note

Write $|w|$ for the absolute value of any complex number w. As for functions $\mathbb{R} \to \mathbb{R}$, we say that $\lim_{t\to 0} f(t) = w$ if, for all $\varepsilon > 0$ there exists $\delta > 0$ such that $|f(t) - w| < \epsilon$ whenever $|t| < \delta$. (Note that t represents a real number here.) In particular, given a real number x, we define the derivative f' of a function $f : \mathbb{R} \to \mathbb{C}$ by $f'(x) = \lim_{t\to 0} \left\{\frac{1}{t}[f(x+t) - f(x)]\right\}$ and we say that f is differentiable if $f'(x)$ exists for all x in $\mathbb{R}$. Then we can prove that f is differentiable if and only if both f_{r} and f_{i} are differentiable, and that $f' = {f_{\mathrm{r}}}' + i{f_{\mathrm{i}}}'$ in this case.

With this, write $\mathbf{D}_\infty$ for the set of all differentiable complex valued functions $f : \mathbb{R} \to \mathbb{C}$. This is a *complex* vector space using pointwise addition (see Example 6.1.7), and the following scalar multiplication: For any w in $\mathbb{C}$ and f in $\mathbf{D}_\infty$, we define $wf : \mathbb{R} \to \mathbb{C}$ by $(wf)(x) = wf(x)$ for all x in $\mathbb{R}$. We will be working in $\mathbf{D}_\infty$ for the rest of this section. In particular, consider the following complex subspace of $\mathbf{D}_\infty$:

$$\mathbf{D}_n^* = \{f : \mathbb{R} \to \mathbb{C} \mid f \text{ is a solution to } (6.10.4.1)\}$$

Clearly, $\mathbf{D}_n \subseteq \mathbf{D}_n^*$, and our interest in $\mathbf{D}_n^*$ comes from

Lemma 6.10.4.1

If $dim_{\mathbb{C}}(\mathbf{D}_n^*) = n$, then $dim_{\mathbb{R}}(\mathbf{D}_n) = n$.

Proof

Observe first that if $dim\ _{\mathbb{C}}(\mathbf{D}_n^*) = n$, then $dim\ _{\mathbb{R}}(\mathbf{D}_n^*) = 2n$. [In fact, if $\{g_1, \dots, g_n\}$ is a $\mathbb{C}$-basis of $\mathbf{D}_n^*$ then $\{g_1, \dots, g_n, ig_1, \dots, ig_n\}$ is a $\mathbb{R}$-basis of $\mathbf{D}_n^*$]. Now observe that the set $\mathbf{D}_n \times \mathbf{D}_n$ of all ordered pairs (f, g) with f and g in $\mathbf{D}_n$ is a real vector space with componentwise operations. Define

$$\theta : \mathbf{D}_n^* \to \mathbf{D}_n \times \mathbf{D}_n \quad \text{given by} \quad \theta(f) = (f_r, f_i) \text{ for } f \text{ in } \mathbf{D}_n^*$$

One verifies that θ is onto and one-to-one, and it is $\mathbb{R}$-linear because $f \to f_r$ and $f \to f_i$ are both $\mathbb{R}$-linear. Hence $\mathbf{D}_n^* \cong \mathbf{D}_n \times \mathbf{D}_n$ as $\mathbb{R}$-spaces. Since $dim\ _{\mathbb{R}}(\mathbf{D}_n^*)$ is finite, it follows that $dim\ _{\mathbb{R}}(\mathbf{D}_n)$ is finite, and we have

$$2dim_{\mathbb{R}}(\mathbf{D}_n) = dim_{\mathbb{R}}(\mathbf{D}_n \times \mathbf{D}_n) = dim_{\mathbb{R}}(\mathbf{D}_n^*) = 2n$$

Hence $dim_{\mathbb{R}}(\mathbf{D}_n) = n$, as required.

It follows that to prove Theorem 6.10.4.1 it suffices to show that $dim_{\mathbb{C}}(\mathbf{D}_n^*) = n$.

□

There is one function that arises frequently in any discussion of differential equations. Given a complex number $w = a + ib$ (where a and b are real), we have $e^w = e^a(\cos b + i \sin b)$. The law of exponents, $e^w e^v = e^{w+v}$ for all w, v in $\mathbb{C}$ is easily verified using the formulas for $\sin(b + b_1)$ and $\cos(b + b_1)$. If x is a variable and $w = a + ib$ is a complex number, define the **exponential function** e^{wx} by

$$e^{wx} = e^{ax}(\cos bx + i \sin bx)$$

Hence e^{wx} is differentiable because its real and imaginary parts are differentiable for all x. Moreover, the following can be proved using equation 6.10.4.1:

$$(e^{wx})' = we^{wx}$$

In addition, Equation 6.10.4.1 gives the **product rule** for differentiation:

$$\text{If } f \text{ and } g \text{ are in } \mathbf{D}_\infty, \text{ then } (fg)' = f'g + fg'$$

We omit the verifications.

To prove that $dim\ _{\mathbb{C}}(\mathbf{D}_n^*) = n$, two preliminary results are required. Here is the first.

Lemma 6.10.4.2

Given f in $\mathbf{D}_\infty$ and w in $\mathbb{C}$, there exists g in $\mathbf{D}_\infty$ such that $g' - wg = f$.

Proof

Define $p(x) = f(x)e^{-wx}$. Then p is differentiable, whence p_r and p_i are both differentiable, hence continuous, and so both have antiderivatives, say $p_r = q_r'$ and $p_i = q_i'$. Then the function $q = q_r + iq_i$ is in $\mathbf{D}_\infty$, and $q' = p$ by (equation 6.10.4.1). Finally define $g(x) = q(x)e^{wx}$. Then

$$g' = q'e^{wx} + qwe^{wx} = pe^{wx} + w(qe^{wx}) = f + wg$$

by the product rule, as required.

The second preliminary result is important in its own right.

□

Lemma 6.10.4.3: Kernel Lemma

Let V be a vector space, and let S and T be linear operators $V \to V$. If S is onto and both $\ker(S)$ and $\ker(T)$ are finite dimensional, then $\ker(TS)$ is also finite dimensional and $dim\ [\ker(TS)] = dim\ [\ker(T)] + dim\ [\ker(S)]$.

Proof

Let $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_m\}$ be a basis of $\ker(T)$ and let $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$ be a basis of $\ker(S)$. Since S is onto, let $\mathbf{u}_i = S(\mathbf{w}_i)$ for some $\mathbf{w}_i$ in V. It suffices to show that

$$B = \{\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_m, \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$$

is a basis of $\ker(TS)$. Note $B \subseteq \ker(TS)$ because $TS(\mathbf{w}_i) = T(\mathbf{u}_i) = \mathbf{0}$ for each i and $TS(\mathbf{v}_j) = T(\mathbf{0}) = \mathbf{0}$ for each j.

Spanning

If $\mathbf{v}$ is in $\ker(TS)$, then $S(\mathbf{v})$ is in $\ker(T)$, say $S(\mathbf{v}) = \sum r_i\mathbf{u}_i = \sum r_iS(\mathbf{w}_i) = S(\sum r_i\mathbf{w}_i)$. It follows that $\mathbf{v} - \sum r_i\mathbf{w}_i$ is in $\ker(S)$ $= span\ \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$, proving that $\mathbf{v}$ is in $span\ (B)$.

Independence

Let $\sum r_i\mathbf{w}_i + \sum t_j\mathbf{v}_j = \mathbf{0}$. Applying S, and noting that $S(\mathbf{v}_j) = \mathbf{0}$ for each j, yields
$\mathbf{0} = \sum r_iS(\mathbf{w}_i) = \sum r_i\mathbf{u}_i$. Hence $r_i = 0$ for each i, and so $\sum t_j\mathbf{v}_j = \mathbf{0}$. This implies that each $t_j = 0$, and so proves the independence of B.

□

Proof of Theorem 6.10.4.1

By Lemma 6.10.4.1, it suffices to prove that $dim\ _{\mathbb{C}}(\mathbf{D}_n^*) = n$. This holds for $n = 1$ because the proof of Theorem 3.7.1 goes through to show that $\mathbf{D}_1^* = \mathbb{C}e^{a_0 x}$. Hence we proceed by induction on n. With an eye on equation (6.10.4.1), consider the polynomial

$$p(t) = t^n - a_{n-1}t^{n-1} - a_{n-2}t^{n-2} - \cdots - a_2t^2 - a_1t - a_0$$

(called the *characteristic polynomial* of equation (6.10.4.1)). Now define a map $D : \mathbf{D}_\infty \to \mathbf{D}_\infty$ by $D(f) = f'$ for all f in $\mathbf{D}_\infty$. Then D is a linear operator, whence $p(D) : \mathbf{D}_\infty \to \mathbf{D}_\infty$ is also a linear operator. Moreover, since $D^k(f) = f^{(k)}$ for each $k \geq 0$, equation (6.10.4.1) takes the form $p(D)(f) = 0$. In other words,

$$\mathbf{D}_n^* = \ker[p(D)]$$

By the fundamental theorem of algebra, which is what allows the solutions to be *complex* valued, let w be a complex root of $p(t)$, so that $p(t) = q(t)(t - w)$ for some complex polynomial $q(t)$ of degree $n - 1$. It follows that $p(D) = q(D)(D - w1_{\mathbf{D}_\infty})$. Moreover $D - w1_{\mathbf{D}_\infty}$ is onto by Lemma 7.4.2, $dim\ _{\mathbb{C}}[\ker(D - w1_{\mathbf{D}_\infty})] = 1$ by the case $n = 1$ above, and $dim\ _{\mathbb{C}}(\ker[q(D)]) = n - 1$ by induction. Hence Lemma 7.4.3 shows that $\ker[P(D)]$ is also finite dimensional and

$$dim\ _{\mathbb{C}}(\ker[p(D)]) = dim\ _{\mathbb{C}}(\ker[q(D)]) + dim\ _{\mathbb{C}}(\ker[D - w1_{\mathbf{D}_\infty}]) = (n - 1) + 1 = n.$$

Since $\mathbf{D}_n^* = \ker[p(D)]$, this completes the induction, and so proves Theorem 7.4.1.

□

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6.11: SUPPLEMENTARY NOTES - NULLITY, RANK AND DIMENSION THEOREM

The SUNY Transfer Pathways description of this course includes this Theorem! I thought you might be interested in knowing that is why I have included this extra bit of information about rank, nullity and the dimension theorem.

6.11.1: Kernel, Range, Nullity, Rank

6.11.1.1: Summary

6.11.1.2: Review Problems

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6.11.1.1: Summary

We have seen that a linear transformation has an inverse if and only if it is bijective ($i.e.$, one-to-one and onto). We also know that linear transformations can be represented by matrices, and we have seen many ways to tell whether a matrix is invertible. Here is a list of them:

Theorem (Invertibility)

Let M be an $n \times n$ matrix, and let

$$L: \Re^n \to \Re^n \tag{6.11.1.1.1}$$

be the linear transformation defined by $L(v) = Mv$. Then the following statements are equivalent:

a) If V is any vector in $\Re^n$, then the system $MX = V$ has exactly one solution.

b) The matrix M is row-equivalent to the identity matrix.

c) If v is any vector in $\Re^n$, then $L(x) = v$ has exactly one solution.

d) The matrix M is invertible.

e) The homogeneous system $MX = 0$ has no non-zero solutions.

f) The determinant of M is not equal to 0.

g) The matrix M is a product of elementary matrices of the form $E_j^i, R^i(\lambda), S_j^i(\gamma)$ with $\lambda \neq 0$.

h) The transpose matrix M^T is invertible.

i) The matrix M does not have 0 as an eigenvalue.

j) The linear transformation L does not have 0 as an eigenvalue.

k) The characteristic polynomial $\det(\lambda I - M)$ does not have 0 as a root.

l) The columns (or rows) of M span $\Re^n$.

m) The columns (or rows) of M are linearly independent.

n) The columns (or rows) of M are a basis for $\Re^n$.

o) The linear transformation L is injective.

p) The linear transformation L is surjective.

q) The linear transformation L is bijective.

Note: it is important that M be an $n \times n$ matrix! If M is not square, then it can't be invertible, and many of the statements above are no longer equivalent to each other.

Proof

Many of these equivalences were proved earlier in other chapters. Some were left as review questions or sample final questions. The rest are left as exercises for the reader.

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6.11.1.2: Review Problems

1.
Consider an arbitrary matrix $M : \Re^m \to \Re^n$.

a) Argue that $Mx = 0$ if only if x is perpendicular to all columns of M^T.

b) Argue that $Mx = 0$ if only if x is perpendicular to all of the linear combinations of the columns of M^T.

c) Argue that $\ker M$ is perpendicular to $\text{ran } M^T$.

d) Argue further $\Re^m = \ker M \oplus \text{ran } M^T$.

e) Argue analogously that $\Re^n = \ker M^T \oplus \text{ran } M$.

The equations in the last two parts describe how a linear transformation $M : \Re^m \to \Re^n$ determines orthogonal decompositions of both it's domain and target. This result sometimes goes by the humble name *The Fundamental Theorem of Linear Algebra*.

2. Let $L: V \to W$ be a linear transformation. Show that $\ker L = \{0_V\}$ if and only if L is one-to-one:

a) *(Trivial kernel $\Rightarrow$ injective.)* Suppose that $\ker L = \{0_V\}$. Show that L is one-to-one. Think about methods of proof--does a proof by contradiction, a proof by induction, or a direct proof seem most appropriate?

b) *(Injective $\Rightarrow$ trivial kernel.)* Now suppose that L is one-to-one. Show that $\ker L = \{0_V\}$. That is, show that 0_V is in $\ker L$, and then show that there are no other vectors in $\ker L$.

3. Let $\{v_1, \ldots, v_n\}$ be a basis for V. Carefully explain why

$$L(V) = span\{Lv_1, \ldots, Lv_n\}. \tag{6.11.1.2.1}$$

4. Suppose $L: \Re^4 \to \Re^3$ whose matrix M in the standard basis is row equivalent to the following matrix:

$$\begin{pmatrix} 1 & 0 & 0 & -1 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 \end{pmatrix} = \text{RREF}(M) \sim M. \tag{6.11.1.2.2}$$

a) *Explain* why the first three columns of the original matrix M form a basis for $L(\Re^4)$.

b) *Find and describe* an algorithm (*i.e.*, a general procedure) for computing a basis for $L(\Re^n)$ when $L: \Re^n \to \Re^m$.

c) *Use* your algorithm to find a basis for $L(\Re^4)$ when $L: \Re^4 \to \Re^3$ is the linear transformation whose matrix M in the standard basis is

$$\begin{pmatrix} 2 & 1 & 1 & 4 \\ 0 & 1 & 0 & 5 \\ 4 & 1 & 1 & 6 \end{pmatrix}. \tag{6.11.1.2.3}$$

5. Claim:
If $\{v_1, \ldots, v_n\}$ is a basis for $\ker L$, where $L: V \to W$, then it is always possible to extend this set to a basis for V.
Choose some simple yet non-trivial linear transformations with non-trivial kernels and verify the above claim for those transformations.

6. Let $P_n(x)$ be the space of polynomials in x of degree less than or equal to n, and consider the derivative operator

$$\frac{d}{dx} : P_n(x) \to P_n(x)\,. \tag{6.11.1.2.4}$$

Find the dimension of the kernel and image of this operator. What happens if the target space is changed to $P_{n-1}(x)$ or $P_{n+1}(x)$?

Now consider $P_2(x,y)$, the space of polynomials of degree two or less in x and y. (Recall how degree is counted; xy is degree two, y is degree one and x^2y is degree three, for example.) Let

$$L := \frac{\partial}{\partial x} + \frac{\partial}{\partial y} : P_2(x,y) \to P_2(x,y). \tag{6.11.1.2.5}$$

(For example, $L(xy) = \frac{\partial}{\partial x}(xy) + \frac{\partial}{\partial y}(xy) = y + x$.) Find a basis for the kernel of L. Verify the dimension formula in this case.

7.
Lets demonstrate some ways the dimension formula can break down if a vector space is infinite dimensional:

a) Let $\mathbb{R}[x]$ be the vector space of all polynomials in the variable x with real coefficients. Let $D = \frac{d}{dx}$ be the usual derivative operator. Show that the range of D is $\mathbb{R}[x]$. What is $\ker D$? *Hint: Use the basis* $x^n \mid n \in \mathbb{N}$.

b) Let $L\colon \mathbb{R}[x] \to \mathbb{R}[x]$ be the linear map

$$L(p(x)) = xp(x)\,. \tag{6.11.1.2.6}$$

What is the kernel and range of M?

c) Let V be an infinite dimensional vector space and $L\colon V \to V$ be a linear operator. Suppose that $\dim \ker L < \infty$, show that $\dim L(V)$ is infinite. Also show that when $\dim L(V) < \infty$ that $\dim \ker L$ is infinite.

8. This question will answer the question, "If I choose a bit vector *at random*, what is the probability that it lies in the span of some other vectors?"

[i.] Given a collection S of k bit vectors in B^3, consider the bit matrix M whose columns are the vectors in S. Show that S is linearly independent if and only if the kernel of M is trivial, namely the set $\ker M = \{v \in B^3 |\ Mv = 0\}$ contains only the zero vector.

[ii.] Give some method for choosing a random bit vector v in B^3. Suppose S is a collection of 2 linearly independent bit vectors in B^3. How can we tell whether $S \cup \{v\}$ is linearly independent? Do you think it is likely or unlikely that $S \cup \{v\}$ is linearly independent? Explain your reasoning.

[iii.] If P is the characteristic polynomial of a 3×3 bit matrix, what must the degree of P be? Given that each coefficient must be either 0 or 1, how many possibilities are there for P? How many of these possible characteristic polynomials have 0 as a root? If M is a 3×3 bit matrix chosen at random, what is the probability that it has 0 as an eigenvalue? (Assume that you are choosing a random matrix M in such a way as to make each characteristic polynomial equally likely.) What is the probability that the columns of M form a basis for B^3? (*Hint: what is the relationship between the kernel of* M *and its eigenvalues?*)

[Note:] We could ask the same question for real vectors: If I choose a real vector at random, what is the probability that it lies in the span of some other vectors? In fact, once we write down a reasonable way of choosing a random real vector, if I choose a real vector in $\Re^n$ at random, the probability that it lies in the span of $n-1$ other real vectors is zero!

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6.E: Exercises

Exercise $6.E.1$

Show the map T: $\mathbb{R}^n \to \mathbb{R}^m$ defined by $T(\vec{x}) = A\vec{x}$ where A is an $m \times n$ matrix and $\vec{x}$ is an $m \times 1$ column vector is a linear transformation.

Answer available at the end of this section.

Exercise $6.E.2$

Show that the function $T_{\vec{u}}$ defined by $T_{\vec{u}}(\vec{v}) = \vec{v} - proj_{\vec{u}}(\vec{v})$ is also a linear transformation.

Answer available at the end of this section.

Exercise $6.E.3$

Let $\vec{u}$ be a fixed vector. The function $T_{\vec{u}}$ defined by $T_{\vec{u}}\vec{v} = \vec{u} + \vec{v}$ has the effect of translating all vectors by adding $\vec{u} \neq \vec{0}$. Show this is not a linear transformation. Explain why it is not possible to represent $T_{\vec{u}}$ in $\mathbb{R}^3$ by multiplying by a 3×3 matrix.

Answer available at the end of this section.

Exercise $6.E.4$

Consider the following functions which map $\mathbb{R}^n$ to $\mathbb{R}^n$.

a. T multiplies the jth component of $\vec{x}$ by a nonzero number b.
b. T replaces the ith component of $\vec{x}$ with b times the jth component added to the ith component.
c. T switches the ith and jth components.

Show these functions are linear transformations and describe their matrices A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $6.E.5$

You are given a linear transformation $T : \mathbb{R}^n \to \mathbb{R}^m$ and you know that

$$T(A_i) = B_i$$

where $[A_1 \cdots a_n]^{-1}$ exists. Show that the matrix of T is of the form

$$[B_1 \cdots B_n][A_1 \cdots A_n]^{-1}$$

Answer available at the end of this section.

Exercise $6.E.6$

Suppose T is a linear transformation such that

$$\begin{aligned} T\begin{bmatrix} 1 \\ 2 \\ -6 \end{bmatrix} &= \begin{bmatrix} 5 \\ 1 \\ 3 \end{bmatrix} \\ T\begin{bmatrix} -1 \\ -1 \\ 5 \end{bmatrix} &= \begin{bmatrix} 1 \\ 1 \\ 5 \end{bmatrix} \\ T\begin{bmatrix} 0 \\ -1 \\ 2 \end{bmatrix} &= \begin{bmatrix} 5 \\ 3 \\ -2 \end{bmatrix} \end{aligned} \tag{6.E.1}$$

Find the matrix of T. That is find A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $6.E.7$

Suppose T is a linear transformation such that

$$\begin{aligned} T\begin{bmatrix} 1 \\ 1 \\ -8 \end{bmatrix} &= \begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix} \\ T\begin{bmatrix} -1 \\ 0 \\ 6 \end{bmatrix} &= \begin{bmatrix} 2 \\ 4 \\ 1 \end{bmatrix} \\ T\begin{bmatrix} 0 \\ -1 \\ 3 \end{bmatrix} &= \begin{bmatrix} 6 \\ 1 \\ -1 \end{bmatrix} \end{aligned} \tag{6.E.2}$$

Find the matrix of T. That is find A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $6.E.8$

Suppose T is a linear transformation such that

$$\begin{aligned} T\begin{bmatrix} 1 \\ 3 \\ -7 \end{bmatrix} &= \begin{bmatrix} -3 \\ 1 \\ 3 \end{bmatrix} \\ T\begin{bmatrix} -1 \\ -2 \\ 6 \end{bmatrix} &= \begin{bmatrix} 1 \\ 3 \\ -3 \end{bmatrix} \\ T\begin{bmatrix} 0 \\ -1 \\ 2 \end{bmatrix} &= \begin{bmatrix} 5 \\ 3 \\ -3 \end{bmatrix} \end{aligned} \tag{6.E.3}$$

Find the matrix of T. That is find A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $6.E.9$

Suppose T is a linear transformation such that

$$\begin{aligned} T\begin{bmatrix} 1 \\ 1 \\ -7 \end{bmatrix} &= \begin{bmatrix} 3 \\ 3 \\ 3 \end{bmatrix} \\ T\begin{bmatrix} -1 \\ 0 \\ 6 \end{bmatrix} &= \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \\ T\begin{bmatrix} 0 \\ -1 \\ 2 \end{bmatrix} &= \begin{bmatrix} 1 \\ 3 \\ -1 \end{bmatrix} \end{aligned} \tag{6.E.4}$$

Find the matrix of T. That is find A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $6.E.10$

Suppose T is a linear transformation such that

$$\begin{aligned} T\begin{bmatrix} 1 \\ 2 \\ -18 \end{bmatrix} &= \begin{bmatrix} 5 \\ 2 \\ 5 \end{bmatrix} \\ T\begin{bmatrix} -1 \\ -1 \\ 15 \end{bmatrix} &= \begin{bmatrix} 3 \\ 3 \\ 5 \end{bmatrix} \\ T\begin{bmatrix} 0 \\ -1 \\ 4 \end{bmatrix} &= \begin{bmatrix} 2 \\ 5 \\ -2 \end{bmatrix} \end{aligned} \tag{6.E.5}$$

Find the matrix of T. That is find A such that $T(\vec{x}) = A\vec{x}$.

Answer available at the end of this section.

Exercise $6.E.11$

Consider the following functions $T : \mathbb{R}^3 \to \mathbb{R}^2$. Show that each is a linear transformation and determine for each the matrix A such that $T(\vec{x}) = A\vec{x}$.

a. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x + 2y + 3z \\ 2y - 3x + z \end{bmatrix}$

b. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 7x + 2y + z \\ 3x - 11y + 2z \end{bmatrix}$

c. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 3x + 2y + z \\ x + 2y + 6z \end{bmatrix}$

d. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 2y - 5x + z \\ x + y + z \end{bmatrix}$

Answer available at the end of this section.

Exercise $6.E.12$

Consider the following functions $T : \mathbb{R}^3 \to \mathbb{R}^2$. Explain why each of these functions T is not linear.

a. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x + 2y + 3z + 1 \\ 2y - 3x + z \end{bmatrix}$

b. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x + 2y^2 + 3z \\ 2y + 3x + z \end{bmatrix}$

c. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} \sin x + 2y + 3z \\ 2y + 3x + z \end{bmatrix}$

d. $T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x + 2y + 3z \\ 2y + 3x - \ln z \end{bmatrix}$

Answer available at the end of this section.

Exercise $6.E.13$

Suppose

$$[A_1 \cdots A_n]^{-1}$$

exists where each $A_j \in \mathbb{R}^n$ and let vectors $\{B_1, \cdots, B_n\}$ in $\mathbb{R}^m$ be given. Show that there **always** exists a linear transformation T such that $T(A_i) = B_i$.

Exercise $6.E.14$

Find the matrix for $T(\vec{w}) = proj_{\vec{v}}(\vec{w})$ where $\vec{v} = \begin{bmatrix} 1 & -2 & 3 \end{bmatrix}^T$.

Answer available at the end of this section.

Exercise $6.E.15$

Find the matrix for $T(\vec{w}) = proj_{\vec{v}}(\vec{w})$ where $\vec{v} = \begin{bmatrix} 1 & 5 & 3 \end{bmatrix}^T$.

Answer available at the end of this section.

Exercise $6.E.16$

Find the matrix for $T(\vec{w}) = proj_{\vec{v}}(\vec{w})$ where $\vec{v} = \begin{bmatrix} 1 & 0 & 3 \end{bmatrix}^T$.

Answer available at the end of this section.

Exercise $6.E.17$

Show that if a function $T : \mathbb{R}^n \to \mathbb{R}^m$ is linear, then it is always the case that $T(\vec{0}) = \vec{0}$.

Exercise 6.E.18

Let T be a linear transformation induced by the matrix $A = \begin{bmatrix} 3 & 1 \\ -1 & 2 \end{bmatrix}$ and S a linear transformation induced by $B = \begin{bmatrix} 0 & -2 \\ 4 & 2 \end{bmatrix}$. Find matrix of $S \circ T$ and find $(S \circ T)(\vec{x})$ for $\vec{x} = \begin{bmatrix} 2 \\ -1 \end{bmatrix}$.

Answer available at the end of this section.

Exercise 6.E.19

Let T be a linear transformation and suppose $T\left(\begin{bmatrix} 1 \\ -4 \end{bmatrix}\right) = \begin{bmatrix} 2 \\ -3 \end{bmatrix}$. Suppose S is a linear transformation induced by the matrix $B = \begin{bmatrix} 1 & 2 \\ -1 & 3 \end{bmatrix}$. Find $(S \circ T)(\vec{x})$ for $\vec{x} = \begin{bmatrix} 1 \\ -4 \end{bmatrix}$.

Answer available at the end of this section.

Exercise 6.E.20

Let T be a linear transformation induced by the matrix $A = \begin{bmatrix} 2 & 3 \\ 1 & 1 \end{bmatrix}$ and S a lienar transformation induced by $B = \begin{bmatrix} -1 & 3 \\ 1 & -2 \end{bmatrix}$. Find matrix of $S \circ T$ and find $(S \circ T)(\vec{x})$ for $\vec{x} = \begin{bmatrix} 5 \\ 6 \end{bmatrix}$.

Exercise 6.E.21

Let T be a linear transformation induced by the matrix $A = \begin{bmatrix} 2 & 1 \\ 5 & 2 \end{bmatrix}$. Find the matrix of T^{-1}.

Answer available at the end of this section.

Exercise 6.E.22

Let T be a linear transformation induced by the matrix $A = \begin{bmatrix} 4 & -3 \\ 2 & -2 \end{bmatrix}$. Find the matrix of T^{-1}.

Exercise 6.E.23

Let T be a linear transformation and suppose $T\left(\begin{bmatrix} 1 \\ 2 \end{bmatrix}\right) = \begin{bmatrix} 9 \\ 8 \end{bmatrix}$, $T\left(\begin{bmatrix} 0 \\ -1 \end{bmatrix}\right) = \begin{bmatrix} -4 \\ -3 \end{bmatrix}$. Find the matrix of T^{-1}.

Exercise 6.E.24

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ through an angle of $\pi/3$.

Answer available at the end of this section.

Exercise $6.E.25$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ through an angle of $\pi/4$.

Answer available at the end of this section.

Exercise $6.E.26$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ through an angle of $-\pi/3$.

Answer available at the end of this section.

Exercise $6.E.27$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ through an angle of $2\pi/3$.

Answer available at the end of this section.

Exercise $6.E.28$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ through an angle of $\pi/12$. Hint: Note that $\pi/12 = \pi/3 - \pi/4$.

Answer available at the end of this section.

Exercise $6.E.29$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ through an angle of $2\pi/3$ and then reflects across the x axis.

Answer available at the end of this section.

Exercise $6.E.30$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ through an angle of $\pi/3$ and then reflects across the x axis.

Answer available at the end of this section.

Exercise $6.E.31$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ through an angle of $\pi/4$ and then reflects across the x axis.

Answer available at the end of this section.

Exercise $6.E.32$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ through an angle of $\pi/6$ and then reflects across the x axis followed by a reflection across the y axis.

Answer available at the end of this section.

Exercise $6.E.33$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ across the x axis and then rotates every vector through an angle of $\pi/4$.

Answer available at the end of this section.

Exercise $6.E.34$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ across the y axis and then rotates every vector through an angle of $\pi/4$.

Answer available at the end of this section.

Exercise $6.E.35$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ across the x axis and then rotates every vector through an angle of $\pi/6$.

Answer available at the end of this section.

Exercise $6.E.36$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ across the y axis and then rotates every vector through an angle of $\pi/6$.

Answer available at the end of this section.

Exercise $6.E.37$

Find the matrix for the linear transformation which rotates every vector in $\mathbb{R}^2$ through an angle of $5\pi/12$. Hint: Note that $5\pi/12 = 2\pi/3 - \pi/4$.

Answer available at the end of this section.

Exercise $6.E.38$

Find the matrix of the linear transformation which rotates every vector in $\mathbb{R}^3$ counter clockwise about the z axis when viewed from the positive z axis through an angle of 30° and then reflects through the xy plane.

Answer available at the end of this section.

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Exercise $6.E.39$

Let $\vec{u} = \begin{bmatrix} a \\ b \end{bmatrix}$ be a unit vector in $\mathbb{R}^2$. Find the matrix which reflects all vectors across this vector, as shown in the following picture.

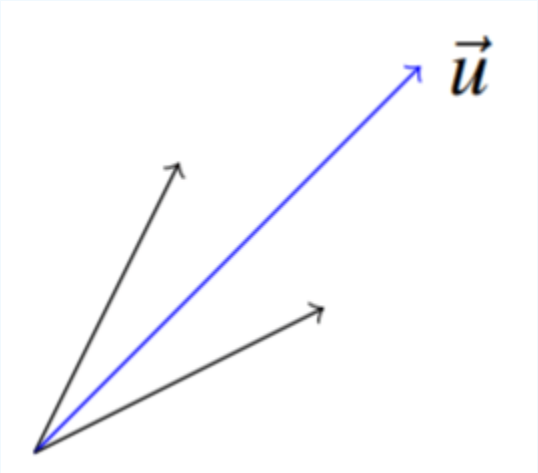


Figure $6.E.1$

Hint: Notice that $\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \cos\theta \\ \sin\theta \end{bmatrix}$ for some θ. First rotate through $-\theta$. Next reflect through the x axis. Finally rotate through θ.

Answer available at the end of this section.

Exercise $6.E.40$

Let T be a linear transformation given by

$$T\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 0 & 1 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix}$$

Is T one to one? Is T onto?

Exercise $6.E.41$

Let T be a linear transformation given by

$$T\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} -1 & 2 \\ 2 & 1 \\ 1 & 4 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix}$$

Is T one to one? Is T onto?

Exercise $6.E.42$

Let T be a linear transformation given by

$$T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 2 & 0 & 1 \\ 1 & 2 & -1 \end{bmatrix}\begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Is T one to one? Is T onto?

Exercise $6.E.43$

Let T be a linear transformation given by

$$T\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 & 3 & -5 \\ 2 & 0 & 2 \\ 2 & 4 & -6 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Is T one to one? Is T onto?

Exercise $6.E.44$

Give an example of a 3×2 matrix with the property that the linear transformation determined by this matrix is one to one but not onto.

Answer available at the end of this section.

Exercise $6.E.45$

Suppose A is an $m \times n$ matrix in which $m \leq n$. Suppose also that the rank of A equals m. Show that the transformation T determined by A maps $\mathbb{R}^n$ onto $\mathbb{R}^m$. Hint: The vectors $\vec{e}_1, \cdots, \vec{e}_m$ occur as columns in the reduced row-echelon form for A.

Answer available at the end of this section.

Exercise $6.E.46$

Suppose A is an $m \times n$ matrix in which $m \geq n$. Suppose also that the rank of A equals n. Show that A is one to one. Hint: If not, there exists a vector, $\vec{x}$ such that $A\vec{x} = 0$, and this implies at least one column of A is a linear combination of the others. Show this would require the rank to be less than n.

Answer available at the end of this section.

Exercise $6.E.47$

Explain why an $n \times n$ matrix A is both one to one and onto if and only if its rank is n.

Answer available at the end of this section.

Exercise $6.E.48$

Let V and W be subspaces of $\mathbb{R}^n$ and $\mathbb{R}^m$ respectively and let $T : V \to W$ be a linear transformation. Suppose that $\{T\vec{v}_1, \cdots, T\vec{v}_r\}$ is linearly independent. Show that it must be the case that $\{T\vec{v}_1, \cdots, T\vec{v}_r\}$ is also linearly independent.

Answer available at the end of this section.

Exercise 6.E.49

Let

$$V = span\left\{\begin{bmatrix}1\\1\\2\\0\end{bmatrix}, \begin{bmatrix}0\\1\\1\\1\end{bmatrix}, \begin{bmatrix}1\\1\\0\\1\end{bmatrix}\right\}$$

Let $T\vec{x} = A\vec{x}$ where A is the matrix

$$\begin{bmatrix}1 & 1 & 1 & 1\\0 & 1 & 1 & 0\\0 & 1 & 2 & 1\\1 & 1 & 1 & 2\end{bmatrix}$$

Give a basis for $im(T)$.

Exercise 6.E.50

Let

$$V = span\left\{\begin{bmatrix}1\\0\\0\\1\end{bmatrix}, \begin{bmatrix}1\\1\\1\\1\end{bmatrix}, \begin{bmatrix}1\\4\\4\\1\end{bmatrix}\right\}$$

Let $T\vec{x} = A\vec{x}$ where A is the matrix

$$\begin{bmatrix}1 & 1 & 1 & 1\\0 & 1 & 1 & 0\\0 & 1 & 2 & 1\\1 & 1 & 1 & 2\end{bmatrix}$$

Find a basis for $im(T)$. In this case, the original vectors do not form an independent set.

Answer available at the end of this section.

Exercise 6.E.51

If $\{\vec{v}_1, \cdots, \vec{v}_r\}$ is linearly independent and T is a one to one linear transformation, show that $\{T\vec{v}_1, \cdots, T\vec{v}_r\}$ is also linearly independent. Give an example which shows that if T is only linear, it can happen that, although $\{\vec{v}_1, \cdots, \vec{v}_r\}$ is linearly independent, $\{T\vec{v}_1, \cdots, T\vec{v}_r\}$ is not. In fact, show that it can happen that each of the $T\vec{v}_j$ equals 0.

Exercise 6.E.52

Let V and W be subspaces of $\mathbb{R}^n$ and $\mathbb{R}^m$ respectively and let $T : V \to W$ be a linear transformation. Show that if T is onto W and if $\{\vec{v}_1, \cdots, \vec{v}_r\}$ is a basis for V, then $span\{T\vec{v}_1, \cdots, T\vec{v}_r\} = W$.

Exercise 6.E.53

Define T: $\mathbb{R}^4 \to \mathbb{R}^3$ as follows.

$$T\vec{x} = \begin{bmatrix} 3 & 2 & 1 & 8 \\ 2 & 2 & -2 & 6 \\ 1 & 1 & -1 & 3 \end{bmatrix} \vec{x}$$

Find a basis for $im(T)$. Also find a basis for $\ker(T)$.

Exercise $6.E.54$

Define T: $\mathbb{R}^3 \to \mathbb{R}^3$ as follows.

$$T\vec{x} = \begin{bmatrix} 1 & 2 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix} \vec{x}$$

where on the right, it is just matrix multiplication of the vector $\vec{x}$ which is meant. Explain why T is an isomorphism of $\mathbb{R}^3$ to $\mathbb{R}^3$.

Exercise $6.E.55$

Suppose T: $\mathbb{R}^3 \to \mathbb{R}^3$ is a linear transformation given by

$$T\vec{x} = A\vec{x}$$

where A is a 3×3 matrix. Show that T is an isomorphism if and only if A is invertible.

Exercise $6.E.56$

Suppose T: $\mathbb{R}^n \to \mathbb{R}^m$ is a linear transformation given by

$$T\vec{x} = A\vec{x}$$

where A is an $m \times n$ matrix. Show that T is never an ismorphism if $m \neq n$. In particular, show that if $m > n$, T cannot be onto and if $m < n$, then T cannot be one to one.

Exercise $6.E.57$

Define T: $\mathbb{R}^2 \to \mathbb{R}^3$ as follows.

$$T\vec{x} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 0 & 1 \end{bmatrix} \vec{x}$$

where on the right, it is just matrix multiplication of the vector $\vec{x}$ which is meant. Show that T is one to one. Next let $W = im(T)$. Show that T is an isomorphism of $\mathbb{R}^2$ and $im(T)$.

Exercise $6.E.58$

In the above problem, find a 2×3 matrix A such that the restriction of A to $im(T)$ gives the same result as T^{-1} on $im(T)$. Hint: You might let A be such that

$$A \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, A \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

now find another vector $\vec{v} \in \mathbb{R}^3$ such that

$$\left\{\begin{bmatrix}1\\1\\0\end{bmatrix},\begin{bmatrix}0\\1\\1\end{bmatrix},\vec{v}\right\}$$

is a basis. You could pick

$$\vec{v}=\begin{bmatrix}0\\0\\1\end{bmatrix}$$

for example. Explain why this one works or one of your choice works. Then you could define $A\vec{v}$ to equal some vector in $\mathbb{R}^2$. Explain why there will be more than one such matrix A which will deliver the inverse isomorphism T^{-1} on $im(T)$.

Exercise $6.E.59$

Now let V equan $span\left\{\begin{bmatrix}1\\0\\1\end{bmatrix},\begin{bmatrix}0\\1\\1\end{bmatrix}\right\}$ and let T: $V\to W$ be a linear transformation where

$$W=span\left\{\begin{bmatrix}1\\0\\1\\0\end{bmatrix},\begin{bmatrix}0\\1\\1\\1\end{bmatrix}\right\}$$

and

$$T\begin{bmatrix}1\\0\\1\end{bmatrix}=\begin{bmatrix}1\\0\\1\\0\end{bmatrix},T\begin{bmatrix}0\\1\\1\end{bmatrix}=\begin{bmatrix}0\\1\\1\\1\end{bmatrix}$$

Explain why T is an isomorphism. Determine a matrix A which, when multiplied on the left gives the same result as T on V and a matrix B which delivers T^{-1} on W. Hint: You need to have

$$A\begin{bmatrix}1&0\\0&1\\1&1\end{bmatrix}=\begin{bmatrix}1&0\\0&1\\1&1\\0&1\end{bmatrix}$$

Now enlarge $\begin{bmatrix}1\\0\\1\end{bmatrix},\begin{bmatrix}0\\1\\1\end{bmatrix}$ to obtain a basis for $\mathbb{R}^3$. You could add in $\begin{bmatrix}0\\0\\1\end{bmatrix}$ for example, and then pick another vector in $\mathbb{R}^4$ and let $A\begin{bmatrix}0\\0\\1\end{bmatrix}$ equal this other vector. Then you would have

$$A\begin{bmatrix}1&0&0\\0&1&0\\1&1&1\end{bmatrix}=\begin{bmatrix}1&0&0\\0&1&0\\1&1&0\\0&1&1\end{bmatrix}$$

This would involve picking for the new vector in $\mathbb{R}^4$ the vector $\begin{bmatrix}0&0&0&1\end{bmatrix}^T$. Then you could find A. You can do something similar to find a matrix for T^{-1} denoted as B.

Exercise $6.E.60$

Let $V=\mathbb{R}^3$ and let

$$W = span(S), \text{ where } S = \left\{ \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} -2 \\ 2 \\ -2 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \\ 3 \end{bmatrix} \right\}$$

Find a basis of W consisting of vectors in S.

Answer available at the end of this section.

Exercise $6.E.61$

Let T be a linear transformation given by

$$T \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Find a basis for $\ker(T)$ and $im(T)$.

Answer available at the end of this section.

Exercise $6.E.62$

Let T be a linear transformation given by

$$T \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Find a basis for $\ker(T)$ and $im(T)$.

Answer available at the end of this section.

Exercise $6.E.63$

Let $V = \mathbb{R}^3$ and let

$$W = span \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 2 \\ -1 \end{bmatrix} \right\}$$

Extend this basis of W to a basis of V.

Answer available at the end of this section.

Exercise $6.E.64$

Let T be a linear transformation given by

$$T \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

What is $\dim(\ker(T))$?

Answer available at the end of this section.

Exercise 6.E.65

Let $B = \left\{ \begin{bmatrix} 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ 2 \end{bmatrix} \right\}$ be a basis of $\mathbb{R}^2$ and let $\vec{x} = \begin{bmatrix} 5 \\ -7 \end{bmatrix}$ be a vector in $\mathbb{R}^2$. Find $C_B(\vec{x})$.

Exercise 6.E.66

Let $B = \left\{ \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 2 \end{bmatrix} \right\}$ be a basis of $\mathbb{R}^3$ and let $\vec{x} = \begin{bmatrix} 5 \\ -1 \\ 4 \end{bmatrix}$ be a vector in $\mathbb{R}^2$. Find $C_B(\vec{x})$.

Answer available at the end of this section.

Exercise 6.E.67

Let $T\colon \mathbb{R}^2 \to \mathbb{R}^2$ be a linear transformation defined by $T\left(\begin{bmatrix} a \\ b \end{bmatrix} \right) = \begin{bmatrix} a+b \\ a-b \end{bmatrix}$.

Consider the two bases

$$B_1 = \{\vec{v}_1, \vec{v}_2\} = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \end{bmatrix} \right\}$$

and

$$B_2 = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$$

Find the matrix M_{B_2,B_1} of T with respect to the bases B_1 and B_2.

Answer available at the end of this section.

Exercise 6.E.68

Write the solution set of the following system as a linear combination of vectors

$$\begin{bmatrix} 1 & -1 & 2 \\ 1 & -2 & 1 \\ 3 & -4 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Answer available at the end of this section.

Exercise 6.E.69

Using Exercise 6.E.68 find the general solution to the following linear system.

$$\begin{bmatrix} 1 & -1 & 2 \\ 1 & -2 & 1 \\ 3 & -4 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 4 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.70$

Write the solution set of the following system as a linear combination of vectors

$$\begin{bmatrix} 0 & -1 & 2 \\ 1 & -2 & 1 \\ 1 & -4 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.71$

Using Exercise $6.E.70$ find the general solution to the following linear system.

$$\begin{bmatrix} 0 & -1 & 2 \\ 1 & -2 & 1 \\ 1 & -4 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.72$

Write the solution set of the following system as a linear combination of vectors.

$$\begin{bmatrix} 1 & -1 & 2 \\ 1 & -2 & 0 \\ 3 & -4 & 4 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.73$

Using Exercise $6.E.72$ find the general solution to the following linear system.

$$\begin{bmatrix} 1 & -1 & 2 \\ 1 & -2 & 0 \\ 3 & -4 & 4 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 4 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.74$

Write the solution set of the following system as a linear combination of vectors

$$\begin{bmatrix} 0 & -1 & 2 \\ 1 & 0 & 1 \\ 1 & -2 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.75$

Using Exercise $6.E.74$ find the general solution to the following linear system.

$$\begin{bmatrix} 0 & -1 & 2 \\ 1 & 0 & 1 \\ 1 & -2 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.76$

Write the solution set of the following system as a linear combination of vectors

$$\begin{bmatrix} 1 & 0 & 1 & 1 \\ 1 & -1 & 1 & 0 \\ 3 & -1 & 3 & 2 \\ 3 & 3 & 0 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.77$

Using Exercise $6.E.76$ find the general solution to the following linear system.

$$\begin{bmatrix} 1 & 0 & 1 & 1 \\ 1 & -1 & 1 & 0 \\ 3 & -1 & 3 & 2 \\ 3 & 3 & 0 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 4 \\ 3 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.78$

Write the solution set of the following system as a linear combination of vectors

$$\begin{bmatrix} 1 & 1 & 0 & 1 \\ 2 & 1 & 1 & 2 \\ 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.79$

Using Exercise $6.E.78$ find the general solution to the following linear system.

$$\begin{bmatrix} 1 & 1 & 0 & 1 \\ 2 & 1 & 1 & 2 \\ 1 & 0 & 1 & 1 \\ 0 & -1 & 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 2 \\ -1 \\ -3 \\ 0 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.80$

Write the solution set of the following system as a linear combination of vectors

$$\begin{bmatrix} 1 & 1 & 0 & 1 \\ 1 & -1 & 1 & 0 \\ 3 & 1 & 1 & 2 \\ 3 & 3 & 0 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.81$

Using Exercise $6.E.80$ find the general solution to the following linear system.

$$\begin{bmatrix} 1 & 1 & 0 & 1 \\ 1 & -1 & 1 & 0 \\ 3 & 1 & 1 & 2 \\ 3 & 3 & 0 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 4 \\ 3 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.82$

Write the solution set of the following system as a linear combination of vectors

$$\begin{bmatrix} 1 & 1 & 0 & 1 \\ 2 & 1 & 1 & 2 \\ 1 & 0 & 1 & 1 \\ 0 & -1 & 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.83$

Using Exercise $6.E.82$ find the general solution to the following linear system.

$$\begin{bmatrix} 1 & 1 & 0 & 1 \\ 2 & 1 & 1 & 2 \\ 1 & 0 & 1 & 1 \\ 0 & -1 & 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 2 \\ -1 \\ -3 \\ 1 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $6.E.84$

Suppose $A\vec{x} = \vec{b}$ has a solution. Explain why the solution is unique precisely when $A\vec{x} = \vec{0}$ has only the trivial solution.

Answer available at the end of this section.

Answers

Exercise $6.E.1$

This result follows from the properties of matrix multiplication.

Exercise $6.E.2$

$$\begin{aligned} T_{\vec{u}}(a\vec{v}+b\vec{w}) &= a\vec{v}+b\vec{w}-\frac{(a\vec{v}+b\vec{w}\bullet\vec{u})}{||\vec{u}||^2}\vec{u} \\ &= a\vec{v}-a\frac{(\vec{v}\bullet\vec{u})}{||\vec{u}||^2}\vec{u}+b\vec{w}-b\frac{(\vec{w}\bullet\vec{u})}{||\vec{u}||^2}\vec{u} \\ &= aT_{\vec{u}}(\vec{v})+bT_{\vec{u}}(\vec{w}) \end{aligned} \tag{6.E.6}$$

Exercise $6.E.3$

Linear transformations take $\vec{0}$ to $\vec{0}$ which T does not. Also $T_{\vec{a}}(\vec{u}+\vec{v}) \neq T_{\vec{a}}\vec{u}+T_{\vec{a}}\vec{v}$.

Exercise $6.E.4$

a. The matrix of T is the elementary matrix which multiplies the jth diagonal entry of the identity matrix by b.
b. The matrix of T is the elementary matrix which takes b times the jth row and adds to the ith row.
c. The matrix of T is the elementary matrix which switches the ith and the jth rows where the two components are in the ith and jth positions.

Exercise $6.E.5$

Suppose

$$\begin{bmatrix} \vec{c}_1^{\,T} \\ \vdots \\ \vec{c}_n^{\,T} \end{bmatrix} = \begin{bmatrix} \vec{a}_1 & \cdots & \vec{a}_n \end{bmatrix}^{-1}$$

Thus $\vec{c}_i^{\,T}\vec{a}_j = \delta_{ij}$. Therefore

$$\begin{aligned} \begin{bmatrix} \vec{b}_1 & \cdots & \vec{b}_n \end{bmatrix} \begin{bmatrix} \vec{a}_1 & \cdots & \vec{a}_n \end{bmatrix}^{-1} \vec{a}_i &= \begin{bmatrix} \vec{b}_1 & \cdots & \vec{b}_n \end{bmatrix} \begin{bmatrix} \vec{c}_1^{\,T} \\ \vdots \\ \vec{c}_n^{\,T} \end{bmatrix} \vec{a}_i \\ &= \begin{bmatrix} \vec{b}_1 & \cdots & \vec{b}_n \end{bmatrix} \vec{e}_i \\ &= \vec{b}_i \end{aligned} \tag{6.E.7}$$

Thus $T\vec{a}_i = \begin{bmatrix} \vec{b}_1 & \cdots & \vec{b}_n \end{bmatrix} \begin{bmatrix} \vec{a}_1 & \cdots & \vec{a}_n \end{bmatrix}^{-1} \vec{a}_i = A\vec{a}_i$. If $\vec{x}$ is arbitrary, then since the matrix $\begin{bmatrix} \vec{a}_1 & \cdots & \vec{a}_n \end{bmatrix}$ is invertible, there exists a unique $\vec{y}$ such that $\begin{bmatrix} \vec{a}_1 & \cdots & \vec{a}_n \end{bmatrix} \vec{y} = \vec{x}$ Hence

$$T\vec{x} = T\left(\sum_{i=1}^n y_i\vec{a}_i\right) = \sum_{i=1}^n y_i T\vec{a}_i = \sum_{i=1}^n y_i A\vec{a}_i = A\left(\sum_{i=1}^n y_i\vec{a}_i\right) = A\vec{x}$$

Exercise $6.E.6$

$$\begin{bmatrix} 5 & 1 & 5 \\ 1 & 1 & 3 \\ 3 & 5 & -2 \end{bmatrix} \begin{bmatrix} 3 & 2 & 1 \\ 2 & 2 & 1 \\ 4 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 37 & 17 & 11 \\ 17 & 7 & 5 \\ 11 & 14 & 6 \end{bmatrix}$$

Exercise $6.E.7$

$$\begin{bmatrix} 1 & 2 & 6 \\ 3 & 4 & 1 \\ 1 & 1 & -1 \end{bmatrix} \begin{bmatrix} 6 & 3 & 1 \\ 5 & 3 & 1 \\ 6 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 52 & 21 & 9 \\ 44 & 23 & 8 \\ 5 & 4 & 1 \end{bmatrix}$$

Exercise $6.E.8$

$$\begin{bmatrix} -3 & 1 & 5 \\ 1 & 3 & 3 \\ 3 & -3 & -3 \end{bmatrix} \begin{bmatrix} 2 & 2 & 1 \\ 1 & 2 & 1 \\ 4 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 15 & 1 & 3 \\ 17 & 11 & 7 \\ -9 & -3 & -3 \end{bmatrix}$$

Exercise $6.E.9$

$$\begin{bmatrix} 3 & 1 & 1 \\ 3 & 2 & 3 \\ 3 & 3 & -1 \end{bmatrix} \begin{bmatrix} 6 & 2 & 1 \\ 5 & 2 & 1 \\ 6 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 29 & 9 & 5 \\ 46 & 13 & 8 \\ 27 & 11 & 5 \end{bmatrix}$$

Exercise $6.E.10$

$$\begin{bmatrix} 5 & 3 & 2 \\ 2 & 3 & 5 \\ 5 & 5 & -2 \end{bmatrix} \begin{bmatrix} 11 & 4 & 1 \\ 10 & 4 & 1 \\ 12 & 3 & 1 \end{bmatrix} = \begin{bmatrix} 109 & 38 & 10 \\ 112 & 35 & 10 \\ 81 & 34 & 8 \end{bmatrix}$$

Exercise $6.E.11$

Exercise $6.E.12$

Exercise $6.E.14$

Recall that $proj_{\vec{u}}(\vec{v}) = \frac{\vec{v}\bullet\vec{u}}{||\vec{u}||^2}\vec{u}$ and so the desired matrix has ith column equal to $proj_{\vec{u}}(\vec{e}_i)$. Therefore, the matrix desired is

$$\frac{1}{14}\begin{bmatrix} 1 & -2 & 3 \\ -2 & 4 & -6 \\ 3 & -6 & 9 \end{bmatrix}$$

Exercise $6.E.15$

$$\frac{1}{35}\begin{bmatrix} 1 & 5 & 3 \\ 5 & 25 & 15 \\ 3 & 15 & 9 \end{bmatrix}$$

Exercise $6.E.16$

$$\frac{1}{10}\begin{bmatrix} 1 & 0 & 3 \\ 0 & 0 & 0 \\ 3 & 0 & 9 \end{bmatrix}$$

Exercise $6.E.18$

The matrix of $S \circ T$ is given by BA.

$$\begin{bmatrix} 0 & -2 \\ 4 & 2 \end{bmatrix}\begin{bmatrix} 3 & 1 \\ -1 & 2 \end{bmatrix} = \begin{bmatrix} 2 & -4 \\ 10 & 8 \end{bmatrix}$$

Now, $(S \circ T)(\vec{x}) = (BA)\vec{x}$.

$$\begin{bmatrix} 2 & -4 \\ 10 & 8 \end{bmatrix}\begin{bmatrix} 2 \\ -1 \end{bmatrix} = \begin{bmatrix} 8 \\ 12 \end{bmatrix}$$

Exercise $6.E.19$

To find $(S \circ T)(\vec{x})$ we compute $S(T(\vec{x}))$.

$$\begin{bmatrix} 1 & 2 \\ -1 & 3 \end{bmatrix}\begin{bmatrix} 2 \\ -3 \end{bmatrix} = \begin{bmatrix} -4 \\ -11 \end{bmatrix}$$

Exercise $6.E.21$

The matrix of T^{-1} is A^{-1}.

$$\begin{bmatrix} 2 & 1 \\ 5 & 2 \end{bmatrix}^{-1} = \begin{bmatrix} -2 & 1 \\ 5 & -2 \end{bmatrix}$$

Exercise $6.E.24$

$$\begin{bmatrix} \cos\left(\frac{\pi}{3}\right) & -\sin\left(\frac{\pi}{3}\right) \\ \sin\left(\frac{\pi}{3}\right) & \cos\left(\frac{\pi}{3}\right) \end{bmatrix} = \begin{bmatrix} \frac{1}{2} & -\frac{1}{2}\sqrt{3} \\ \frac{1}{2}\sqrt{3} & \frac{1}{2} \end{bmatrix}$$

Exercise $6.E.25$

$$\begin{bmatrix} \cos\left(\frac{\pi}{4}\right) & -\sin\left(\frac{\pi}{4}\right) \\ \sin\left(\frac{\pi}{4}\right) & \cos\left(\frac{\pi}{4}\right) \end{bmatrix} = \begin{bmatrix} \frac{1}{2}\sqrt{2} & -\frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} & \frac{1}{2}\sqrt{2} \end{bmatrix}$$

Exercise $6.E.26$

$$\begin{bmatrix} \cos\left(-\frac{\pi}{3}\right) & -\sin\left(-\frac{\pi}{3}\right) \\ \sin\left(-\frac{\pi}{3}\right) & \cos\left(-\frac{\pi}{3}\right) \end{bmatrix} = \begin{bmatrix} \frac{1}{2} & \frac{1}{2}\sqrt{3} \\ -\frac{1}{2}\sqrt{3} & \frac{1}{2} \end{bmatrix}$$

Exercise $6.E.27$

$$\begin{bmatrix} \cos\left(\frac{2\pi}{3}\right) & -\sin\left(\frac{2\pi}{3}\right) \\ \sin\left(\frac{2\pi}{3}\right) & \cos\left(\frac{2\pi}{3}\right) \end{bmatrix} = \begin{bmatrix} -\frac{1}{2} & -\frac{1}{2}\sqrt{3} \\ \frac{1}{2}\sqrt{3} & -\frac{1}{2} \end{bmatrix}$$

Exercise $6.E.28$

$$\begin{aligned} &\begin{bmatrix} \cos\left(\frac{\pi}{3}\right) & -\sin\left(\frac{\pi}{3}\right) \\ \sin\left(\frac{\pi}{3}\right) & \cos\left(\frac{\pi}{3}\right) \end{bmatrix}\begin{bmatrix} \cos\left(-\frac{\pi}{4}\right) & -\sin\left(-\frac{\pi}{4}\right) \\ \sin\left(-\frac{\pi}{4}\right) & \cos\left(-\frac{\pi}{4}\right) \end{bmatrix} \\ &= \begin{bmatrix} \frac{1}{4}\sqrt{2}\sqrt{3} + \frac{1}{4}\sqrt{2} & \frac{1}{4}\sqrt{2} - \frac{1}{4}\sqrt{2}\sqrt{3} \\ \frac{1}{4}\sqrt{2}\sqrt{3} - \frac{1}{4}\sqrt{2} & \frac{1}{4}\sqrt{2}\sqrt{3} + \frac{1}{4}\sqrt{2} \end{bmatrix} \end{aligned} \tag{6.E.8}$$

Exercise $6.E.29$

$$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}\begin{bmatrix} \cos\left(\frac{2\pi}{3}\right) & -\sin\left(\frac{2\pi}{3}\right) \\ \sin\left(\frac{2\pi}{3}\right) & \cos\left(\frac{2\pi}{3}\right) \end{bmatrix} = \begin{bmatrix} -\frac{1}{2} & -\frac{1}{2}\sqrt{3} \\ -\frac{1}{2}\sqrt{3} & \frac{1}{2} \end{bmatrix}$$

Exercise $6.E.30$

$$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}\begin{bmatrix} \cos\left(\frac{\pi}{3}\right) & -\sin\left(\frac{\pi}{3}\right) \\ \sin\left(\frac{\pi}{3}\right) & \cos\left(\frac{\pi}{3}\right) \end{bmatrix} = \begin{bmatrix} \frac{1}{2} & -\frac{1}{2}\sqrt{3} \\ -\frac{1}{2}\sqrt{3} & -\frac{1}{2} \end{bmatrix}$$

Exercise $6.E.31$

$$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}\begin{bmatrix} \cos\left(\frac{\pi}{4}\right) & -\sin\left(\frac{\pi}{4}\right) \\ \sin\left(\frac{\pi}{4}\right) & \cos\left(\frac{\pi}{4}\right) \end{bmatrix} = \begin{bmatrix} \frac{1}{2}\sqrt{2} & -\frac{1}{2}\sqrt{2} \\ -\frac{1}{2}\sqrt{2} & -\frac{1}{2}\sqrt{2} \end{bmatrix}$$

Exercise $6.E.32$

$$\begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}\begin{bmatrix} \cos\left(\frac{\pi}{6}\right) & -\sin\left(\frac{\pi}{6}\right) \\ \sin\left(\frac{\pi}{6}\right) & \cos\left(\frac{\pi}{6}\right) \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}\sqrt{3} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2}\sqrt{3} \end{bmatrix}$$

Exercise $6.E.33$

$$\begin{bmatrix} \cos\left(\frac{\pi}{4}\right) & -\sin\left(\frac{\pi}{4}\right) \\ \sin\left(\frac{\pi}{4}\right) & \cos\left(\frac{\pi}{4}\right) \end{bmatrix}\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} = \begin{bmatrix} \frac{1}{2}\sqrt{2} & \frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} & -\frac{1}{2}\sqrt{2} \end{bmatrix}$$

Exercise $6.E.34$

$$\begin{bmatrix} \cos\left(\frac{\pi}{4}\right) & -\sin\left(\frac{\pi}{4}\right) \\ \sin\left(\frac{\pi}{4}\right) & \cos\left(\frac{\pi}{4}\right) \end{bmatrix} \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}\sqrt{2} & -\frac{1}{2}\sqrt{2} \\ -\frac{1}{2}\sqrt{2} & \frac{1}{2}\sqrt{2} \end{bmatrix}$$

Exercise $6.E.35$

$$\begin{bmatrix} \cos\left(\frac{\pi}{6}\right) & -\sin\left(\frac{\pi}{6}\right) \\ \sin\left(\frac{\pi}{6}\right) & \cos\left(\frac{\pi}{6}\right) \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} = \begin{bmatrix} \frac{1}{2}\sqrt{3} & \frac{1}{2} \\ \frac{1}{2} & -\frac{1}{2}\sqrt{3} \end{bmatrix}$$

Exercise $6.E.36$

$$\begin{bmatrix} \cos\left(\frac{\pi}{6}\right) & -\sin\left(\frac{\pi}{6}\right) \\ \sin\left(\frac{\pi}{6}\right) & \cos\left(\frac{\pi}{6}\right) \end{bmatrix} \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}\sqrt{3} & -\frac{1}{2} \\ -\frac{1}{2} & \frac{1}{2}\sqrt{3} \end{bmatrix}$$

Exercise $6.E.37$

$$\begin{bmatrix} \cos\left(\frac{2\pi}{3}\right) & -\sin\left(\frac{2\pi}{3}\right) \\ \sin\left(\frac{2\pi}{3}\right) & \cos\left(\frac{2\pi}{3}\right) \end{bmatrix} \begin{bmatrix} \cos\left(-\frac{\pi}{4}\right) & -\sin\left(-\frac{\pi}{4}\right) \\ \sin\left(-\frac{\pi}{4}\right) & \cos\left(-\frac{\pi}{4}\right) \end{bmatrix} = \begin{bmatrix} \frac{1}{4}\sqrt{2}\sqrt{3}-\frac{1}{4}\sqrt{2} & -\frac{1}{4}\sqrt{2}\sqrt{3}-\frac{1}{4}\sqrt{2} \\ \frac{1}{4}\sqrt{2}\sqrt{3}+\frac{1}{4}\sqrt{2} & \frac{1}{4}\sqrt{2}\sqrt{3}-\frac{1}{4}\sqrt{2} \end{bmatrix}$$

Note that it doesn't matter about the order in this case.

Exercise $6.E.38$

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{bmatrix} \begin{bmatrix} \cos\left(\frac{\pi}{6}\right) & -\sin\left(\frac{\pi}{6}\right) & 0 \\ \sin\left(\frac{\pi}{6}\right) & \cos\left(\frac{\pi}{6}\right) & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{2}\sqrt{3} & -\frac{1}{2} & 0 \\ \frac{1}{2} & \frac{1}{2}\sqrt{3} & 0 \\ 0 & 0 & -1 \end{bmatrix}$$

Exercise $6.E.39$

$$\begin{aligned} &\begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} \cos(-\theta) & -\sin(\theta) \\ \sin(-\theta) & \cos(-\theta) \end{bmatrix} \\ &= \begin{bmatrix} \cos^2\theta - \sin^2\theta & 2\cos\theta\sin\theta \\ 2\cos\theta\sin\theta & \sin^2\theta - \cos^2\theta \end{bmatrix} \end{aligned} \tag{6.E.9}$$

Now to write in terms of (a, b), note that $a/\sqrt{a^2+b^2} = \cos\theta$, $b/\sqrt{a^2+b^2} = \sin\theta$. Now plug this in to the above. The result is

$$\begin{bmatrix} \frac{a^2-b^2}{a^2+b^2} & 2\frac{ab}{a^2+b^2} \\ 2\frac{ab}{a^2+b^2} & \frac{b^2-a^2}{a^2+b^2} \end{bmatrix} = \frac{1}{a^2+b^2} \begin{bmatrix} a^2-b^2 & 2ab \\ 2ab & b^2-a^2 \end{bmatrix}$$

Since this is a unit vector, $a^2 + b^2 = 1$ and so you get

$$\begin{bmatrix} a^2-b^2 & 2ab \\ 2ab & b^2-a^2 \end{bmatrix}$$

Exercise $6.E.44$

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}$$

Exercise $6.E.45$

This says that the columns of A have a subset of m vectors which are linearly independent. Therefore, this set of vectors is a basis for $\mathbb{R}^m$. It follows that the span of the columns is all of $\mathbb{R}^m$. Thus A is onto.

Exercise $6.E.46$

The columns are independent. Therefore, A is one to one.

Exercise $6.E.47$

The rank is n is the same as saying the columns are independent which is the same as saying A is one to one which is the same as saying the columns are a basis. Thus the span of the columns of A is all of $\mathbb{R}^n$ and so A is onto. If A is onto, then the columns must be linearly independent since otherwise the span of these columns would have dimension less than n and so the dimension of $\mathbb{R}^n$ would be less than n.

Exercise $6.E.48$

If $\sum_i^r a_i\vec{v}_r = 0$, then using linearity properties of T we get

$$0 = T(0) = T\left(\sum_i^r a_i\vec{v}_r\right) = \sum_i^r a_i T(\vec{v}_r).$$

Since we assume that $\{T\vec{v}_a, \cdots, T\vec{v}_r\}$ is linearly independent, we must have all $a_i = 0$, and therefore we conclude that $\{\vec{v}_1, \cdots, \vec{v}_r\}$ is also linearly independent.

Exercise $6.E.50$

Since the third vector is a linear combinations of the first two, then the image of the third vector will also be a linear combinations of the image of the first two. However the image of the first two vectors are linearly independent (check!), and hence form a basis of the image.

Thus a basis for $im(T)$ is:

$$V = span\left\{\begin{bmatrix}2\\0\\1\\3\end{bmatrix}, \begin{bmatrix}4\\2\\4\\5\end{bmatrix}\right\}$$

Exercise $6.E.60$

In this case $\dim(W) = 1$ and a basis for W consisting of vectors in S can be obtained by taking any (nonzero) vector from S.

Exercise $6.E.61$

A basis for $\ker(T)$ is $\left\{\begin{bmatrix}1\\-1\end{bmatrix}\right\}$ and a basis for $im(T)$ is $\left\{\begin{bmatrix}1\\1\end{bmatrix}\right\}$. There are many other possibilities for the specific bases, but in this case $\dim(\ker(T)) = 1$ and $\dim(im(T)) = 1$.

Exercise $6.E.62$

In this case $\ker(T) = \{0\}$ and $im(T) = \mathbb{R}^2$ (pick any basis of $\mathbb{R}^2$).

Exercise $6.E.63$

There are many possible such extensions, one is (how do we know?):

$$\left\{\begin{bmatrix}1\\1\\1\end{bmatrix}, \begin{bmatrix}-1\\2\\-1\end{bmatrix}, \begin{bmatrix}0\\0\\1\end{bmatrix}\right\}$$

Exercise $6.E.64$

We can easily see that $\dim(im(T)) = 1$, and thus $\dim(\ker(T)) = 3 - \dim(im(T)) = 3 - 1 = 2$.

Exercise $6.E.66$

$$C_B(\vec{x}) = \begin{bmatrix}2\\1\\-1\end{bmatrix}$$

Exercise $6.E.67$

$$M_{B_2B_1} = \begin{bmatrix}1 & 0\\-1 & 1\end{bmatrix}$$

Exercise $6.E.68$

Solution is: $\begin{bmatrix}-3\hat{t}\\-\hat{t}\\\hat{t}\end{bmatrix}$, $\hat{t}_3 \in \mathbb{R}$. A basis for the solution space is $\begin{bmatrix}-3\\-1\\1\end{bmatrix}$

Exercise $6.E.69$

Note that this has the same matrix as the above problem. Solution is: $\begin{bmatrix}-3\hat{t}_3\\-\hat{t}_3\\\hat{t}_3\end{bmatrix} + \begin{bmatrix}0\\-1\\0\end{bmatrix}$, $\hat{t}_3 \in \mathbb{R}$

Exercise $6.E.70$

Solution is: $\begin{bmatrix}3\hat{t}\\2\hat{t}\\\hat{t}\end{bmatrix}$, A basis is $\begin{bmatrix}3\\2\\1\end{bmatrix}$

Exercise $6.E.71$

Solution is: $\begin{bmatrix}3\hat{t}\\2\hat{t}\\\hat{t}\end{bmatrix} + \begin{bmatrix}-3\\-1\\0\end{bmatrix}$, $\hat{t} \in \mathbb{R}$

Exercise $6.E.72$

Solution is: $\begin{bmatrix}-4\hat{t}\\-2\hat{t}\\\hat{t}\end{bmatrix}$. A basis is $\begin{bmatrix}-4\\-2\\1\end{bmatrix}$

Exercise $6.E.73$

Solution is: $\begin{bmatrix}-4\hat{t}\\-2\hat{t}\\\hat{t}\end{bmatrix} + \begin{bmatrix}0\\-1\\0\end{bmatrix}$, $\hat{t} \in \mathbb{R}$

Exercise $6.E.74$

Solution is: $\begin{bmatrix}-\hat{t}\\2\hat{t}\\\hat{t}\end{bmatrix}$, $\hat{t} \in \mathbb{R}$

Exercise $6.E.75$

Solution is: $\begin{bmatrix}-\hat{t}\\2\hat{t}\\\hat{t}\end{bmatrix} + \begin{bmatrix}-1\\-1\\0\end{bmatrix}$

Exercise $6.E.76$

Solution is: $\begin{bmatrix} 0 \\ -\hat{t} \\ -\hat{t} \\ \hat{t} \end{bmatrix}$, $\hat{t} \in \mathbb{R}$

Exercise $6.E.77$

Solution is: $\begin{bmatrix} 0 \\ -\hat{t} \\ -\hat{t} \\ \hat{t} \end{bmatrix} + \begin{bmatrix} 2 \\ -1 \\ -1 \\ 0 \end{bmatrix}$

Exercise $6.E.78$

Solution is: $\begin{bmatrix} -s-t \\ s \\ s \\ t \end{bmatrix}$, $s,t \in \mathbb{R}$. A basis is

$$\left\{ \begin{bmatrix} -1 \\ 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right\}$$

Exercise $6.E.79$

Solution is:

$$\begin{bmatrix} -\hat{t} \\ \hat{t} \\ \hat{t} \\ 0 \end{bmatrix} + \begin{bmatrix} -8 \\ 5 \\ 0 \\ 5 \end{bmatrix}$$

Exercise $6.E.80$

Solution is:

$$\begin{bmatrix} -\frac{1}{2}s - \frac{1}{2}t \\ \frac{1}{2}s - \frac{1}{2}t \\ s \\ t \end{bmatrix}$$

for $s,t \in \mathbb{R}$. A basis is

$$\left\{ \begin{bmatrix} -1 \\ 1 \\ 2 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \\ 0 \\ 1 \end{bmatrix} \right\}$$

Exercise $6.E.81$

Solution is:

$$\begin{bmatrix} \frac{3}{2} \\ -\frac{1}{2} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} -\frac{1}{2}s - \frac{1}{2}t \\ \frac{1}{2}s - \frac{1}{2}t \\ s \\ t \end{bmatrix}$$

Exercise $6.E.82$

Solution is: $\begin{bmatrix} -\hat{t} \\ \hat{t} \\ \hat{t} \\ 0 \end{bmatrix}$, a basis is $\begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \end{bmatrix}$.

Exercise $6.E.83$

Solution is: $\begin{bmatrix} -\hat{t} \\ \hat{t} \\ \hat{t} \\ 0 \end{bmatrix} + \begin{bmatrix} -9 \\ 5 \\ 0 \\ 6 \end{bmatrix}, t \in \mathbb{R}$.

Exercise $6.E.84$

If not, then there would be a infintely many solutions to $A\vec{x} = \vec{0}$ and each of these added to a solution to $A\vec{x} = \vec{b}$ would be a solution to $A\vec{x} = \vec{b}$.

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6.11.1: KERNEL, RANGE, NULLITY, RANK

Given a linear transformation

$$L: V \to W\,, \tag{6.11.1.1}$$

we want to know if it has an inverse, $i.e.$, is there a linear transformation

$$M: W \to V \tag{6.11.1.2}$$

such that for any vector $v \in V$, we have

$$MLv = v\,, \tag{6.11.1.3}$$

and for any vector $w \in W$, we have

$$LMw = w\,. \tag{6.11.1.4}$$

A linear transformation is just a special kind of function from one vector space to another. So before we discuss which linear transformations have inverses, let us first discuss inverses of arbitrary functions. When we later specialize to linear transformations, we'll also find some nice ways of creating subspaces.

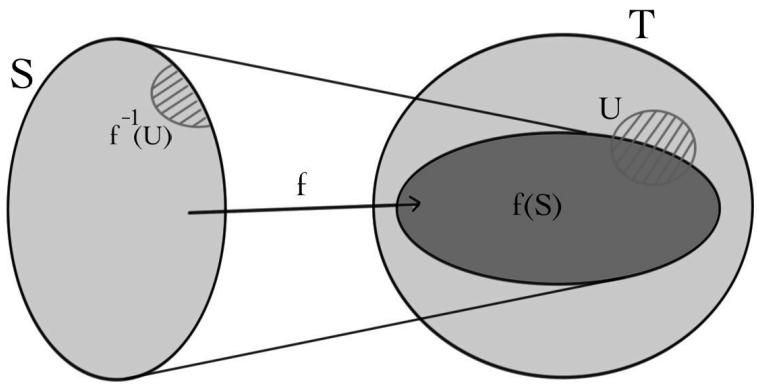
Let $f: S \to T$ be a function from a set S to a set T. Recall that S is called the $domain$ of f, T is called the $codomain$ or $target$ of f, and the set

$$\mathrm{ran}(f) = \mathrm{im}(f) = f(S) = \{f(s) | s \in S\} \subset T\,, \tag{6.11.1.5}$$

is called the $range$ or $image$ of f. The image of f is the set of elements of T to which the function f maps, $i.e.$, the things in T which you can get to by starting in S and applying f. We can also talk about the pre-image of any subset $U \subset T$:

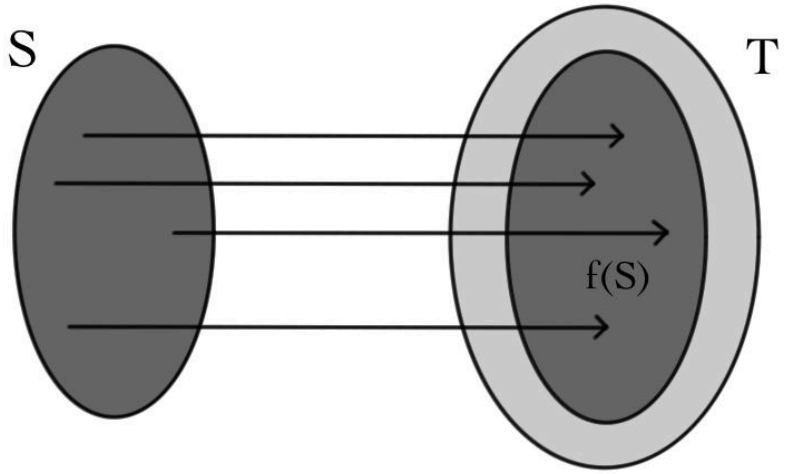
$$f^{-1}(U) = \{s \in S | f(s) \in U\} \subset S. \tag{6.11.1.6}$$

The pre-image of a set U is the set of all elements of S which map to U.



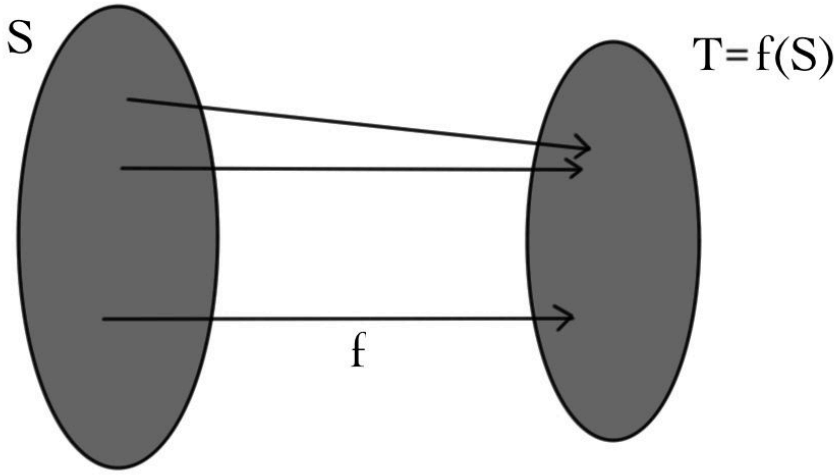
For the function $f: S \to T$, S is the domain, T is the target, $f(S)$ is the image/range and $f^{-1}(U)$ is the pre-image of $U \subset T$.

The function f is $one\text{-}to\text{-}one$ if different elements in S always map to different elements in T. That is, f is one-to-one if for any elements $x \neq y \in S$, we have that $f(x) \neq f(y)$:

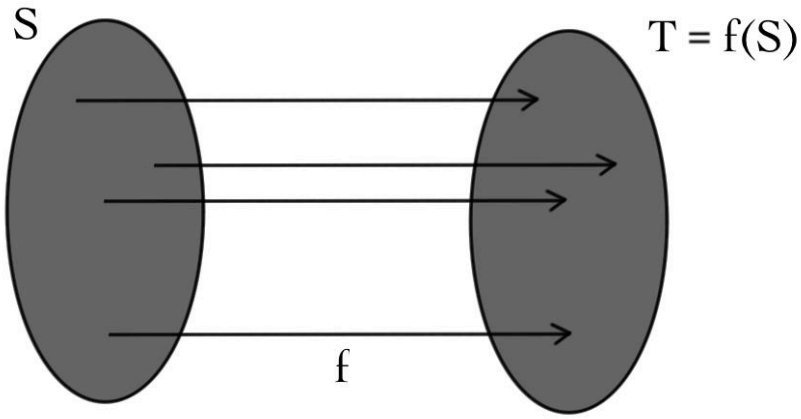


One-to-one functions are also called $injective$ functions. Notice that injectivity is a condition on the pre-images of f.

The function f is $onto$ if every element of T is mapped to by some element of S. That is, f is onto if for any $t \in T$, there exists some $s \in S$ such that $f(s) = t$. Onto functions are also called $surjective$ functions. Notice that surjectivity is a condition on the image of f:



If f is both injective and surjective, it is $bijective$:



Theorem

A function $f: S \to T$ has an inverse function $g: T \to S$ if and only if it is bijective.

Proof

This is an "if and only if" statement so the proof has two parts:

1. *(Existence of an inverse $\Rightarrow$ bijective.)*

a) Suppose that f has an inverse function g. We need to show f is bijective, which we break down into injective and surjective: The function f is injective: Suppose that we have $s, s' \in S$ such that $f(x) = f(y)$. We must have that $g(f(s)) = s$ for any $s \in S$, so in particular $g(f(s)) = s$ and $g(f(s')) = s'$. But since $f(s) = f(s')$, we have $g(f(s)) = g(f(s'))$ so $s = s'$. Therefore, f is injective.

b) The function f is surjective: Let t be any element of T. We must have that $f(g(t)) = t$. Thus, $g(t)$ is an element of S which maps to t. So f is surjective.

2. *(Bijectivity $\Rightarrow$ existence of an inverse.)*

Suppose that f is bijective. Hence f is surjective, so every element $t \in T$ has at least one pre-image. Being bijective, f is also injective, so every t has no more than one pre-image. Therefore, to construct an inverse function g, we simply define $g(t)$ to be the unique pre-image $f^{-1}(t)$ of t.

Now let us specialize to functions f that are linear maps between two vector spaces. Everything we said above for arbitrary functions is exactly the same for linear functions. However, the structure of vector spaces lets us say much more about one-to-one and onto functions whose domains are vector spaces than we can say about functions on general sets. For example, we know that a linear function always sends 0_V to 0_W, *i.e.*,

$$f(0_V) = 0_W. \tag{6.11.1.7}$$

In review exercise 3, you will show that a linear transformation is one-to-one if and only if 0_V is the only vector that is sent to 0_W: In contrast to arbitrary functions between sets, by looking at just one (very special) vector, we can figure out whether f is one-to-one!

Let $L: V \to W$ be a linear transformation. Suppose L is \emph{not} injective. Then we can find $v_1 \neq v_2$ such that $Lv_1 = Lv_2$. So $v_1 - v_2 \neq 0$, but

$$L(v_1 - v_2) = 0. \tag{6.11.1.8}$$

Definition: linear transformation

Let $L: V \to W$ be a linear transformation. The set of all vectors v such that $Lv = 0_W$ is called the *kernel of* L:

$$\ker L = \{v \in V | Lv = 0_W\} \subset V. \tag{6.11.1.9}$$

Theorem

A linear transformation L is injective if and only if

$$\ker L = \{0_V\}. \tag{6.11.1.10}$$

Proof
The proof of this theorem is review exercise 2.

Notice that if L has matrix M in some basis, then finding the kernel of L is equivalent to solving the homogeneous system

$$MX = 0. \tag{6.11.1.11}$$

Example 131

Let $L(x, y) = (x + y, x + 2y, y)$. Is L one-to-one?

To find out, we can solve the linear system:

\[

$$\begin{pmatrix} 1 & 1 & 0 \\ 1 & 2 & 0 \\ 0 & 1 & 0 \end{pmatrix} \tag{6.11.1.12}$$

\sim

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix} \tag{6.11.1.13}$$

$$

Then all solutions of $MX = 0$ are of the form $x = y = 0$. In other words, $\ker L = \{0\}$, and so L is injective.

Theorem

Let $L: V \xrightarrow{\text{linear}} W$. Then $\ker L$ is a subspace of V.

Proof
Notice that if $L(v) = 0$ and $L(u) = 0$, then for any constants c, d, $L(cu + dv) = 0$. Then by the subspace theorem, the kernel of L is a subspace of V.

Example 132

Let $L: \Re^3 \to \Re$ be the linear transformation defined by $L(x, y, z) = (x + y + z)$. Then $\ker L$ consists of all vectors $(x, y, z) \in \Re^3$ such that $x + y + z = 0$. Therefore, the set

$$V = \{(x, y, z) \in \Re^3 \mid x + y + z = 0\} \tag{6.11.1.14}$$

is a subspace of $\mathfrak{R}^3$.

When $L : V \to V$, the above theorem has an interpretation in terms of the eigenspaces of L: Suppose L has a zero eigenvalue. Then the associated eigenspace consists of all vectors v such that $Lv = 0v = 0$; in other words, the 0-eigenspace of L is exactly the kernel of L.

In the example where $L(x, y) = (x + y, x + 2y, y)$, the map L is clearly not surjective, since L maps $\mathfrak{R}^2$ to a plane through the origin in $\mathfrak{R}^3$. But any plane through the origin is a subspace. In general notice that if $w = L(v)$ and $w' = L(v')$, then for any constants c, d , linearity of L ensures that

$$cw + dw' = L(cv + dv') \,. \tag{6.11.1.15}$$

Now the subspace theorem strikes again, and we have the following theorem:

Theorem

Let $L: V \to W$. Then the image $L(V)$ is a subspace of W.

Example 133

Let $L(x, y) = (x + y, x + 2y, y)$. The image of L is a plane through the origin and thus a subspace of $\mathbb{R}^3$. Indeed the matrix of L in the standard basis is

$$\begin{pmatrix} 1 & 1 \\ 1 & 2 \\ 0 & 1 \end{pmatrix} . \tag{6.11.1.16}$$

The columns of this matrix encode the possible outputs of the function L because

$$L(x, y) = \begin{pmatrix} 1 & 1 \\ 1 & 2 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = x \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} + y \begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix} . \tag{6.11.1.17}$$

Thus

$$L(\mathbb{R}^2) = span \left\{ \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix} \right\} \tag{6.11.1.18}$$

Hence, when bases and a linear transformation is are given, people often refer to its image as the $column\ space$ of the corresponding matrix.

To find a basis of the image of L, we can start with a basis $S = \{v_1, \dots, v_n\}$ for V. Then
the most general input for L is of the form $\alpha^1 v_1 + \cdots + \alpha^n v_n$. In turn, its most general output looks like

$$L\left(\alpha^1 v_1 + \cdots + \alpha^n v_n\right) = \alpha^1 L v_1 + \cdots + \alpha^n L v_n \in span\{Lv_1, \dots Lv_n\} \,. \tag{6.11.1.19}$$

Thus

$$L(V) = span L(S) = span\{Lv_1, \dots, Lv_n\} \,. \tag{6.11.1.20}$$

However, the set $\{Lv_1, \dots, Lv_n\}$ may not be linearly independent; we must solve

$$c^1 L v_1 + \cdots + c^n L v_n = 0 \,, \tag{6.11.1.21}$$

to determine whether it is. By finding relations amongst the elements of $L(S) = \{Lv_1, \dots, Lv_n\}$, we can discard vectors until a basis is arrived at. The size of this basis is the dimension of the image of L, which is known as the $rank$ of L.

Definition

The $rank$ of a linear transformation L is the dimension of its image, written

$$rankL = \dim L(V) = \dim\ ran\, L. \tag{6.11.1.22}$$

The $nullity$ of a linear transformation is the dimension of the kernel, written

$$nulL = \dim \ker L. \tag{6.11.1.23}$$

Theorem: Dimension formula

Let $L\colon V \to W$ be a linear transformation, with V a finite-dimensional vector space. Then:

$$\begin{aligned} \dim V &= \dim \ker V + \dim L(V) \\ &= nulL + rankL. \end{aligned}$$

Proof
Pick a basis for V:

$$\{v_1, \dots, v_p, u_1, \dots, u_q\}, \tag{6.11.1.24}$$

where $v_1, \dots, v_p$ is also a basis for $\ker L$. This can always be done, for example, by finding a basis for the kernel of L and then extending to a basis for V. Then $p = nulL$ and $p + q = \dim V$. Then we need to show that $q = rankL$. To accomplish this, we show that $\{L(u_1), \dots, L(u_q)\}$ is a basis for $L(V)$.

To see that $\{L(u_1), \dots, L(u_q)\}$ spans $L(V)$, consider any vector w in $L(V)$. Then we can find constants c^i, d^j such that:

$$\begin{aligned} w &= L(c^1 v_1 + \cdots + c^p v_p + d^1 u_1 + \cdots + d^q u_q) \\ &= c^1 L(v_1) + \cdots + c^p L(v_p) + d^1 L(u_1) + \cdots + d^q L(u_q) \\ &= d^1 L(u_1) + \cdots + d^q L(u_q) \text{ since } L(v_i) = 0, \\ \Rightarrow L(V) &= span\{L(u_1), \dots, L(u_q)\}. \end{aligned}$$

Now we show that $\{L(u_1), \dots, L(u_q)\}$ is linearly independent. We argue by contradiction: Suppose there exist constants d^j (not all zero) such that

$$\begin{aligned} 0 &= d^1 L(u_1) + \cdots + d^q L(u_q) \\ &= L(d^1 u_1 + \cdots + d^q u_q). \end{aligned}$$

But since the u^j are linearly independent, then $d^1 u_1 + \cdots + d^q u_q \neq 0$, and so $d^1 u_1 + \cdots + d^q u_q$ is in the kernel of L. But then $d^1 u_1 + \cdots + d^q u_q$ must be in the span of $\{v_1, \dots, v_p\}$, since this was a basis for the kernel. This contradicts the assumption that $\{v_1, \dots, v_p, u_1, \dots, u_q\}$ was a basis for V, so we are done.

- Topic hierarchy

6.11.1.1: Summary

6.11.1.2: Review Problems

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7: INNER PRODUCT SPACES

7.1: Inner Products and Norms

7.1E: Inner Products and Norms Exercises

7.2: Orthogonal Sets of Vectors

7.2E: Orthogonal Sets of Vectors Exercises

Gram Schmidt Orthonormalization Process GeoGebra Demo by SKKU-Matrix-Lab

7.3: Orthogonal Diagonalization

7.3E: Orthogonal Diagonalization Exercises

7.4: Isometries

7.4E: Isometries Exercises

7.5: An Application to Fourier Approximation

7.5E: An Application to Fourier Approximation Exercises

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7.1: INNER PRODUCTS AND NORMS

Definition: Inner Products

An inner product on a real vector space V is a function that assigns a real number $\langle v, w\rangle$ to every pair $\mathbf{v}, \mathbf{w}$ of vectors in V in such a way that the following axioms are satisfied.

- $P1. \langle \mathbf{v}, \mathbf{w}\rangle$ is a real number for all $\mathbf{v}$ and $\mathbf{w}$ in V.
- $P2 \langle v, w\rangle = \langle w, v\rangle$ for all $\mathbf{v}$ and $\mathbf{w}$ in V.
- $P3. \langle v + w, u\rangle = \langle \mathbf{v}, \mathbf{u}\rangle + \langle \mathbf{w}, \mathbf{u}\rangle$ for all $\mathbf{u}, \mathbf{v}$, and $\mathbf{w}$ in V.
- $P4. \langle r\mathbf{v}, \mathbf{w}\rangle = r\langle \mathbf{v}, \mathbf{w}\rangle$ for all $\mathbf{v}$ and $\mathbf{w}$ in V and all r in $\mathbb{R}$.
- $P5. \langle \mathbf{v}, \mathbf{v}\rangle > 0$ for all $\mathbf{v} \neq \mathbf{0}$ in V.

A real vector space V with an inner product $\langle , \rangle$ will be called an inner product space. Note that every subspace of an inner product space is again an inner product space using the same inner product. [1]

Example 7.1.1

$\mathbb{R}^n$ is an inner product space with the dot product as inner product:

$$\langle \mathbf{v}, \mathbf{w}\rangle = \mathbf{v} \cdot \mathbf{w} \text{ for all } \mathbf{v}, \mathbf{w} \in \mathbb{R}^n$$

See Theorem 5.3.1. This is also called the euclidean inner product, and $\mathbb{R}^n$, equipped with the dot product, is called **euclidean** n-space.

Example 7.1.2

If A and B are $m \times n$ matrices, define $\langle A, B\rangle = \operatorname{tr}\left(AB^T\right)$ where $\operatorname{tr}(X)$ is the trace of the square matrix X. Show that $\langle , \rangle is an inner product in \mathbf{M}_{mn}$.

Solution

P1 is clear. Since $\operatorname{tr}(P) = \operatorname{tr}\left(P^T\right)$ for every $m \times n$ matrix P, we have P2:

$$\langle A, B\rangle = \operatorname{tr}\left(AB^T\right) = \operatorname{tr}\left[\left(AB^T\right)^T\right] = \operatorname{tr}\left(BA^T\right) = \langle B, A\rangle.$$

Next, P3 and P4 follow because trace is a linear transformation $\mathbf{M}_{mn} \to \mathbb{R}$ (Exercise 19). Turning to P5, let $\mathbf{r}_1, \mathbf{r}_2, \ldots, \mathbf{r}_m$ denote the rows of the matrix A. Then the (i, j)-entry of AA^T is $\mathbf{r}_i \cdot \mathbf{r}_j$, so

$$\langle A, A\rangle = \operatorname{tr}\left(AA^T\right) = \mathbf{r}_1 \cdot \mathbf{r}_1 + \mathbf{r}_2 \cdot \mathbf{r}_2 + \cdots + \mathbf{r}_m \cdot \mathbf{r}_m$$

But $\mathbf{r}_j \cdot \mathbf{r}_j$ is the sum of the squares of the entries of $\mathbf{r}_j$, so this shows that $\langle A, A\rangle$ is the sum of the squares of all nm entries of A. Axiom P5 follows.

The next example is important in analysis.

Example 7.1.3

Let $\mathbf{C}[a, b]$ denote the vector space of continuous functions from $[a, b]$ to $\mathbb{R}$, a subspace of $\mathbf{F}[a, b]$. Show that

$$\langle f, g\rangle = \int_a^b f(x)g(x)dx$$

defines an inner product on $\mathbf{C}[a, b]$. [2]

Solution

Axioms P1 and P2 are clear. As to axiom P4,

$$\langle rf, g\rangle = \int_a^b rf(x)g(x)dx = r\int_a^b f(x)g(x)dx = r\langle f, g\rangle$$

Axiom $\mathrm{P3}$ is similar. Finally, theorems of calculus show that $\langle f, f\rangle = \int_a^b f(x)^2dx \geq 0$ and, if f is continuous, that this is zero if and only if f is the zero function. This gives axiom P5.

If $\mathbf{v}$ is any vector, then, using axiom $\mathrm{P3}$, we get

$$\langle \mathbf{0}, \mathbf{v}\rangle = \langle \mathbf{0} + \mathbf{0}, \mathbf{v}\rangle = \langle \mathbf{0}, \mathbf{v}\rangle + \langle \mathbf{0}, \mathbf{v}\rangle$$

and it follows that the number $\langle \mathbf{0}, \mathbf{v}\rangle$ must be zero. This observation is recorded for reference in the following theorem, along with several other properties of inner products. The other proofs are left as Exercise 20.

Theorem 7.1.1

Let $\langle , \rangle$ be an inner product on a space V; let $\mathbf{v}, \boldsymbol{u}$, and $\mathbf{w}$ denote vectors in V; and let r denote a real number.

1. $\langle \boldsymbol{u}, \boldsymbol{v} + \boldsymbol{w}\rangle = \langle \mathbf{u}, \mathbf{v}\rangle + \langle \mathbf{u}, \boldsymbol{w}\rangle$.
2. $\langle \boldsymbol{v}, r\boldsymbol{w}\rangle = r\langle \mathbf{v}, \boldsymbol{w}\rangle = \langle r\mathbf{v}, \boldsymbol{w}\rangle$.
3. $\langle \boldsymbol{v}, \mathbf{0}\rangle = 0 = \langle \mathbf{0}, \boldsymbol{v}\rangle$.
4. $\langle \boldsymbol{v}, \mathbf{v}\rangle = 0$ if and only if $\mathbf{v} = \mathbf{0}$.

If $\langle , \rangle$ is an inner product on a space V, then, given $\mathbf{u}, \mathbf{v}$, and $\mathbf{w}$ in V,

$$\langle r\mathbf{u} + s\mathbf{v}, \mathbf{w}\rangle = \langle r\mathbf{u}, \mathbf{w}\rangle + \langle s\mathbf{v}, \mathbf{w}\rangle = r\langle \mathbf{u}, \mathbf{w}\rangle + s\langle \mathbf{v}, \mathbf{w}\rangle$$

for all r and s in $\mathbb{R}$ by axioms $\mathrm{P3}$ and $\mathrm{P4}$. Moreover, there is nothing special about the fact that there are two terms in the linear combination or that it is in the first component:

$$\langle r_1\mathbf{v}_1 + r_2\mathbf{v}_2 + \cdots + r_n\mathbf{v}_n, \mathbf{w}\rangle = r_1\langle \mathbf{v}_1, \mathbf{w}\rangle + r_2\langle \mathbf{v}_2, \mathbf{w}\rangle + \cdots + r_n\langle \mathbf{v}_n, \mathbf{w}\rangle$$

and

$$\langle \mathbf{v}, s_1\mathbf{w}_1 + s_2\mathbf{w}_2 + \cdots + s_m\mathbf{w}_m\rangle = s_1\langle \mathbf{v}, \mathbf{w}_1\rangle + s_2\langle \mathbf{v}, \mathbf{w}_2\rangle + \cdots + s_m\langle \mathbf{v}, \mathbf{w}_m\rangle$$

hold for all r_i and s_i in $\mathbb{R}$ and all $\mathbf{v}, \mathbf{w}, \mathbf{v}_i$, and $\mathbf{w}_j$ in V. These results are described by saying that inner products "preserve" linear combinations. For example,

$$\begin{aligned}\langle 2\mathbf{u} - \mathbf{v}, 3\mathbf{u} + 2\mathbf{v}\rangle &= \langle 2\mathbf{u}, 3\mathbf{u}\rangle + \langle 2\mathbf{u}, 2\mathbf{v}\rangle + \langle -\mathbf{v}, 3\mathbf{u}\rangle + \langle -\mathbf{v}, 2\mathbf{v}\rangle \\ &= 6\langle \mathbf{u}, \mathbf{u}\rangle + 4\langle \mathbf{u}, \mathbf{v}\rangle - 3\langle \mathbf{v}, \mathbf{u}\rangle - 2\langle \mathbf{v}, \mathbf{v}\rangle \\ &= 6\langle \mathbf{u}, \mathbf{u}\rangle + \langle \mathbf{u}, \mathbf{v}\rangle - 2\langle \mathbf{v}, \mathbf{v}\rangle\end{aligned}$$

If A is a symmetric $n \times n$ matrix and $\mathbf{x}$ and $\mathbf{y}$ are columns in $\mathbb{R}^n$, we regard the 1×1 matrix $\mathbf{x}^TA\mathbf{y}$ as a number. If we write

$$\langle \mathbf{x}, \mathbf{y}\rangle = \mathbf{x}^TA\mathbf{y} \quad \text{for all columns } \mathbf{x}, \mathbf{y} \text{ in } \mathbb{R}^n$$

then axioms $\mathrm{P1} - \mathrm{P4}$ follow from matrix arithmetic (only $\mathrm{P2}$ requires that A is symmetric). Axiom $\mathrm{P5}$ reads

$$\mathbf{x}^TA\mathbf{x} > 0 \quad \text{for all columns } \mathbf{x} \neq \mathbf{0} \text{ in } \mathbb{R}^n$$

and this condition characterizes the positive definite matrices (Theorem 8.3.2). This proves the first assertion in the next theorem.

Theorem 7.1.2

If A is any $n \times n$ positive definite matrix, then

$$\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^T A \mathbf{y} \text{ for all columns } \mathbf{x}, \mathbf{y} \text{ in } \mathbb{R}^n$$

defines an inner product on $\mathbb{R}^n$, and every inner product on $\mathbb{R}^n$ arises in this way.

Proof

Given an inner product $\langle , \rangle on \mathbb{R}^n$, let $\{\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n\}$ be the standard basis of $\mathbb{R}^n$. If $\mathbf{x} = \sum_{i=1}^n x_i \mathbf{e}_i$ and $\mathbf{y} = \sum_{j=1}^n y_j \mathbf{e}_j$ are two vectors in $\mathbb{R}^n$, compute $\langle \mathbf{x}, \mathbf{y} \rangle$ by adding the inner product of each term $x_i \mathbf{e}_i$ to each term $y_j \mathbf{e}_j$. The result is a double sum.

$$\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{i=1}^n \sum_{j=1}^n \langle x_i \mathbf{e}_i, y_j \mathbf{e}_j \rangle = \sum_{i=1}^n \sum_{j=1}^n x_i \langle \mathbf{e}_i, \mathbf{e}_j \rangle y_j$$

As the reader can verify, this is a matrix product:

$$\langle \mathbf{x}, \mathbf{y} \rangle = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} \begin{bmatrix} \langle \mathbf{e}_1, \mathbf{e}_1 \rangle & \langle \mathbf{e}_1, \mathbf{e}_2 \rangle & \cdots & \langle \mathbf{e}_1, \mathbf{e}_n \rangle \\ \langle \mathbf{e}_2, \mathbf{e}_1 \rangle & \langle \mathbf{e}_2, \mathbf{e}_2 \rangle & \cdots & \langle \mathbf{e}_2, \mathbf{e}_n \rangle \\ \vdots & \vdots & \cdots & \vdots \\ \langle \mathbf{e}_n, \mathbf{e}_1 \rangle & \langle \mathbf{e}_n, \mathbf{e}_2 \rangle & \cdots & \langle \mathbf{e}_n, \mathbf{e}_n \rangle \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

□

Hence $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^T A \mathbf{y}$, where A is the $n \times n$ matrix whose (i, j)-entry is $\langle \mathbf{e}_i, \mathbf{e}_j \rangle$. The fact that $\langle \mathbf{e}_i, \mathbf{e}_j \rangle = \langle \mathbf{e}_j, \mathbf{e}_i \rangle$ shows that A is symmetric. Finally, A is positive definite by Theorem 8.3.2.

Thus, just as every linear operator $\mathbb{R}^n \to \mathbb{R}^n$ corresponds to an $n \times n$ matrix, every inner product on $\mathbb{R}^n$ corresponds to a positive definite $n \times n$ matrix. In particular, the dot product corresponds to the identity matrix I_n.

Note

If we refer to the inner product space $\mathbb{R}^n$ without specifying the inner product, we mean that the dot product is to be used.

Example 7.1.4

Let the inner product $\langle , \rangle be define on \mathbb{R}^2$ by

$$\left\langle \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}, \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \right\rangle = 2v_1 w_1 - v_1 w_2 - v_2 w_1 + v_2 w_2$$

Find a symmetric 2×2 matrix A such that $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^T A \mathbf{y}$ for all $\mathbf{x}, \mathbf{y}$ in $\mathbb{R}^2$.

Solution

The (i, j)-entry of the matrix A is the coefficient of $v_i w_j$ in the expression, so $A = \begin{bmatrix} 2 & -1 \\ -1 & 1 \end{bmatrix}$. Incidentally, if $\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}$, then

$$\langle \mathbf{x}, \mathbf{x} \rangle = 2x^2 - 2xy + y^2 = x^2 + (x - y)^2 \geq 0$$

for all $\mathbf{x}$, so $\langle \mathbf{x}, \mathbf{x} \rangle = 0$ implies $\mathbf{x} = \mathbf{0}$. Hence $\langle , \rangle$ is indeed an inner product, so A is positive definite.

Let $\langle , \rangle$ be an inner product on \mathbb{R}^n\) given as in Theorem 10.1.2 by a positive definite matrix A. If $\mathbf{x} = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix}^T$, then $\langle \mathbf{x}, \mathbf{x} \rangle = \mathbf{x}^T A \mathbf{x}$ is an expression in the variables $x_1, x_2, \ldots, x_n$ called a quadratic form. These are studied in detail in Section 8.8.

Definition: 7.1.2

As in $\mathbb{R}^n$, if $\langle , \rangle is an inner product on a space V$, the $\mathbf{norm}^3 \|\mathbf{v}\|$ of a vector $\mathbf{v}$ in V is defined by

$$\|\mathbf{v}\| = \sqrt{\langle \mathbf{v}, \mathbf{v} \rangle}$$

We define the distance between vectors $\mathbf{v}$ and $\mathbf{w}$ in an inner product space V to be

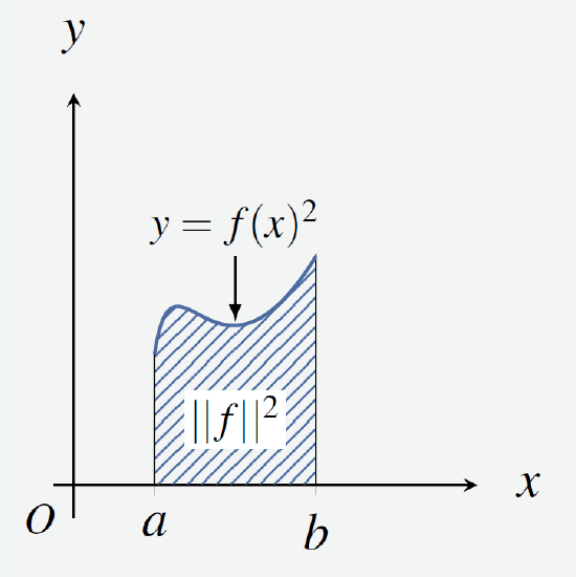
$$\mathrm{d}(\mathbf{v}, \boldsymbol{w}) = \|\mathbf{v} - \boldsymbol{w}\|$$

Note that axiom P5 guarantees that $\langle \mathbf{v}, \mathbf{v} \rangle \geq 0$, so $\|\mathbf{v}\|$ is a real number.

Example 7.1.5

The norm of a continuous function $f = f(x)$ in $\mathbf{C}[a, b]$ (with the inner product from Example 10.1.3) is given by

$$\|f\| = \sqrt{\int_a^b f(x)^2 dx}$$



Hence $\|f\|^2$ is the area beneath the graph of $y = f(x)^2$ between $x = a$ and $x = b$ (see the diagram).

Example 7.1.6

Show that $\langle \mathbf{u} + \mathbf{v}, \mathbf{u} - \mathbf{v} \rangle = \|\mathbf{u}\|^2 - \|\mathbf{v}\|^2$ in any inner product space.

Solution

$$\begin{aligned}\langle \mathbf{u}+\mathbf{v}, \mathbf{u}-\mathbf{v}\rangle &= \langle \mathbf{u}, \mathbf{u}\rangle - \langle \mathbf{u}, \mathbf{v}\rangle + \langle \mathbf{v}, \mathbf{u}\rangle - \langle \mathbf{v}, \mathbf{v}\rangle \\ &= \|\mathbf{u}\|^2 - \langle \mathbf{u}, \mathbf{v}\rangle + \langle \mathbf{u}, \mathbf{v}\rangle - \|\mathbf{v}\|^2 \\ &= \|\mathbf{u}\|^2 - \|\mathbf{v}\|^2\end{aligned}$$

A vector $\mathbf{v}$ in an inner product space V is called a unit vector if $\|\mathbf{v}\| = 1$. The set of all unit vectors in V is called the unit ball in V. For example, if $V = \mathbb{R}^2$ (with the dot product) and $\mathbf{v} = (x, y)$, then

$$\|\mathbf{v}\|^2 = 1 \quad \text{if and only if} \quad x^2 + y^2 = 1$$

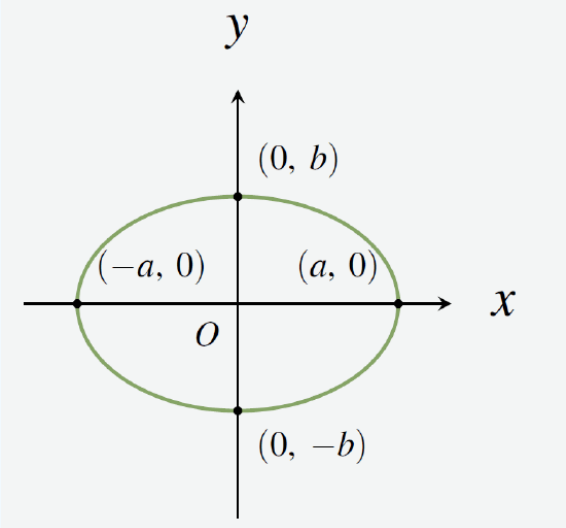
Hence the unit ball in $\mathbb{R}^2$ is the unit circle $x^2 + y^2 = 1$ with centre at the origin and radius 1 . However, the shape of the unit ball varies with the choice of inner product.

Example 7.1.7

Let $a > 0$ and $b > 0$. If $\mathbf{v} = (x, y)$ and $\mathbf{w} = (x_1, y_1)$, define an inner product on $\mathbb{R}^2$ by

$$\langle \mathbf{v}, \mathbf{w}\rangle = \frac{xx_1}{a^2} + \frac{yy_1}{b^2}$$

The reader can verify (Exercise 5) that this is indeed an inner product. In this case



$$\|\mathbf{v}\|^2 = 1 \quad \text{if and only if} \quad \frac{x^2}{a^2} + \frac{y^2}{b^2} = 1$$

so the unit ball is the ellipse shown in the diagram.

Example 10.1.7 graphically illustrates the fact that norms and distances in an inner product space V vary with the choice of inner product in V.

Theorem 7.1.3

If $\mathbf{v} \neq 0$ is any vector in an inner product space V, then $\frac{1}{\|\mathbf{v}\|}\mathbf{V}$ is the unique unit vector that is a positive multiple of $\mathbf{v}$.

The next theorem reveals an important and useful fact about the relationship between norms and inner products, extending the Cauchy inequality for $\mathbb{R}^n$ (Theorem 5.3.2).

Theorem \({7{.}1{.}\eatSpaces{4} \endSpaces}\): Cauchy-Schwartz Inequality

If $\mathbf{v}$ and $\mathbf{w}$ are two vectors in an inner product space V, then

$$\langle \mathbf{v}, \boldsymbol{w} \rangle^2 \leq \|\mathbf{v}\|^2 \|\boldsymbol{w}\|^2$$

Moreover, equality occurs if and only if one of $\mathbf{v}$ and $\mathbf{w}$ is a scalar multiple of the other.

Proof

Write $\|\mathbf{v}\| = a$ and $\|\mathbf{w}\| = b$. Using Theorem 10.1.1 we compute:

$$\begin{aligned} \|b\mathbf{v} - a\mathbf{w}\|^2 &= b^2\|\mathbf{v}\|^2 - 2ab\langle \mathbf{v}, \mathbf{w} \rangle + a^2\|\mathbf{w}\|^2 = 2ab(ab - \langle \mathbf{v}, \mathbf{w} \rangle) \\ \|b\mathbf{v} + a\mathbf{w}\|^2 &= b^2\|\mathbf{v}\|^2 + 2ab\langle \mathbf{v}, \mathbf{w} \rangle + a^2\|\mathbf{w}\|^2 = 2ab(ab + \langle \mathbf{v}, \mathbf{w} \rangle) \end{aligned}$$

It follows that $ab - \langle \mathbf{v}, \mathbf{w} \rangle \geq 0$ and $ab + \langle \mathbf{v}, \mathbf{w} \rangle \geq 0$, and hence that $-ab \leq \langle \mathbf{v}, \mathbf{w} \rangle \leq ab$. But then $| \langle \mathbf{v}, \mathbf{w} \rangle | \leq ab = \|\mathbf{v}\|\|\mathbf{w}\|$, as desired.

Conversely, if $|\langle \mathbf{v}, \mathbf{w} \rangle| = \|\mathbf{v}\|\|\mathbf{w}\| = ab$ then $\langle \mathbf{v}, \mathbf{w} \rangle = \pm ab$. Hence (10.1) shows that $b\mathbf{v} - a\mathbf{w} = \mathbf{0}$ or $b\mathbf{v} + a\mathbf{w} = \mathbf{0}$. It follows that one of $\mathbf{v}$ and $\mathbf{w}$ is a scalar multiple of the other, even if $a = 0$ or $b = 0$.

Example 7.1.8

If f and g are continuous functions on the interval $[a, b]$, then (see Example 10.1.3)

$$\left\{ \int_a^b f(x)g(x)dx \right\}^2 \leq \int_a^b f(x)^2 dx \int_a^b g(x)^2 dx$$

Another famous inequality, the so-called **triangle inequality**, also comes from the Cauchy-Schwarz inequality. It is included in the following list of basic properties of the norm of a vector.

Theorem 7.1.5

If V is an inner product space, the norm $\| \cdot \|$ has the following properties.

1. $\|v\| \geq 0$ for every vector $\mathbf{v}$ in V.
2. $\|v\| = 0$ if and only if $\mathbf{v} = \mathbf{0}$.
3. $\|r\mathbf{v}\| = |r|\|\mathbf{v}\|$ for every $\mathbf{v}$ in V and every r in $\mathbb{R}$.
4. $\|v + \boldsymbol{w}\| \leq \|\mathbf{v}\| + \|\boldsymbol{w}\|$ for all $\mathbf{v}$ and $\mathbf{w}$ in V (**triangle inequality**).

Proof

Because $\|\mathbf{v}\| = \sqrt{\langle \mathbf{v}, \mathbf{v} \rangle}$, properties (1) and (2) follow immediately from (3) and (4) of Theorem 10.1.1. As to (3), compute

$$\|r\mathbf{v}\|^2 = \langle r\mathbf{v}, r\mathbf{v} \rangle = r^2\langle \mathbf{v}, \mathbf{v} \rangle = r^2\|\mathbf{v}\|^2$$

Hence (3) follows by taking positive square roots. Finally, the fact that $\langle \mathbf{v}, \mathbf{w} \rangle \leq \|\mathbf{v}\|\|\mathbf{w}\|$ by the CauchySchwarz inequality gives

$$\begin{aligned} \|\mathbf{v} + \mathbf{w}\|^2 = \langle \mathbf{v} + \mathbf{w}, \mathbf{v} + \mathbf{w} \rangle &= \|\mathbf{v}\|^2 + 2\langle \mathbf{v}, \mathbf{w} \rangle + \|\mathbf{w}\|^2 \\ &\leq \|\mathbf{v}\|^2 + 2\|\mathbf{v}\|\|\mathbf{w}\| + \|\mathbf{w}\|^2 \\ &= (\|\mathbf{v}\| + \|\mathbf{w}\|)^2 \end{aligned}$$

Hence (4) follows by taking positive square roots.

□

It is worth noting that the usual triangle inequality for absolute values,

$$|r+s| \leq |r| + |s| \text{ for all real numbers } r \text{ and } s,$$

is a special case of (4) where $V = \mathbb{R} = \mathbb{R}^1$ and the dot product $\langle r, s \rangle = rs$ is used.

In many calculations in an inner product space, it is required to show that some vector $\mathbf{v}$ is zero. This is often accomplished most easily by showing that its norm $\|\mathbf{v}\|$ is zero. Here is an example.

Example 7.1.9

Let $\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ be a spanning set for an inner product space V. If $\mathbf{v}$ in V satisfies $\langle \mathbf{v}, \mathbf{v}_i \rangle = 0$ for each $i = 1, 2, \ldots, n$, show that $\mathbf{v} = \mathbf{0}$.

Solution

Write $\mathbf{v} = r_1\mathbf{v}_1 + \cdots + r_n\mathbf{v}_n, r_i$ in $\mathbb{R}$. To show that $\mathbf{v} = \mathbf{0}$, we show that $\|\mathbf{v}\|^2 = \langle \mathbf{v}, \mathbf{v} \rangle = 0$.

Compute:

$$\langle \mathbf{v}, \mathbf{v} \rangle = \langle \mathbf{v}, r_1\mathbf{v}_1 + \cdots + r_n\mathbf{v}_n \rangle = r_1 \langle \mathbf{v}, \mathbf{v}_1 \rangle + \cdots + r_n \langle \mathbf{v}, \mathbf{v}_n \rangle = 0$$

by hypothesis, and the result follows.

The norm properties in Theorem 10.1.5 translate to the following properties of distance familiar from geometry. The proof is Exercise 21.

Theorem 7.1.6

Let V be an inner product space.

1. $d(\boldsymbol{v}, \mathbf{w}) \geq 0$ for all $\mathbf{v}, \boldsymbol{w}$ in V.
2. $d(\boldsymbol{v}, \mathbf{w}) = 0$ if and only if $\mathbf{v} = \mathbf{w}$.
3. $d(\mathbf{v}, \mathbf{w}) = d(\mathbf{w}, \mathbf{v})$ for all $\mathbf{v}$ and $\mathbf{w}$ in V.
4. $d(\boldsymbol{v}, \boldsymbol{w}) \leq d(\mathbf{v}, \boldsymbol{u}) + d(\mathbf{u}, \boldsymbol{w})$ for all $\mathbf{v}, \boldsymbol{u}$, and $\boldsymbol{w}$ in V.

---

[1] If we regard $\mathbb{C}^n$ as a vector space over the field $\mathbb{C}$ of complex numbers, then the "standard inner product" on $\mathbb{C}^n$ defined in Section 8.6 does not satisfy Axiom P4 (see Theorem 8.6.1(3)).

[2] This example (and others later that refer to it) can be omitted with no loss of continuity by students with no calculus background.

[3] If the dot product is used in $\mathbb{R}^n$, the norm $\|\mathbf{x}\|$ of a vector $\mathbf{x}$ is usually called the length of $\mathbf{x}$.

[4] Hermann Amandus Schwarz (1843-1921) was a German mathematician at the University of Berlin. He had strong geometric intuition, which he applied with great ingenuity to particular problems. A version of the inequality appeared in 1885.

7.1E: Inner Products and Norms Exercises

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7.1E: Inner Products and Norms Exercises

Exercise 7.1E.1

In each case, determine which of axioms P1-P5 fail to hold.

a. $V = \mathbb{R}^2, \langle (x_1, y_1), (x_2, y_2) \rangle = x_1 y_1 x_2 y_2$
b. $V = \mathbb{R}^3, \langle (x_1, x_2, x_3), \quad (y_1, y_2, y_3) \rangle = x_1 y_1 - x_2 y_2 + x_3 y_3$
c. $V = \mathbb{C}, \langle z, w \rangle = z\bar{w}$, where $\bar{w}$ is complex conjugation
d. $V = \mathbf{P}_3, \langle p(x), q(x) \rangle = p(1)q(1)$
e. $V = \mathbf{M}_{22}, \langle A, B \rangle = \det(AB)$
f. $V = \mathbf{F}[0,1], \langle f, g \rangle = f(1)g(0) + f(0)g(1)$

Answer available at the end of this section.

Exercise 7.1E.2

Let V be an inner product space. If $U \subseteq V$ is a subspace, show that U is an inner product space using the same inner product.

Answer available at the end of this section.

Exercise 7.1E.3

In each case, find a scalar multiple of $\mathbf{v}$ that is a unit vector.

a. $\mathbf{v} = f$ in $\mathbf{C}[0,1]$ where $f(x) = x^2$ $\langle \mathbf{f}, \mathbf{g} \rangle \int_0^1 f(x)g(x)dx$
b. $\mathbf{v} = f$ in $\mathbf{C}[-\pi, \pi]$ where $f(x) = \cos x$ $\langle \mathbf{f}, \mathbf{g} \rangle \int_{-\pi}^{\pi} f(x)g(x)dx$
c. $\mathbf{v} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$ in $\mathbb{R}^2$ where $\langle \mathbf{v}, \quad \mathbf{w} \rangle = \mathbf{v}^T \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \mathbf{w}$
d. $\mathbf{v} = \begin{bmatrix} 3 \\ -1 \end{bmatrix}$ in $\mathbb{R}^2, \langle \mathbf{v}, \mathbf{w} \rangle = \mathbf{v}^T \begin{bmatrix} 1 & -1 \\ -1 & 2 \end{bmatrix} \mathbf{w}$

Answer available at the end of this section.

Exercise 7.1E.4

In each case, find the distance between $\mathbf{u}$ and $\mathbf{v}$.

a. $\mathbf{u} = (3, -1, 2, 0), \mathbf{v} = (1, 1, 1, 3); \langle \mathbf{u}, \mathbf{v} \rangle = \mathbf{u} \cdot \mathbf{v}$
b. $\mathbf{u} = (1, 2, -1, 2), \mathbf{v} = (2, 1, -1, 3); \langle \mathbf{u}, \mathbf{v} \rangle = \mathbf{u}.\ \mathbf{v}$
c. $\mathbf{u} = f, \mathbf{v} = g$ in $\mathbf{C}[0,1]$ where $f(x) = x^2$ and $g(x) = 1 - x; \langle f, g \rangle = \int_0^1 f(x)g(x)dx$
d. $\mathbf{u} = f, \mathbf{v} = g$ in $\mathbf{C}[-\pi, \pi]$ where $f(x) = 1$ and $g(x) = \cos x; \langle f, g \rangle = \int_{-\pi}^{\pi} f(x)g(x)dx$

Answer available at the end of this section.

Exercise 7.1E.5

Let $a_1, a_2, \ldots, a_n$ be positive numbers. Given $\mathbf{v} = (v_1, v_2, \ldots, v_n)$ and $\mathbf{w} = (w_1, \ w_2, \ldots, w_n)$, define $\langle \mathbf{v}, \mathbf{w} \rangle = a_1 v_1 w_1 + \ldots + a_n v_n w_n$. Show that this is an inner product on $\mathbb{R}^n$.

Exercise 7.1E.6

If $\{\mathbf{b}_1, \ldots, \mathbf{b}_n\}$ is a basis of V and if $\mathbf{v} = v_1\mathbf{b}_1 + \cdots + v_n\mathbf{b}_n$ and $\mathbf{w} = w_1\mathbf{b}_1 + \cdots + w_n\mathbf{b}_n$ are vectors in V, define

$$\langle \mathbf{v}, \mathbf{w} \rangle = v_1w_1 + \cdots + v_nw_n.$$

Show that this is an inner product on V.

Exercise 7.1E.7

If $p = p(x)$ and $q = q(x)$ are polynomials in $\mathbf{P}_n$, define

$$\langle p, q \rangle = p(0)q(0) + p(1)q(1) + \cdots + p(n)q(n)$$

Show that this is an inner product on $\mathbf{P}_n$. [Hint for P5: Theorem 6.5.4 or Appendix D.]

Exercise 7.1E.8

Let $\mathbf{D}_n$ denote the space of all functions from the set $\{1, 2, 3, \ldots, n\}$ to $\mathbb{R}$ with pointwise addition and scalar multiplication (see Exercise 35 Section 6.3). Show that $\langle , \rangle$ is an inner product on $\mathbf{D}_n$ if $\langle f, g \rangle = f(1)g(1) + f(2)g(2) + \ldots + f(n)g(n)$.

Answer available at the end of this section.

Exercise 7.1E.9

Let re (z) denote the real part of the complex number z. Show that $\langle , \rangle$ is an inner product on $\mathbb{C}$ if $\langle z, w \rangle = re(z\bar{w})$.

Exercise 7.1E.10

If $T : V \to V$ is an isomorphism of the inner product space V, show that

$$\langle \mathbf{v}, \mathbf{w} \rangle_1 = \langle T(\mathbf{v}), T(\mathbf{w}) \rangle$$

defines a new inner product $\langle , \rangle_1$ on V.

Exercise 7.1E.11

Show that every inner product $\langle , \rangle$ on $\mathbb{R}^n$ has the form $\langle \mathbf{x}, \mathbf{y} \rangle = (U\mathbf{x}) \cdot (U\mathbf{y})$ for some upper triangular matrix U with positive diagonal entries. [Hint: Theorem 8.3.3.]

Exercise 7.1E.12

In each case, show that $\langle \mathbf{v}, \mathbf{w} \rangle = \mathbf{v}^T A\mathbf{w}$ defines an inner product on $\mathbb{R}^2$ and hence show that A is positive definite.

a. $A = \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix}$

b. $A = \begin{bmatrix} 5 & -3 \\ -3 & 2 \end{bmatrix}$

c. $A = \begin{bmatrix} 3 & 2 \\ 2 & 3 \end{bmatrix}$

d. $A = \begin{bmatrix} 3 & 4 \\ 4 & 6 \end{bmatrix}$

Answer available at the end of this section.

Exercise 7.1E.13

In each case, find a symmetric matrix A such that $\langle \mathbf{v}, \mathbf{w} \rangle = \mathbf{v}^T A \mathbf{w}$.

a. $\left\langle \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}, \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \right\rangle = v_1 w_1 + 2v_1 w_2 +$

b. $\left\langle \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}, \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \right\rangle = v_1 w_1 - v_1 w_2 - v_2 w_1 +$

c. $\left\langle \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix}, \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} \right\rangle = 2v_1 w_1 + v_2 w_2 +$

Answer available at the end of this section.

Exercise 7.1E.14

If A is symmetric and $\mathbf{x}^T A \mathbf{x} = 0$ for all columns $\mathbf{x}$ in $\mathbb{R}^n$, show that $A = 0$. [Hint: Consider $\langle \mathbf{x} + \mathbf{y}, \mathbf{x} + \mathbf{y} \rangle$ where $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^T A \mathbf{y}$.]

Answer available at the end of this section.

Exercise 7.1E.15

Show that the sum of two inner products on V is again an inner product.

Exercise 7.1E.16

Let $\|\mathbf{u}\| = 1, \|\mathbf{v}\| = 2, \|\mathbf{w}\| = \sqrt{3}$, $\langle \mathbf{u}, \mathbf{v} \rangle = -1, \langle \mathbf{u}, \mathbf{w} \rangle = 0$ and $\langle \mathbf{v}, \mathbf{w} \rangle = 3$. Compute:

a. $\langle \mathbf{v} + \mathbf{w}, 2\mathbf{u} - \mathbf{v} \rangle$
b. $\langle \mathbf{u} - 2\mathbf{v} - \mathbf{w}, 3\mathbf{w} - \mathbf{v} \rangle$

Answer available at the end of this section.

Exercise 7.1E.17

Given the data in Exercise 16, show that $\mathbf{u} + \mathbf{v} = \mathbf{w}$.

Exercise 7.1E.18

Show that no vectors exist such that $\|\mathbf{u}\| = 1, \|\mathbf{v}\| = 2$, and $\langle \mathbf{u}, \mathbf{v} \rangle = -3$.

Exercise $7.1E.19$

Complete Example 10.1.2.

Answer available at the end of this section.

Exercise $7.1E.20$

Prove Theorem 10.1.1.

Answer available at the end of this section.

Exercise $7.1E.21$

Prove Theorem 10.1.6.

Exercise $7.1E.22$

Let $\mathbf{u}$ and $\mathbf{v}$ be vectors in an inner product space V.

a. Expand $\langle 2\mathbf{u}-7\mathbf{v}, 3\mathbf{u}+5\mathbf{v}\rangle$.
b. Expand $\langle 3\mathbf{u}-4\mathbf{v}, 5\mathbf{u}+\mathbf{v}\rangle$.
c. Show that $\|\mathbf{u}+\mathbf{v}\|^2 = \|\mathbf{u}\|^2 + 2\langle \mathbf{u}, \mathbf{v}\rangle + \|\mathbf{v}\|^2$.
d. Show that $\|\mathbf{u}-\mathbf{v}\|^2 = \|\mathbf{u}\|^2 - 2\langle \mathbf{u}, \mathbf{v}\rangle + \|\mathbf{v}\|^2$.

Answer available at the end of this section.

Exercise $7.1E.23$

Show that $\|\mathbf{v}\|^2 + \|\mathbf{w}\|^2 = \frac{1}{2}\left\{\|\mathbf{v}+\mathbf{w}\|^2 + \|\mathbf{v}-\mathbf{w}\|^2\right\}$ for any $\mathbf{v}$ and $\mathbf{w}$ in an inner product space.

Exercise $7.1E.24$

Let $\langle , \rangle$ be an inner product on a vector space V. Show that the corresponding distance function is translation invariant. That is, show that $\mathrm{d}(\mathbf{v}, \mathbf{w}) = \mathrm{d}(\mathbf{v}+\mathbf{u}, \mathbf{w}+\mathbf{u})$ for all $\mathbf{v}, \mathbf{w}$, and $\mathbf{u}$ in V.

Answer available at the end of this section.

Exercise $7.1E.25$

a. Show that $\langle \mathbf{u}, \mathbf{v}\rangle = \frac{1}{4}\left[\|\mathbf{u}+\mathbf{v}\|^2 = \|\mathbf{u}-\mathbf{v}\|^2\right]$ for all $\mathbf{u}, \mathbf{v}$ in an inner product space V.
b. If $\langle , \rangle and \langle , \rangle'$ are two inner products on V that have equal associated norm functions, show that $\langle \mathbf{u}, \mathbf{v}\rangle = \langle \mathbf{u}, \mathbf{v}\rangle'$ holds for all $\mathbf{u}$ and v.

Exercise $7.1E.26$

Let $\mathbf{v}$ denote a vector in an inner product space V.

a. Show that $W = \{\mathbf{w} \mid \mathbf{w} \text{ in } V, \langle \mathbf{v}, \mathbf{w} \rangle = 0\}$ is a subspace of V.
b. If $V = \mathbb{R}^3$ with the dot product, and if $\mathbf{v} = (1, -1, 2)$, find a basis for W(W as in (a)).

Answer available at the end of this section.

Exercise 7.1E.27

Given vectors $\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_n$ and $\mathbf{v}$, assume that $\langle \mathbf{v}, \mathbf{w}_i \rangle = 0$ for each i. Show that $\langle \mathbf{v}, \mathbf{w} \rangle = 0$ for all $\mathbf{w}$ in $\text{span}\{\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_n\}$.

Exercise 7.1E.28

If $V = \text{span}\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$ and $\langle \mathbf{v}, \mathbf{v}_i \rangle = \langle \mathbf{w}, \mathbf{v}_i \rangle$ holds for each i. Show that $\mathbf{v} = \mathbf{w}$.

Answer available at the end of this section.

Exercise 7.1E.29

Use the Cauchy-Schwarz inequality in an inner product space to show that:

a. If $\|\mathbf{u}\| \leq 1$, then $\langle \mathbf{u}, \mathbf{v} \rangle^2 \leq \|\mathbf{v}\|^2$ for all $\mathbf{v}$ in V.
b. $(x \cos\theta + y \sin\theta)^2 \leq x^2 + y^2$ for all real x, y, and θ.
c. $\|r_1\mathbf{v}_1 + \cdots + r_n\mathbf{v}_n\|^2 \leq [r_1 \|\mathbf{v}_1\| + \cdots + r_n \|\mathbf{v}_n\|]^2$ for all vectors $\mathbf{v}_i$, and all $r_i > 0$ in $\mathbb{R}$.

Answer available at the end of this section.

Exercise 7.1E.30

If A is a $2 \times n$ matrix, let $\mathbf{u}$ and $\mathbf{v}$ denote the rows of A.

a. Show that $AA^T = \begin{bmatrix} \|\mathbf{u}\|^2 & \mathbf{u} \cdot \mathbf{v} \\ \mathbf{u} \cdot \mathbf{v} & \|\mathbf{v}\|^2 \end{bmatrix}$.
b. Show that $\det(AA^T) \geq 0$.

Exercise 7.1E.31

a. If $\mathbf{v}$ and $\mathbf{w}$ are nonzero vectors in an inner product space V, show that $-1 \leq \frac{\langle \mathbf{v}, \mathbf{w} \rangle}{\|\mathbf{v}\|\|\mathbf{w}\|} \leq 1$, and hence that a unique angle θ exists such that $\frac{\langle \mathbf{v}, \mathbf{w} \rangle}{\|\mathbf{v}\|\|\mathbf{w}\|} = \cos\theta$ and $0 \leq \theta \leq \pi$. This angle θ is called the angle between $\mathbf{v}$ and $\mathbf{w}$.
b. Find the angle between $\mathbf{v} = (1, 2, -1, 1, 3)$ and $\mathbf{w} = (2, 1, 0, 2, 0)$ in $\mathbb{R}^5$ with the dot product.
c. If θ is the angle between $\mathbf{v}$ and $\mathbf{w}$, show that the law of cosines is valid:

$$\|\mathbf{v} - \mathbf{w}\| = \|\mathbf{v}\|^2 + \|\mathbf{w}\|^2 - 2\|\mathbf{v}\|\|\mathbf{w}\| \cos\theta.$$

Exercise 7.1E.32

If $V = \mathbb{R}^2$, define $\|(x, y)\| = |x| + |y|$.

a. Show that $\|\cdot\|$ satisfies the conditions in Theorem 10.1.5.
b. Show that $\|\cdot\|$ does not arise from an inner product on $\mathbb{R}^2$ given by a matrix A. [Hint: If it did, use Theorem 10.1.2 to find numbers a, b, and c such that $\|(x, y)\|^2 = ax^2 + bxy + cy^2$ for all x and y.]

Answers

Exercise $7.1E.1$

b. Pf fails
d. P5 fails
f. P5 fails

Exercise $7.1E.2$

Axioms P1–P5 hold in U because they hold in V.

Exercise $7.1E.3$

b. $\frac{1}{\sqrt{\pi}}f$
d. $\frac{1}{\sqrt{17}}\begin{bmatrix} 3 \\ -1 \end{bmatrix}$

Exercise $7.1E.4$

b. $\$\sqrt{3}$
d. $\$\sqrt{3\pi}$

Exercise $7.1E.8$

P1 and P2 are clear since $f(i)$ and $g(i)$ are real numbers.

$$\text{P3:}\quad \begin{aligned} \langle f+g,h\rangle &= \sum_i (f+g)(i)\cdot h(i) \\ &= \sum_i (f(i)+g(i))\cdot h(i) \\ &= \sum_i [f(i)h(i)+g(i)h(i)] \\ &= \sum_i f(i)h(i)+\sum_i g(i)h(i) \\ &= \langle f,h\rangle + \langle g,h\rangle. \end{aligned} \tag{7.1E.1}$$

$$\text{P4:}\quad \begin{aligned} \langle rf,g\rangle &= \sum_i (rf)(i)\cdot g(i) \\ &= \sum_i rf(i)\cdot g(i) \\ &= r\sum_i f(i)\cdot g(i) \\ &= r\langle f,g\rangle \end{aligned} \tag{7.1E.2}$$

P5: If $f\neq 0$, then $\langle f,f\rangle = \sum_i f(i)^2 > 0$ because some $f(i)\neq 0$.

Exercise $7.1E.12$

b. $\langle \mathbf{v},\quad \mathbf{v}\rangle = 5v_1^2 - 6v_1v_2 + 2v_2^2 = \frac{1}{5}\left[(5v_1-3v_2)^2+v_2^2\right]$
d. $\langle \mathbf{v},\mathbf{v}\rangle = 3v_1^2+8v_1v_2+6v_2^2 = \frac{1}{3}\left[(3v_1+4v_2)^2+\ 2v_2^2\right]$

Exercise $7.1E.13$

b.
$$\begin{bmatrix} 1 & -2 \\ -2 & 1 \end{bmatrix} \tag{7.1E.3}$$

c.
$$\begin{bmatrix} 1 & 0 & -2 \\ 0 & 2 & 0 \\ -2 & 0 & 5 \end{bmatrix} \tag{7.1E.4}$$

Exercise $7.1E.14$

By the condition, $\langle \mathbf{x},\mathbf{y}\rangle = \frac{1}{2}\langle \mathbf{x}+\mathbf{y},\mathbf{x}+\mathbf{y}\rangle = 0$ for all $\mathbf{x},\mathbf{y}$. Let $\mathbf{e}_i$ denote column i of I. If $A=[a_{ij}]$, then $a_{ij}=\mathbf{e}_i^TA\mathbf{e}_j = \{\mathbf{e}_i,\mathbf{e}_j\} = 0$ for all i and j.

Exercise $7.1E.16$

b. -15

Exercise $7.1E.19$

Exercise $7.1E.20$

1. Using P2: $\langle \mathbf{u},\mathbf{v}+\mathbf{w}\rangle = \langle \mathbf{v}+\mathbf{w},\mathbf{u}\rangle = \langle \mathbf{v},\mathbf{u}\rangle + \langle \mathbf{w},\mathbf{u}\rangle = \langle \mathbf{u},\mathbf{v}\rangle + \langle \mathbf{u},\mathbf{w}\rangle$.
2. Using P2 and P4: $\langle \mathbf{v},r\mathbf{w}\rangle = \langle r\mathbf{w},\mathbf{v}\rangle = r\langle \mathbf{w},\mathbf{v}\rangle = r\langle \mathbf{v},\mathbf{w}\rangle$.
3. Using P3: $\langle \mathbf{0},\mathbf{v}\rangle = \langle \mathbf{0}+\mathbf{0},\mathbf{v}\rangle = \langle \mathbf{0},\mathbf{v}\rangle + \langle \mathbf{0},\mathbf{v}\rangle$, so $\langle \mathbf{0},\mathbf{v}\rangle = 0$. The rest is P2.
4. Assume that $\langle \mathbf{v},\mathbf{v}\rangle = 0$. If $\mathbf{v}\neq \mathbf{0}$ this contradicts P5, so $\mathbf{v}=\mathbf{0}$. Conversely, if $\mathbf{v}=\mathbf{0}$, then $\langle \mathbf{v},\mathbf{v}\rangle = 0$ by Part 3 of this theorem.

Exercise $7.1E.22$

b. $15\|\mathbf{u}\|^2 - 17\langle \mathbf{u},\mathbf{v}\rangle - 4\|\mathbf{v}\|^2$
d. $\|\mathbf{u}+\mathbf{v}\|^2 = \langle \mathbf{u}+\mathbf{v},\mathbf{u}+\mathbf{v}\rangle = \|\mathbf{u}\|^2 + 2\langle \mathbf{u},\mathbf{v}\rangle + \|\mathbf{v}\|^2$

Exercise $7.1E.24$

Exercise $7.1E.26$

b. $\{(1,1,0),(0,2,1)\}$

Exercise $7.1E.28$

$\langle \mathbf{v}-\mathbf{w},\mathbf{v}_i\rangle = \langle \mathbf{v},\mathbf{v}_i\rangle - \langle \mathbf{w},\mathbf{v}_i\rangle = 0\$ foreach \$i\$, so \$\mathbf{v}=\mathbf{w}$ by Exercise 27.

Exercise $7.1E.29$

b. If $\mathbf{u} = (\cos\theta, \sin\theta)$ in $\mathbb{R}^2$ (with the dot product) then $\|\mathbf{u}\| = 1$. Use (a) with $\mathbf{v} = (x, y)$.

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7.2: ORTHOGONAL SETS OF VECTORS

The idea that two lines can be perpendicular is fundamental in geometry, and this section is devoted to introducing this notion into a general inner product space V. To motivate the definition, recall that two nonzero geometric vectors $\mathbf{x}$ and $\mathbf{y}$ in $\mathbb{R}^n$ are perpendicular (or orthogonal) if and only if $\mathbf{x} \cdot \mathbf{y} = 0$. In general, two vectors $\mathbf{v}$ and $\mathbf{w}$ in an inner product space V are said to be orthogonal if

$$\langle \mathbf{v}, \mathbf{w} \rangle = 0$$

A set $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_n\}$ of vectors is called an orthogonal set of vectors if

1. $\text{Each } \mathbf{f}_i \neq \mathbf{0}$.
2. $\langle \mathbf{f}_i, \mathbf{f}_j \rangle = 0$ for all $i \neq j$.

If, in addition, $\|\mathbf{f}_i\| = 1$ for each i, the set $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_n\}$ is called an orthonormal set.

Example 7.2.1

$\{\sin x, \cos x\}$ is orthogonal in $\mathbf{C}[-\pi, \pi]$ because

$$\int_{-\pi}^{\pi} \sin x \cos x dx = \left[-\frac{1}{4}\cos 2x\right]_{-\pi}^{\pi} = 0$$

The first result about orthogonal sets extends Pythagoras' theorem in $\mathbb{R}^n$ (Theorem 5.3.4) and the same proof works.

Theorem 7.2.1

If $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_n\}$ is an orthogonal set of vectors, then

$$\|\boldsymbol{f}_1 + \boldsymbol{f}_2 + \cdots + \boldsymbol{f}_n\|^2 = \|\boldsymbol{f}_1\|^2 + \|\boldsymbol{f}_2\|^2 + \cdots + \|\boldsymbol{f}_n\|^2$$

The proof of the next result is left to the reader.

Theorem 7.2.2

Let $\{\boldsymbol{f}_1, \boldsymbol{f}_2, \dots, \boldsymbol{f}_n\}$ be an orthogonal set of vectors.

1. $\{r_1\boldsymbol{f}_1, r_2\boldsymbol{f}_2, \dots, r_n\boldsymbol{f}_n\}$ is also orthogonal for any $r_i \neq 0$ in $\mathbb{R}$.
2. $\left\{\frac{1}{\|\mathbf{f}_1\|}\boldsymbol{f}_1, \frac{1}{\|\boldsymbol{f}_2\|}\mathbf{f}_2, \dots, \frac{1}{\|\boldsymbol{f}_n\|}\mathbf{f}_n\right\}$ is an orthonormal set.

As before, the process of passing from an orthogonal set to an orthonormal one is called normalizing the orthogonal set. The proof of Theorem 5.3.5 goes through to give

Theorem 7.2.3

Every orthogonal set of vectors is linearly independent.

Example 7.2.2

Show that $\left\{\begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 2 \end{bmatrix}\right\}$ is an orthogonal basis of $\mathbb{R}^3$ with inner product

$$\langle \mathbf{v}, \mathbf{w} \rangle = \mathbf{v}^T A \mathbf{w}, \text{ where } A = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Solution

We have

$$\left\langle \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \right\rangle = \begin{bmatrix} 2 & -1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 \\ 1 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} = 0$$

and the reader can verify that the other pairs are orthogonal too. Hence the set is orthogonal, so it is linearly independent by Theorem 10.2 .3 . Because $\dim \mathbb{R}^3 = 3$, it is a basis.

The proof of Theorem 5.3.6 generalizes to give the following:

Theorem 7.2.4 Expansion Theorem

Let $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_n\}$ be an orthogonal basis of an inner product space V. If $\mathbf{v}$ is any vector in V, then

$$\mathbf{v} = \frac{\langle \mathbf{v}, \mathbf{f}_1 \rangle}{\|\mathbf{f}_1\|^2}\mathbf{f}_1 + \frac{\langle \mathbf{v}, \mathbf{f}_2 \rangle}{\|\mathbf{f}_2\|^2}\mathbf{f}_2 + \cdots + \frac{\langle \mathbf{v}, \mathbf{f}_n \rangle}{\|\mathbf{f}_n\|^2}\mathbf{f}_n$$

is the expansion of $\mathbf{v}$ as a linear combination of the basis vectors.

The coefficients $\frac{\langle \mathbf{v}, \mathbf{f}_1 \rangle}{\|\mathbf{f}_1\|^2}, \frac{\langle \mathbf{v}, \mathbf{f}_2 \rangle}{\|\mathbf{f}_2\|^2}, \dots, \frac{\langle \mathbf{v}, \mathbf{f}_n \rangle}{\|\mathbf{f}_n\|^2}$ in the expansion theorem are sometimes called the Fourier coefficients of $\mathbf{v}$ with respect to the orthogonal basis $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_n\}$. This is in honor of the French mathematician J.B.J. Fourier (1768-1830). His original work was with a particular orthogonal set in the space $\mathbf{C}[a, b]$, about which there will be more to say in Section 10.5.

Example 7.2.3

If $a_0, a_1, \dots, a_n$ are distinct numbers and $p(x)$ and $q(x)$ are in $\mathbf{P}_n$, define

$$\langle p(x), q(x) \rangle = p(a_0)\, q(a_0) + p(a_1)\, q(a_1) + \cdots + p(a_n)\, q(a_n)$$

This is an inner product on $\mathbf{P}_n$. (Axioms P1-P4 are routinely verified, and P5 holds because 0 is the only polynomial of degree n with $n + 1$ distinct roots. See Theorem 6.5.4 or Appendix D.) Recall that the Lagrange polynomials $\delta_0(x), \delta_1(x), \dots, \delta_n(x)$ relative to the numbers $a_0, a_1, \dots, a_n$ are defined as follows (see Section 6.5):

$$\delta_k(x) = \frac{\prod_{i \neq k}(x - a_i)}{\prod_{i \neq k}(a_k - a_i)} \quad k = 0, 1, 2, \dots, n$$

where $\prod_{i \neq k}(x - a_i)$ means the product of all the terms

$$(x - a_0), (x - a_1), (x - a_2), \dots, (x - a_n)$$

except that the k th term is omitted. Then $\{\delta_0(x), \delta_1(x), \ldots, \delta_n(x)\}$ is orthonormal with respect to $\langle , \rangle because \delta_k(a_i) = 0$ if $i \neq k$ and $\delta_k(a_k) = 1$. These facts also show that $\langle p(x), \delta_k(x) \rangle = p(a_k)$ so the expansion theorem gives

$$p(x) = p(a_0)\,\delta_0(x) + p(a_1)\,\delta_1(x) + \cdots + p(a_n)\,\delta_n(x)$$

for each $p(x)$ in $\mathbf{P}_n$. This is the Lagrange interpolation expansion of $p(x)$, Theorem 6.5.3, which is important in numerical integration.

Lemma 7.2.1 Orthogonal Lemma

Let $\{f_1, f_2, \ldots, f_m\}$ be an orthogonal set of vectors in an inner product space V, and let $\mathbf{v}$ be any vector not in $\operatorname{span}\{f_1, f_2, \ldots, f_m\}$. Define

$$f_{m+1} = \mathbf{v} - \frac{\langle \mathbf{v}, f_1 \rangle}{\|f_1\|^2}\mathbf{f}_1 - \frac{\langle \mathbf{v}, f_2 \rangle}{\|f_2\|^2}\mathbf{f}_2 - \cdots - \frac{\langle \mathbf{v}, f_m \rangle}{\|f_m\|^2}\mathbf{f}_m$$

Then $\{f_1, \mathbf{f}_2, \ldots, \mathbf{f}_m, f_{m+1}\}$ is an orthogonal set of vectors.

The proof of this result (and the next) is the same as for the dot product in $\mathbb{R}^n$ (Lemma 8.1.1 and Theorem 8.1.2).

Theorem 7.2.5 Gram-Schmidt Orthogonalization Algorithm

Let V be an inner product space and let $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$ be any basis of V. Define vectors $\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_n$ in V successively as follows:

$$\begin{aligned}
f_1 &= \mathbf{v}_1 \\
f_2 &= \mathbf{v}_2 - \frac{\langle \mathbf{v}_2, \mathbf{f}_1 \rangle}{\|f_1\|^2}\mathbf{f}_1 \\
f_3 &= \mathbf{v}_3 - \frac{\langle \mathbf{v}_3, \mathbf{f}_1 \rangle}{\|\mathbf{f}_1\|^2}\mathbf{f}_1 - \frac{\langle \mathbf{v}_3, f_2 \rangle}{\|f_2\|^2}\mathbf{f}_2 \\
f_k &= \mathbf{v}_k - \frac{\langle \mathbf{v}_k, f_1 \rangle}{\|f_1\|^2}\mathbf{f}_1 - \frac{\langle \mathbf{v}_k, f_2 \rangle}{\|f_2\|^2}\mathbf{f}_2 - \cdots - \frac{\langle \mathbf{v}_k, f_{k-1} \rangle}{\|f_{k-1}\|^2}\mathbf{f}_{k-1}
\end{aligned}$$

for each $k = 2, 3, \ldots, n$. Then

1. $\{f_1, \mathbf{f}_2, \ldots, \mathbf{f}_n\}$ is an orthogonal basis of V.
2. $\operatorname{span}\{f_1, f_2, \ldots, f_k\} = \operatorname{span}\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$ holds for each $k = 1, 2, \ldots, n$.

The purpose of the Gram-Schmidt algorithm is to convert a basis of an inner product space into an orthogonal basis. In particular, it shows that every finite dimensional inner product space has an orthogonal basis.

Example 7.2.4

Consider $V = \mathbf{P}_3$ with the inner product $\langle p, q \rangle = \int_{-1}^{1} p(x)q(x)dx$. If the Gram-Schmidt algorithm is applied to the basis $\{1, x, x^2, x^3\}$, show that the result is the orthogonal basis

$$\left\{1, x, \frac{1}{3}\left(3x^2 - 1\right), \frac{1}{5}\left(5x^3 - 3x\right)\right\}$$

Solution

Take $\mathbf{f}_1 = 1$. Then the algorithm gives

$$\mathbf{f}_2 = x - \frac{\langle x, \mathbf{f}_1 \rangle}{\|\mathbf{f}_1\|^2}\mathbf{f}_1 = x - \frac{0}{2}\mathbf{f}_1 = x$$
$$\mathbf{f}_3 = x^2 - \frac{\langle x^2, \mathbf{f}_1 \rangle}{\|\mathbf{f}_1\|^2}\mathbf{f}_1 - \frac{\langle x^2, \mathbf{f}_2 \rangle}{\|\mathbf{f}_2\|^2}\mathbf{f}_2$$
$$= x^2 - \frac{\frac{2}{3}}{2}1 - \frac{0}{\frac{2}{3}}x$$
$$= \frac{1}{3}\left(3x^2 - 1\right)$$

The verification that $\mathbf{f}_4 = \frac{1}{5}\left(5x^3 - 3x\right)$ is omitted.

The polynomials in Example 7.2.4 are such that the leading coefficient is 1 in each case. In other contexts (the study of differential equations, for example) it is customary to take multiples $p(x)$ of these polynomials such that $p(1) = 1$. The resulting orthogonal basis of $\mathbf{P}_3$ is

$$\left\{1, x, \frac{1}{3}\left(3x^2 - 1\right), \frac{1}{5}\left(5x^3 - 3x\right)\right\}$$

and these are the first four Legendre polynomials, so called to honor the French mathematician A. M. Legendre (1752-1833). They are important in the study of differential equations.

If V is an inner product space of dimension n, let $E = \{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_n\}$ be an orthonormal basis of V (by Theorem 10.2.5). If $\mathbf{v} = v_1\mathbf{f}_1 + v_2\mathbf{f}_2 + \cdots + v_n\mathbf{f}_n$ and $\mathbf{w} = w_1\mathbf{f}_1 + w_2\mathbf{f}_2 + \cdots + w_n\mathbf{f}_n$ are two vectors in V, we have $C_E(\mathbf{v}) = \begin{bmatrix} v_1 & v_2 & \cdots & v_n \end{bmatrix}^T$ and $C_E(\mathbf{w}) = \begin{bmatrix} w_1 & w_2 & \cdots & w_n \end{bmatrix}^T$. Hence

$$\langle \mathbf{v}, \mathbf{w} \rangle = \left\langle \sum_i v_i\mathbf{f}_i, \sum_j w_j\mathbf{f}_j \right\rangle = \sum_{i,j} v_i w_j \langle \mathbf{f}_i, \mathbf{f}_j \rangle = \sum_i v_i w_i = C_E(\mathbf{v}) \cdot C_E(\mathbf{w})$$

This shows that the coordinate isomorphism $C_E : V \to \mathbb{R}^n$ preserves inner products, and so proves

Corollary 7.2.1

If V is any n-dimensional inner product space, then V is isomorphic to $\mathbb{R}^n$ as inner product spaces. More precisely, if E is any orthonormal basis of V, the coordinate isomorphism

$$C_E : V \to \mathbb{R}^n \text{ satisfies } \langle \mathbf{v}, \mathbf{w} \rangle = C_E(\mathbf{v}) \cdot C_E(\mathbf{w})$$

for all $\mathbf{v}$ and $\boldsymbol{w}$ in V.

The orthogonal complement of a subspace U of $\mathbb{R}^n$ was defined (in Chapter 8) to be the set of all vectors in $\mathbb{R}^n$ that are orthogonal to every vector in U. This notion has a natural extension in an arbitrary inner product space. Let U be a subspace of an inner product space V. As in $\mathbb{R}^n$, the orthogonal complement $U^\perp$ of U in V is defined by

$$U^\perp = \{\mathbf{v} \mid \mathbf{v} \in V, \langle \mathbf{v}, \mathbf{u} \rangle = 0 \text{ for all } \mathbf{u} \in U\}$$

Theorem 7.2.6

Let U be a finite dimensional subspace of an inner product space V.

1. $U^\perp$ is a subspace of V and $V = U \oplus U^\perp$.
2. If $\dim V = n$, then $\dim U + \dim U^\perp = n$.
3. If $\dim V = n$, then $U^{\perp\perp} = U$.

Proof

1. $U^{\perp}$ is a subspace by Theorem 10.1.1. If $\mathbf{v}$ is in $U \cap U^{\perp}$, then $\langle \mathbf{v}, \mathbf{v} \rangle = 0$, so $\mathbf{v} = \mathbf{0}$ again by Theorem 10.1.1. Hence $U \cap U^{\perp} = \{\mathbf{0}\}$, and it remains to show that $U + U^{\perp} = V$. Given $\mathbf{v}$ in V, we must show that $\mathbf{v}$ is in $U + U^{\perp}$, and this is clear if $\mathbf{v}$ is in U. If $\mathbf{v}$ is not in U, let $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_m\}$ be an orthogonal basis of U. Then the orthogonal lemma shows that $\mathbf{v} - \left(\frac{\langle \mathbf{v}, \mathbf{f}_1 \rangle}{\|\mathbf{f}_1\|^2} \mathbf{f}_1 + \frac{\langle \mathbf{v}, \mathbf{f}_2 \rangle}{\|\mathbf{f}_2\|^2} \mathbf{f}_2 + \cdots + \frac{\langle \mathbf{v}, \mathbf{f}_m \rangle}{\|\mathbf{f}_m\|^2} \mathbf{f}_m \right)$ is in $U^{\perp}$, so $\mathbf{v}$ is in $U + U^{\perp}$ as required.
2. This follows from Theorem 9.3.6.
3. We have $\dim U^{\perp\perp} = n - \dim U^{\perp} = n - (n - \dim U) = \dim U$, using (2) twice. As $U \subseteq U^{\perp\perp}$ always holds (verify), (3) follows by Theorem 6.4.2.

We digress briefly and consider a subspace U of an arbitrary vector space V. As in Section 9.3, if W is any complement of U in V, that is, $V = U \oplus W$, then each vector $\mathbf{v}$ in V has a unique representation as a $\operatorname{sum} \mathbf{v} = \mathbf{u} + \mathbf{w}$ where $\mathbf{u}$ is in U and $\mathbf{w}$ is in W. Hence we may define a function $T : V \to V$ as follows:

$$T(\mathbf{v}) = \mathbf{u} \quad \text{where } \mathbf{v} = \mathbf{u} + \mathbf{w}, \mathbf{u} \text{ in } U, \mathbf{w} \text{ in } W$$

Thus, to compute $T(\mathbf{v})$, express $\mathbf{v}$ in any way at all as the sum of a vector $\mathbf{u}$ in U and a vector in W; then $T(\mathbf{v}) = \mathbf{u}$.

This function T is a linear operator on V. Indeed, if $\mathbf{v}_1 = \mathbf{u}_1 + \mathbf{w}_1$ where $\mathbf{u}_1$ is in U and $\mathbf{w}_1$ is in W, then $\mathbf{v} + \mathbf{v}_1 = (\mathbf{u} + \mathbf{u}_1) + (\mathbf{w} + \mathbf{w}_1)$ where $\mathbf{u} + \mathbf{u}_1$ is in U and $\mathbf{w} + \mathbf{w}_1$ is in W, so

$$T(\mathbf{v} + \mathbf{v}_1) = \mathbf{u} + \mathbf{u}_1 = T(\mathbf{v}) + T(\mathbf{v}_1)$$

Similarly, $T(a\mathbf{v}) = aT(\mathbf{v})$ for all a in $\mathbb{R}$, so T is a linear operator. Furthermore, $\operatorname{im} T = U$ and $\ker T = W$ as the reader can verify, and T is called the projection on U with kernel W.

If U is a subspace of V, there are many projections on U, one for each complementary subspace W with $V = U \oplus W$. If V is an inner product space, we single out one for special attention. Let U be a finite dimensional subspace of an inner product space V.

Definition: Orthogonal Projection on a Subspace

The projection on U with kernel $U^{\perp}$ is called the orthogonal projection on U (or simply the projection on U) and is denoted $\operatorname{proj}_U : V \to V$.

Theorem 7.2.7

Let U be a finite dimensional subspace of an inner product space V and let $\mathbf{v}$ be a vector in V.

1. $\operatorname{proj}_U : V \to V$ is a linear operator with image U and kernel $U^{\perp}$.
2. $\operatorname{proj}_U \mathbf{v}$ is in U and $\mathbf{v} - \operatorname{proj}_U \mathbf{v}$ is in $U^{\perp}$.
3. If $\{\boldsymbol{f}_1, \mathbf{f}_2, \dots, \boldsymbol{f}_m\}$ is any orthogonal basis of U, then

$$\operatorname{proj}_U \mathbf{v} = \frac{\langle \mathbf{v}, \boldsymbol{f}_1 \rangle}{\|\boldsymbol{f}_1\|^2} \boldsymbol{f}_1 + \frac{\langle \mathbf{v}, \boldsymbol{f}_2 \rangle}{\|\boldsymbol{f}_2\|^2} \mathbf{f}_2 + \cdots + \frac{\langle \mathbf{v}, \boldsymbol{f}_m \rangle}{\|\boldsymbol{f}_m\|^2} \mathbf{f}_m$$

Proof. Only (3) remains to be proved. But since $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_n\}$ is an orthogonal basis of U and since $\operatorname{proj}_U \mathbf{v}$ is in U, the result follows from the expansion theorem (Theorem 10.2.4) applied to the finite dimensional space U.

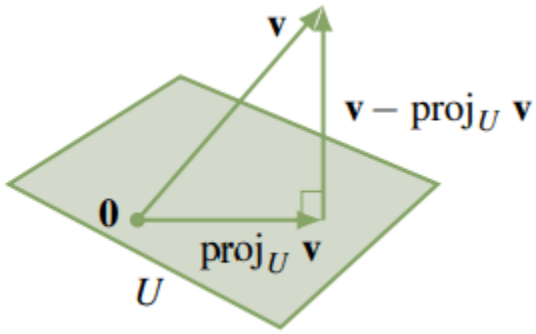
Note that there is no requirement in Theorem 10.2.7 that V is finite dimensional.

Example 7.2.5

Let U be a subspace of the finite dimensional inner product space V. Show that $\operatorname{proj}_U^{\perp} \mathbf{v} = \mathbf{v} - \operatorname{proj}_U \mathbf{v}$ for all $\mathbf{v} \in V$.

Solution

We have $V = U^{\perp} \oplus U^{\perp\perp}$ by Theorem 10.2.6. If we write $\mathbf{p} = \text{proj}_U \mathbf{v}$, then $\overline{\mathbf{v}} = (\mathbf{v} - \mathbf{p}) + \mathbf{p}$ where $\mathbf{v} - \mathbf{p}$ is in $U^{\perp}$ and $\mathbf{p}$ is in $U = U^{\perp\perp}$ by Theorem 10.2.7. Hence $\text{proj}_U^{\perp} \mathbf{v} = \mathbf{v} - \mathbf{p}$. See Exercise 8.1.7.



The vectors $\mathbf{v}, \text{proj}_U \mathbf{v}$, and $\mathbf{v} - \text{proj}_U \mathbf{v}$ in Theorem 7.2.7 can be visualized geometrically as in the diagram (where U is shaded and $\dim U = 2$). This suggests that $\text{proj}_U \mathbf{v}$ is the vector in U closest to $\mathbf{v}$. This is, in fact, the case.

Theorem 7.2.8

Let U be a finite dimensional subspace of an inner product space V. If $\mathbf{v}$ is any vector in V, then $\text{proj}_U \mathbf{v}$ is the vector in U that is closest to $\mathbf{v}$. Here closest means that

$$\|\mathbf{v} - \text{proj}_U \mathbf{v}\| < \|\mathbf{v} - \mathbf{u}\|$$

for all $\mathbf{u}$ in $U, \mathbf{u} \neq \text{proj}_U \mathbf{v}$.

Proof. Write $\mathbf{p} = \text{proj}_U \mathbf{v}$, and consider $\mathbf{v} - \mathbf{u} = (\mathbf{v} - \mathbf{p}) + (\mathbf{p} - \mathbf{u})$. Because $\mathbf{v} - \mathbf{p}$ is in $U^{\perp}$ and $\mathbf{p} - \mathbf{u}$ is in U, Pythagoras' theorem gives

$$\|\mathbf{v} - \mathbf{u}\|^2 = \|\mathbf{v} - \mathbf{p}\|^2 + \|\mathbf{p} - \mathbf{u}\|^2 > \|\mathbf{v} - \mathbf{p}\|^2$$

because $\mathbf{p} - \mathbf{u} \neq 0$. The result follows.

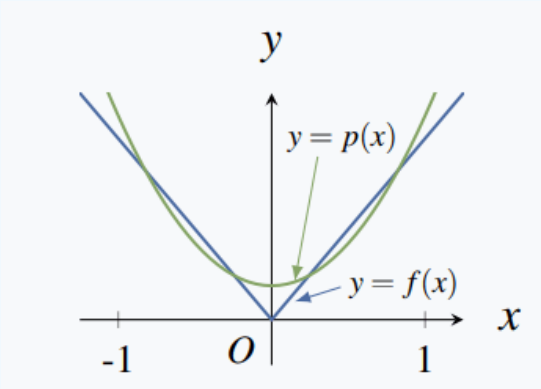
Example 7.2.6

Consider the space $\mathbf{C}[-1, 1]$ of real-valued continuous functions on the interval $[-1, 1]$ with inner product $\langle f, g \rangle = \int_{-1}^{1} f(x)g(x)dx$. Find the polynomial $p = p(x)$ of degree at most 2 that best approximates the absolute-value function f given by $f(x) = |x|$.

Solution

Here we want the vector p in the subspace $U = \mathbf{P}_2$ of $\mathbf{C}[-1, 1]$ that is closest to f. In Example 10.2.4 the Gram-Schmidt algorithm was applied to give an orthogonal basis $\{\mathbf{f}_1 = 1, \mathbf{f}_2 = x, \mathbf{f}_3 = 3x^2 - 1\}$ of $\mathbf{P}_2$ (where, for convenience, we have changed $\mathbf{f}_3$ by a numerical factor). Hence the required polynomial is

$$\begin{aligned} p &= \text{proj}_{\mathbf{P}_2} f \\ &= \frac{\langle f, \mathbf{f}_1 \rangle}{\|\mathbf{f}_1\|^2}\mathbf{f}_1 + \frac{\langle f, \mathbf{f}_2 \rangle}{\|\mathbf{f}_2\|^2}\mathbf{f}_2 + \frac{\langle f, \mathbf{f}_3 \rangle}{\|\mathbf{f}_3\|^2}\mathbf{f}_3 \\ &= \frac{1}{2}\mathbf{f}_1 + 0\mathbf{f}_2 + \frac{1/2}{8/5}\mathbf{f}_3 \\ &= \frac{3}{16}\left(5x^2 + 1\right) \end{aligned}$$



The graphs of $p(x)$ and $f(x)$ are given in the diagram.

If polynomials of degree at most n are allowed in Example 10.2.6, the polynomial in $\mathbf{P}_n$ is $\text{proj}_{\mathbf{P}_n} f$, and it is calculated in the same way. Because the subspaces $\mathbf{P}_n$ get larger as n increases, it turns out that the approximating polynomials $\text{proj}_{\mathbf{P}_n} f$ get closer and closer to f. In fact, solving many practical problems comes down to approximating some interesting vector $\mathbf{v}$ (often a function) in an infinite dimensional inner product space V by vectors in finite dimensional subspaces (which can be computed). If $U_1 \subseteq U_2$ are finite dimensional subspaces of V, then

$$\left\|\mathbf{v} - \text{proj}_{U_2}\mathbf{v}\right\| \leq \left\|\mathbf{v} - \text{proj}_{U_1}\mathbf{v}\right\|$$

by Theorem 10.2.8 (because $\text{proj}_{U_1}\mathbf{v}$ lies in U_1 and hence in U_2). Thus $\text{proj}_{U_2}\mathbf{v}$ is a better approximation to $\mathbf{v}$ than $\text{proj}_{U_1}\mathbf{v}$. Hence a general method in approximation theory might be described as follows: Given $\mathbf{v}$, use it to construct a sequence of finite dimensional subspaces

$$U_1 \subseteq U_2 \subseteq U_3 \subseteq \cdots$$

of V in such a way that $\left\|\mathbf{v} - \text{proj}_{U_k}\mathbf{v}\right\|$ approaches zero as k increases. Then $\text{proj}_{U_k}\mathbf{v}$ is a suitable approximation to $\mathbf{v}$ if k is large enough. For more information, the interested reader may wish to consult Interpolation and Approximation by Philip J. Davis (New York: Blaisdell, 1963).

7.2E: Orthogonal Sets of Vectors Exercises

Gram Schmidt Orthonormalization Process GeoGebra Demo by SKKU-Matrix-Lab

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7.2E: Orthogonal Sets of Vectors Exercises

Use the dot product in $\mathbb{R}^n$ unless otherwise instructed.

Exercise 7.2E.1

In each case, verify that B is an orthogonal basis of V with the given inner product and use the expansion theorem to express $\mathbf{v}$ as a linear combination of the basis vectors.

a. $\mathbf{v} = \begin{bmatrix} a \\ b \end{bmatrix}, B = \left\{ \begin{bmatrix} 1 \\ -1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right\}, V = \mathbb{R}^2$ $\langle \mathbf{v}, \mathbf{w} \rangle = \mathbf{v}^T A \mathbf{w}$ where $A = \begin{bmatrix} 2 & 2 \\ 2 & 5 \end{bmatrix}$

b. $\mathbf{v} = \begin{bmatrix} a \\ b \\ c \end{bmatrix}, B = \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -6 \\ 1 \end{bmatrix} \right\}, V = \mathbb{R}^3, \langle \mathbf{v}, \mathbf{w} \rangle = \mathbf{v}^T A \mathbf{w}$ where $A = \begin{bmatrix} 2 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 2 \end{bmatrix}$

c. $\mathbf{v} = a + bx + cx^2, B = \{1x, 2 - 3x^2\}, V = \mathbf{P}_2, \langle p, q \rangle = p(0)q(0) + p(1)q(1) + p(-1)q(-1)$

d. $\mathbf{v} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$ $B = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \right\}, V = \mathbf{M}_{22}, \langle X, Y \rangle = \text{tr}\left(XY^T\right)$

Answer available at the end of this section.

Exercise 7.2E.2

Let $\mathbb{R}^3$ have the inner product $\langle (x, y, z), (x', y', z') \rangle = 2xx' + yy' + 3zz'$. In each case, use the Gram-Schmidt algorithm to transform B into an orthogonal basis.

a. $B = \{(1, 1, 0), (1, 0, 1), (0, 1, 1)\}$
b. $B = \{(1, 1, 1), (1, -1, 1), (1, 1, 0)\}$

Answer available at the end of this section.

Exercise 7.2E.3

Let $\mathbf{M}_{22}$ have the inner product $\langle X, Y \rangle = \text{tr}\left(XY^T\right)$. In each case, use the Gram-Schmidt algorithm to transform B into an orthogonal basis.

a. $B = \left\{ \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right\}$

b. $B = \left\{ \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \right\}$

Answer available at the end of this section.

Exercise 7.2E.4

In each case, use the Gram-Schmidt process to convert the basis $B = \{1, x, x^2\}$ into an orthogonal basis of $\mathbf{P}_2$.

a. $\langle p, q \rangle = p(0)q(0) + p(1)q(1) + p(2)q(2)$
b. $\langle p, q \rangle = \int_0^2 p(x)q(x)dx$

Answer available at the end of this section.

Exercise 7.2E.5

Show that $\left\{1, x-\frac{1}{2}, x^2-x+\frac{1}{6}\right\}$, is an orthogonal basis of $\mathbf{P}_2$ with the inner product

$$\langle p, q\rangle = \int_0^1 p(x)q(x)dx$$

and find the corresponding orthonormal basis.

Exercise 7.2E.6

In each case find $U^\perp$ and compute $\dim U$ and $\dim U^\perp$.

a. $U = \text{span}\{(1,1,2,0),(3,-1,2,1),(1,-3,-2,1)\}$ in $\mathbb{R}^4$
b. $U = \text{span}\{(1,1,0,0)\}$ in $\mathbb{R}^4$
c. $U = \text{span}\{1, x\}$ in $\mathbf{P}_2$ with $\langle p, q\rangle = p(0)q(0) + p(1)q(1) + p(2)q(2)$
d. $U = \text{span}\{x\}$ in $\mathbf{P}_2$ with $\langle p, q\rangle = \int_0^1 p(x)q(x)dx$
e. $U = \text{span}\left\{\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}\right\}$ in $\mathbf{M}_{22}$ with $\langle X, Y\rangle = \text{tr}\left(XY^T\right)$
f. $U = \text{span}\left\{\begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}\right\}$ in $\mathbf{M}_{22}$ with $\langle X, Y\rangle = \text{tr}\left(XY^T\right)$

Answer available at the end of this section.

Exercise 7.2E.7

Let $\langle X, Y\rangle = \text{tr}\left(XY^T\right)$ in $\mathbf{M}_{22}$. In each case find the matrix in U closest to A.

a. $U = \text{span}\left\{\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}\right\}$ $A = \begin{bmatrix} 1 & -1 \\ 2 & 3 \end{bmatrix}$
b. $U = \text{span}\left\{\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}\right\}$, $A = \begin{bmatrix} 2 & 1 \\ 3 & 2 \end{bmatrix}$

Answer available at the end of this section.

Exercise 7.2E.8

In $\mathbf{P}_2$, let

$$\langle p(x), q(x)\rangle = p(0)q(0) + p(1)q(1) + p(2)q(2)$$

In each case find the polynomial in U closest to $f(x)$.

a. $U = \text{span}\left\{1 + x, x^2\right\}, f(x) = 1 + x^2$
b. $U = \text{span}\left\{1, 1 + x^2\right\}; f(x) = x$

Answer available at the end of this section.

Exercise 7.2E.9

Using the inner product given by $\langle p, q\rangle = \int_0^1 p(x)q(x)dx$ on $\mathbf{P}_2$, write $\mathbf{v}$ as the sum of a vector in U and a vector in $U^\perp$.

a. $\mathbf{v} = x^2, U = \text{span}\{x + 1, 9x - 5\}$

b. $\mathbf{v} = x^2 + 1, U = \text{span}\{1, 2x - 1\}$

Answer available at the end of this section.

Exercise 7.2E.10

a. Show that $\{\mathbf{u}, \mathbf{v}\}$ is orthogonal if and only if $\|\mathbf{u} + \mathbf{v}\|^2 = \|\mathbf{u}\|^2 + \|\mathbf{v}\|^2$
b. If $\mathbf{u} = \mathbf{v} = (1, 1)$ and $\mathbf{w} = (-1, 0)$, show that $\|\mathbf{u} + \mathbf{v} + \mathbf{w}\|^2 = \|\mathbf{u}\|^2 + \|\mathbf{v}\|^2 + \|\mathbf{w}\|^2$ but $\{\mathbf{u}, \mathbf{v}, \mathbf{w}\}$ is not orthogonal. Hence the converse to Pythagoras' theorem need not hold for more than two vectors.

Exercise 7.2E.11

Let $\mathbf{v}$ and $\mathbf{w}$ be vectors in an inner product space V. Show that:

a. $\mathbf{v}$ is orthogonal to $\mathbf{w}$ if and only if

$$\|\mathbf{v} + \mathbf{w}\| = \|\mathbf{v} - \mathbf{w}\|$$

b. $\mathbf{v} + \mathbf{w}$ and $\mathbf{v} - \mathbf{w}$ are orthogonal if and only if $\|\mathbf{v}\| = \|\mathbf{w}\|$

Answer available at the end of this section.

Exercise 7.2E.12

Let U and W be subspaces of an n dimensional inner product space V. Suppose $\langle \mathbf{u}, \mathbf{v} \rangle = 0$ for all $\mathbf{u} \in U$ and $\mathbf{w} \in W$ and $\dim U + \dim W = n$. Show that $U^\perp = W$.

Exercise 7.2E.13

If U and W are subspaces of an inner product space, show that $(U + W)^\perp = U^\perp \cap W^\perp$.

Exercise 7.2E.14

If X is any set of vectors in an inner product space V, define

$$X^\perp = \{\mathbf{v} \mid \mathbf{v} \text{ in } V, \langle \mathbf{v}, \mathbf{x} \rangle = 0 \text{ for all } \mathbf{x} \text{ in } X\}$$

a. Show that $X^\perp$ is a subspace of V.
b. If $U = \text{span}\{\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_m\}$, show that $U^\perp = \{\mathbf{u}_1, \ldots, \mathbf{u}_m\}^\perp$.
c. If $X \subseteq Y$, show that $Y^\perp \subseteq X^\perp$.
d. Show that $X^\perp \cap Y^\perp = (X \cup Y)^\perp$.

Answer available at the end of this section.

Exercise 7.2E.15

If $\dim V = n$ and $\mathbf{w} \neq \mathbf{0}$ in V, show that $\dim\{\mathbf{v} \mid \mathbf{v} \text{ in } V, \langle \mathbf{v}, \mathbf{w} \rangle = 0\} = n - 1$.

Exercise 7.2E.16

If the Gram-Schmidt process is used on an orthogonal basis $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ of V, show that $\mathbf{f}_k = \mathbf{v}_k$ holds for each $k = 1, 2, \dots, n$. That is, show that the algorithm reproduces the same basis.

Exercise 7.2E.17

If $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_{n-1}\}$ is orthonormal in an inner product space of dimension n, prove that there are exactly two vectors $\mathbf{f}_n$ such that $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_{n-1}, \mathbf{f}_n\}$ is an orthonormal basis.

Exercise 7.2E.18

Let U be a finite dimensional subspace of an inner product space V, and let $\mathbf{v}$ be a vector in V.

a. Show that $\mathbf{v}$ lies in U if and only if $\mathbf{v} = \text{proj}_U(\mathbf{v})$.
b. If $V = \mathbb{R}^3$, show that $(-5, 4, -3)$ lies in $\text{span}\{(3, -2, 5), (-1, 1, 1)\}$ but that $(-1, 0, 2)$ does not.

Answer available at the end of this section.

Exercise 7.2E.19

Let $\mathbf{n} \neq \mathbf{0}$ and $\mathbf{w} \neq \mathbf{0}$ be nonparallel vectors in $\mathbb{R}^3$ (as in Chapter 4).

a. Show that $\left\{\mathbf{n}, \mathbf{n} \times \mathbf{w}, \mathbf{w} - \frac{\mathbf{n} \cdot \mathbf{w}}{\|\mathbf{n}\|^2}\mathbf{n}\right\}$ is an orthogonal basis of $\mathbb{R}^3$.
b. Show that span $\left\{\mathbf{n} \times \mathbf{w}, \mathbf{w} - \frac{\mathbf{n} \cdot \mathbf{w}}{\|\mathbf{n}\|^2}\mathbf{n}\right\}$ is the plane through the origin with normal $\mathbf{n}$.

Answer available at the end of this section.

Exercise 7.2E.20

Let $E = \{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_n\}$ be an orthonormal basis of V.

a. Show that $\langle \mathbf{v}, \mathbf{w} \rangle = C_E(\mathbf{v}) \cdot C_E(\mathbf{w})$ for all $\langle \mathbf{v}, \mathbf{w} \rangle$ in V.
b. If $P = [p_{ij}]$ is an $n \times n$ matrix, define $\mathbf{b}_i = p_{i1}\mathbf{f}_1 + \cdots + p_{in}\mathbf{f}_n$ for each i. Show that $B = \{\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_n\}$ is an orthonormal basis if and only if P is an orthogonal matrix.

Answer available at the end of this section.

Exercise 7.2E.21

Let $\{\mathbf{f}_1, \dots, \mathbf{f}_n\}$ be an orthogonal basis of V. If $\mathbf{v}$ and $\mathbf{w}$ are in V, show that

$$\langle \mathbf{v}, \mathbf{w} \rangle = \frac{\langle \mathbf{v}, \mathbf{f}_1 \rangle \langle \mathbf{w}, \mathbf{f}_1 \rangle}{\|\mathbf{f}_1\|^2} + \cdots + \frac{\langle \mathbf{v}, \mathbf{f}_n \rangle \langle \mathbf{w}, \mathbf{f}_n \rangle}{\|\mathbf{f}_n\|^2}$$

Exercise 7.2E.22

Let $\{\mathbf{f}_1, \dots, \mathbf{f}_n\}$ be an orthonormal basis of V, and let $\mathbf{v} = v_1\mathbf{f}_1 + \cdots + v_n\mathbf{f}_n$ and $\mathbf{w} = w_1\mathbf{f}_1 + \cdots + w_n\mathbf{f}_n$. Show that

$$\langle \mathbf{v}, \mathbf{w} \rangle = v_1 w_1 + \cdots + v_n w_n$$

and

$$\|\mathbf{v}\|^2 = v_1^2 + \cdots + v_n^2$$

Exercise 7.2E.23

Let $\mathbf{v}$ be a vector in an inner product space V.

a. Show that $\|\mathbf{v}\| \geq \|\text{proj}_U \mathbf{v}\|$ holds for all finite dimensional subspaces U. [Hint: Pythagoras' theorem.]
b. If $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_m\}$ is any orthogonal set in V, prove Bessel's inequality:

$$\frac{\langle \mathbf{v}, \mathbf{f}_1 \rangle^2}{\|\mathbf{f}_1\|^2} + \cdots + \frac{\langle \mathbf{v}, \mathbf{f}_m \rangle^2}{\|\mathbf{f}_m\|^2} \leq \|\mathbf{v}\|^2$$

Answer available at the end of this section.

Exercise 7.2E.24

Let $B = \{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_n\}$ be an orthogonal basis of an inner product space V. Given $\mathbf{v} \in V$, let θ_i be the angle between $\mathbf{v}$ and $\mathbf{f}_i$ for each i (see Exercise 10.1.31). Show that

$$\cos^2 \theta_1 + \cos^2 \theta_2 + \cdots + \cos^2 \theta_n = 1$$

[The $\cos \theta_i$ are called direction cosines for $\mathbf{v}$ corresponding to B.]

Exercise 7.2E.25

a. Let S denote a set of vectors in a finite dimensional inner product space V, and suppose that $\langle \mathbf{u}, \mathbf{v} \rangle = 0$ for all $\mathbf{u}$ in S implies $\mathbf{v} = \mathbf{0}$. Show that $V = \text{span}\, S$. [Hint: Write $U = \text{span}\, S$ and use Theorem 10.2.6.]
b. Let $A_1, A_2, \ldots, A_k$ be $n \times n$ matrices. Show that the following are equivalent.
   i. If $A_i \mathbf{b} = \mathbf{0}$ for all i (where $\mathbf{b}$ is a column in $\mathbb{R}^n$), then $\mathbf{b} = \mathbf{0}$.
   ii. The set of all rows of the matrices A_i spans $\mathbb{R}^n$.

Exercise 7.2E.26

Let $[x_i) = (x_1, x_2, \ldots)$ denote a sequence of real numbers x_i, and let

$$V = \{[x_i) \mid \text{ only finitely many } x_i \neq 0\}$$

Define componentwise addition and scalar multiplication on V as follows:

$$[x_i) + [y_i) = [x_i + y_i), \text{ and } a[x_i) = [ax_i) \text{ for } a \text{ in } \mathbb{R}.$$

Given $[x_i)$ and $[y_i)$ in V, define $\langle [x_i), [y_i) \rangle = \sum_{i=0}^{\infty} x_i y_i$. (Note that this makes sense since only finitely many x_i and y_i are nonzero.) Finally define

$$U = \left\{ [x_i) \text{ in } V \mid \sum_{i=0}^{\infty} x_i = 0 \right\}$$

a. Show that V is a vector space and that U is a subspace.
b. Show that $\langle , \rangle$ *is an inner product on* V.
c. Show that $U^{\perp} = \{\mathbf{0}\}$.

d. Hence show that $U \oplus U^{\perp} \neq V$ and $U \neq U^{\perp\perp}$.

Answers

Exercise $7.2E.1$

b. $$\frac{1}{14}\left\{(6a+2b+6c)\begin{bmatrix}1\\1\\1\end{bmatrix}+(7c-7a)\begin{bmatrix}-1\\0\\1\end{bmatrix}+(a-2b+c)\begin{bmatrix}1\\-6\\1\end{bmatrix}\right\}$$

d. $$\left(\frac{a+d}{2}\right)\begin{bmatrix}1&0\\0&1\end{bmatrix}+\left(\frac{a-d}{2}\right)\begin{bmatrix}1&0\\0&-1\end{bmatrix}+\left(\frac{b+c}{2}\right)\begin{bmatrix}0&1\\1&0\end{bmatrix}+\left(\frac{b-c}{2}\right)\begin{bmatrix}0&1\\-1&0\end{bmatrix}$$

Exercise $7.2E.2$

b. $\{(1,1,1),(1,-5,1),(3,0,-2)\}$

Exercise $7.2E.3$

b. $\left\{\begin{bmatrix}1&1\\0&1\end{bmatrix},\begin{bmatrix}1&-2\\3&1\end{bmatrix},\begin{bmatrix}1&-2\\-2&1\end{bmatrix},\begin{bmatrix}1&0\\0&-1\end{bmatrix}\right\}$

Exercise $7.2E.4$

b. $\left\{1, x-1, x^2-2x+\frac{2}{3}\right\}$

Exercise $7.2E.6$

b. $U^{\perp}=\operatorname{span}\left\{\begin{bmatrix}1&-1&0&0\end{bmatrix},\begin{bmatrix}0&0&1&0\end{bmatrix},\begin{bmatrix}0&0&0&1\end{bmatrix}\right\}, \dim U^{\perp}=3, \dim U=1$

d. $U^{\perp}=\operatorname{span}\left\{2-3x, 1-2x^2\right\}, \dim U^{\perp}=2, \dim U=1$

f. $U^{\perp}=\operatorname{span}\left\{\begin{bmatrix}1&-1\\-1&0\end{bmatrix}\right\}, \dim U^{\perp}=$

Exercise $7.2E.7$

b. $U=\operatorname{span}\left\{\begin{bmatrix}1&0\\0&1\end{bmatrix},\begin{bmatrix}1&1\\1&-1\end{bmatrix},\begin{bmatrix}0&1\\-1&0\end{bmatrix}\right\}; \operatorname{proj}_U(A)=\begin{bmatrix}3&0\\2&1\end{bmatrix}$

Exercise $7.2E.8$

b. $U=\operatorname{span}\left\{1,5-3x^2\right\}; \operatorname{proj}_U(x)=\frac{3}{13}\left(\mid 1+2x^2\right)$

Exercise $7.2E.9$

b. $B=\{1,2x-1\}$ is an orthogonal basis of U because $\int_0^1(2x-1)dx=0$. Using it, we get $\operatorname{proj}_U\left(x^2+1\right)=x+\frac{5}{6}$, so $x^2+1=\left(x+\frac{5}{6}\right)+\left(x^2-x+\frac{1}{6}\right)$.

Exercise $7.2E.11$

b. This follows from $\langle \mathbf{v}+\mathbf{w}, \mathbf{v}-\mathbf{w}\rangle = \|\mathbf{v}\|^2-\|\mathbf{w}\|^2$.

Exercise $7.2E.14$

b. $U^{\perp} \subseteq \{\mathbf{u}_1, \ldots, \mathbf{u}_m\}^{\perp}$ because each $\mathbf{u}_i$ is in U. Conversely, if $\langle \mathbf{v}, \mathbf{u}_i\rangle = 0$ for each i, and $\mathbf{u}=r_1\mathbf{u}_1+\ldots+r_m\mathbf{u}_m$ is any vector in U, then $\langle \mathbf{v}, \mathbf{u}\rangle = r_1\langle \mathbf{v}, \mathbf{u}_1\rangle + \cdots + r_m\langle \mathbf{v}, \mathbf{u}_m\rangle = 0$.

Exercise $7.2E.18$

b. $\operatorname{proj}_U(-5,4,-3)=(-5,4,-3)$; $\operatorname{proj}_U(-1,0,2)=\frac{1}{38}(-17,24,73)$

Exercise $7.2E.19$

b. The plane is $\mathrm{U}=\{\mathbf{x} \mid \mathbf{x}\cdot\mathbf{n}=0\}$ so $\operatorname{span}\left\{\mathbf{n}\times\mathbf{w}, \mathbf{w}-\frac{\mathbf{n}\cdot\mathbf{w}}{\|\mathbf{n}\|^2}\mathbf{n}\right\} \subseteq U$. This is equality because both spaces have dimension 2 (using (a)).

Exercise $7.2E.20$

b. $C_E(\mathbf{b}_i)$ is column i of P. Since $C_E(\mathbf{b}_i)\cdot C_E(\mathbf{b}_j)=\langle \mathbf{b}_i, \mathbf{b}_j\rangle$ by (a), the result follows.

Exercise $7.2E.23$

b. If $U=\operatorname{span}\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_m\}$, then $\operatorname{proj}_U(\mathbf{v})=\sum_{i=1}^m \frac{\langle \mathbf{v}_1, \mathbf{f}_i\rangle}{\|\mathbf{f}_i\|^2}\mathbf{f}_i$ by Theorem 10.2.7. Hence $\|\operatorname{proj}_U(\mathbf{v})\|^2=\sum_{i=1}^m \frac{\langle \mathbf{v}_1, \mathbf{f}_i\rangle}{\|\mathbf{f}_i\|^2}\mathbf{f}_i$ by Pythagoras' theorem. Now use (a).

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7.3: ORTHOGONAL DIAGONALIZATION

There is a natural way to define a symmetric linear operator T on a finite dimensional inner product space V. If T is such an operator, it is shown in this section that V has an orthogonal basis consisting of eigenvectors of T. This yields another proof of the principal axis theorem in the context of inner product spaces.

Theorem 7.3.1

Let $T : V \to V$ be a linear operator on a finite dimensional space V. Then the following conditions are equivalent.

1. V has a basis consisting of eigenvectors of T.
2. There exists a basis B of V such that $M_B(T)$ is diagonal.

Proof

We have $M_B(T) = [C_B[T(\mathbf{b}_1)]\, C_B[T(\mathbf{b}_2)] \cdots C_B[T(\mathbf{b}_n)]]$ where $B = \{\mathbf{b}_1, \mathbf{b}_2, \ldots, \mathbf{b}_n\}$ is any basis of V. By comparing columns:

$$M_B(T) = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{bmatrix} \text{ if and only if } T(\mathbf{b}_i) = \lambda_i \mathbf{b}_i \text{ for each } i$$

□

Theorem 10.3.1 follows.

Definition: Diagonalizable

A linear operator T on a finite dimensional space V is called diagonalizable if V has a basis consisting of eigenvectors of T.

Example 7.3.1

Let $T : \mathbf{P}_2 \to \mathbf{P}_2$ be given by

$$T(a + bx + cx^2) = (a + 4c) - 2bx + (3a + 2c)x^2$$

Find the eigenspaces of T and hence find a basis of eigenvectors.

Solution

If $B_0 = \{1, x, x^2\}$, then

$$M_{B_0}(T) = \begin{bmatrix} 1 & 0 & 4 \\ 0 & -2 & 0 \\ 3 & 0 & 2 \end{bmatrix}$$

so $c_T(x) = (x + 2)^2(x - 5)$, and the eigenvalues of T are $\lambda = -2$ and $\lambda = 5$. One sees that

$$\left\{\begin{bmatrix}0\\1\\0\end{bmatrix},\begin{bmatrix}4\\0\\-3\end{bmatrix},\begin{bmatrix}1\\0\\1\end{bmatrix}\right\}$$

is a basis of eigenvectors of $M_{B_0}(T)$, so $B=\{x,4-3x^2,1+x^2\}$ is a basis of $\mathbf{P}_2$ consisting of eigenvectors of T.

If V is an inner product space, the expansion theorem gives a simple formula for the matrix of a linear operator with respect to an orthogonal basis.

Theorem 7.3.2

Let $T:V\to V$ be a linear operator on an inner product space V. If $B=\{\boldsymbol{b}_1,\boldsymbol{b}_2,\ldots,\boldsymbol{b}_n\}$ is an orthogonal basis of V, then

$$M_B(T)=\left[\frac{\langle \boldsymbol{b}_i,T(\boldsymbol{b}_j)\rangle}{\|\boldsymbol{b}_i\|^2}\right]$$

Proof

Write $M_B(T)=[a_{ij}]$. The j th column of $M_B(T)$ is $C_B[T(\mathbf{e}_j)]$, so

$$T(\mathbf{b}_j)=a_{1j}\mathbf{b}_1+\cdots+a_{ij}\mathbf{b}_i+\cdots+a_{nj}\mathbf{b}_n$$

On the other hand, the expansion theorem (Theorem 10.2.4) gives

$$\mathbf{v}=\frac{\langle \mathbf{b}_1,\mathbf{v}\rangle}{\|\mathbf{b}_1\|^2}\mathbf{b}_1+\cdots+\frac{\langle \mathbf{b}_i,\mathbf{v}\rangle}{\|\mathbf{b}_i\|^2}\mathbf{b}_i+\cdots+\frac{\langle \mathbf{b}_n,\mathbf{v}\rangle}{\|\mathbf{b}_n\|^2}\mathbf{b}_n$$

for any $\mathbf{v}$ in V. The result follows by taking $\mathbf{v}=T(\mathbf{b}_j)$.

□

Example 7.3.2

Let $T:\mathbb{R}^3\to\mathbb{R}^3$ be given by

$$T(a,b,c)=(a+2b-c,2a+3c,-a+3b+2c)$$

If the dot product in $\mathbb{R}^3$ is used, find the matrix of T with respect to the standard basis $B=\{\mathbf{e}_1,\mathbf{e}_2,\mathbf{e}_3\}$ where $\mathbf{e}_1=(1,0,0),\mathbf{e}_2=(0,1,0),\mathbf{e}_3=(0,0,1)$.

Solution

The basis B is orthonormal, so Theorem 10.3.2 gives

$$M_B(T)=\begin{bmatrix}\mathbf{e}_1\cdot T(\mathbf{e}_1) & \mathbf{e}_1\cdot T(\mathbf{e}_2) & \mathbf{e}_1\cdot T(\mathbf{e}_3)\\ \mathbf{e}_2\cdot T(\mathbf{e}_1) & \mathbf{e}_2\cdot T(\mathbf{e}_2) & \mathbf{e}_2\cdot T(\mathbf{e}_3)\\ \mathbf{e}_3\cdot T(\mathbf{e}_1) & \mathbf{e}_3\cdot T(\mathbf{e}_2) & \mathbf{e}_3\cdot T(\mathbf{e}_3)\end{bmatrix}=\begin{bmatrix}1&2&-1\\2&0&3\\-1&3&2\end{bmatrix}$$

Of course, this can also be found in the usual way.

It is not difficult to verify that an $n\times n$ matrix A is symmetric if and only if $\mathbf{x}\cdot(A\mathbf{y})=(A\mathbf{x})\cdot\mathbf{y}$ holds for all columns $\mathbf{x}$ and $\mathbf{y}$ in $\mathbb{R}^n$. The analog for operators is as follows:

Theorem 7.3.3

Let V be a finite dimensional inner product space. The following conditions are equivalent for a linear operator $T : V \to V$.

1. $\langle v, T(\mathbf{w})\rangle = \langle T(\mathbf{v}), \mathbf{w}\rangle$ for all $\mathbf{v}$ and $\mathbf{w}$ in V.
2. The matrix of T is symmetric with respect to every orthonormal basis of V.
3. The matrix of T is symmetric with respect to some orthonormal basis of V.
4. There is an orthonormal basis $B = \{\boldsymbol{f}_1, \boldsymbol{f}_2, \ldots, \boldsymbol{f}_n\}$ of V such that $\langle \boldsymbol{f}_i, T(\boldsymbol{f}_j)\rangle = \langle T(\boldsymbol{f}_i), \boldsymbol{f}_j\rangle$ holds for all i and j.

Proof

1. $\Rightarrow$ 2. Let $B = \{\mathbf{f}_1, \ldots, \mathbf{f}_n\}$ be an orthonormal basis of V, and write $M_B(T) = [a_{ij}]$. Then $a_{ij} = \langle \mathbf{f}_i, T(\mathbf{f}_j)\rangle$ by Theorem 10.3.2. Hence (1.) and axiom P2 give

$$a_{ij} = \langle \mathbf{f}_i, T(\mathbf{f}_j)\rangle = \langle T(\mathbf{f}_i), \mathbf{f}_j\rangle = \langle \mathbf{f}_j, T(\mathbf{f}_i)\rangle = a_{ji}$$

for all i and j. This shows that $M_B(T)$ is symmetric.

2. $\Rightarrow$ 3. This is clear.
3. $\Rightarrow$ 4. Let $B = \{\mathbf{f}_1, \ldots, \mathbf{f}_n\}$ be an orthonormal basis of V such that $M_B(T)$ is symmetric. By (3.) and Theorem 10.3.2, $\langle \mathbf{f}_i, T(\mathbf{f}_j)\rangle = \langle \mathbf{f}_j, T(\mathbf{f}_i)\rangle$ for all i and j, so (4.) follows from axiom P2.
4. $\Rightarrow$ 1. Let $\mathbf{v}$ and $\mathbf{w}$ be vectors in V and write them as $\mathbf{v} = \sum_{i=1}^n v_i\mathbf{f}_i$ and $\mathbf{w} = \sum_{j=1}^n w_j\mathbf{f}_j$. Then

$$\begin{aligned}\langle \mathbf{v}, T(\mathbf{w})\rangle = \left\langle \sum_i v_i\mathbf{f}_i, \sum_j w_j T\mathbf{f}_j \right\rangle &= \sum_i \sum_j v_i w_j \langle \mathbf{f}_i, T(\mathbf{f}_j)\rangle \\ &= \sum_i \sum_j v_i w_j \langle T(\mathbf{f}_i), \mathbf{f}_j\rangle \\ &= \left\langle \sum_i v_i T(\mathbf{f}_i), \sum_j w_j\mathbf{f}_j \right\rangle \\ &= \langle T(\mathbf{v}), \mathbf{w}\rangle\end{aligned}$$

where we used (4.) at the third stage. This proves (1.).

square

A linear operator T on an inner product space V is called symmetric if $\langle \mathbf{v}, T(\mathbf{w})\rangle = \langle T(\mathbf{v}), \mathbf{w}\rangle$ holds for all $\mathbf{v}$ and $\mathbf{w}$ in V.

Example 7.3.3

If A is an $n \times n$ matrix, let $T_A : \mathbb{R}^n \to \mathbb{R}^n$ be the matrix operator given by $T_A(\mathbf{v}) = A\mathbf{v}$ for all columns $\mathbf{v}$. If the dot product is used in $\mathbb{R}^n$, then T_A is a symmetric operator if and only if A is a symmetric matrix.

Solution

If E is the standard basis of $\mathbb{R}^n$, then E is orthonormal when the dot product is used. We have $M_E(T_A) = A$ (by Example 9.1.4), so the result follows immediately from part (3) of Theorem 10.3.3.

It is important to note that whether an operator is symmetric depends on which inner product is being used (see Exercise 2).

If V is a finite dimensional inner product space, the eigenvalues of an operator $T : V \to V$ are the same as those of $M_B(T)$ for any orthonormal basis B (see Theorem 9.3.3). If T is symmetric, $M_B(T)$ is a symmetric matrix and so has real eigenvalues by Theorem 5.5.7. Hence we have the following:

Theorem 7.3.4

A symmetric linear operator on a finite dimensional inner product space has real eigenvalues.

If U is a subspace of an inner product space V, recall that its orthogonal complement is the subspace $U^\perp$ of V defined by

$$U^\perp = \{\mathbf{v} \text{ in } V \mid \langle \mathbf{v}, \mathbf{u} \rangle = 0 \text{ for all } \mathbf{u} \text{ in } U\}$$

Theorem 7.3.5

Let $T : V \to V$ be a symmetric linear operator on an inner product space V, and let U be a T-invariant subspace of V. Then:

1. The restriction of T to U is a symmetric linear operator on U.
2. $U^\perp$ is also T-invariant.

Proof

1. U is itself an inner product space using the same inner product, and condition 1 in Theorem 10.3.3 that T is symmetric is clearly preserved.
2. If $\mathbf{v}$ is in $U^\perp$, our task is to show that $T(\mathbf{v})$ is also in $U^\perp$; that is, $\langle T(\mathbf{v}), \mathbf{u} \rangle = 0$ for all $\mathbf{u}$ in U. But if $\mathbf{u}$ is in U, then $T(\mathbf{u})$ also lies in U because U is T-invariant, so
$$\langle T(\mathbf{v}), \mathbf{u} \rangle = \langle \mathbf{v}, T(\mathbf{u}) \rangle$$
using the symmetry of T and the definition of $U^\perp$.

□

The principal axis theorem (Theorem 8.2.2) asserts that an $n \times n$ matrix A is symmetric if and only if $\mathbb{R}^n$ has an orthogonal basis of eigenvectors of A. The following result not only extends this theorem to an arbitrary n-dimensional inner product space, but the proof is much more intuitive.

Theorem 7.3.6: Principal Axis Theorem

The following conditions are equivalent for a linear operator T on a finite dimensional inner product space V.

1. T is symmetric.
2. V has an orthogonal basis consisting of eigenvectors of T.

Proof

$\Rightarrow 2$. Assume that T is symmetric and proceed by induction on $n = \dim V$. If $n = 1$, every nonzero vector in V is an eigenvector of T, so there is nothing to prove. If $n \geq 2$, assume inductively that the theorem holds for spaces of dimension less than n . Let λ_1 be a real eigenvalue of T (by Theorem 10.3.4) and choose an eigenvector $\mathbf{f}_1$ corresponding to λ_1. Then $U = \mathbb{R}\mathbf{f}_1$ is T-invariant, so $U^\perp$ is also T-invariant by Theorem 10.3.5 (T is symmetric). Because $\dim U^\perp = n - 1$ (Theorem 10.2.6), and because the restriction of T to $U^\perp$ is a symmetric operator (Theorem 10.3.5), it follows by induction that $U^\perp$ has an orthogonal basis $\{\mathbf{f}_2, \ldots, \mathbf{f}_n\}$ of eigenvectors of T. Hence $B = \{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_n\}$ is an orthogonal basis of V, which proves (2.).

$\Rightarrow 1$. If $B = \{\mathbf{f}_1, \ldots, \mathbf{f}_n\}$ is a basis as in (2.), then $M_B(T)$ is symmetric (indeed diagonal), so T is symmetric by Theorem 10.3.3.

square

The matrix version of the principal axis theorem is an immediate consequence of Theorem 10.3.6. If A is an $n \times n$ symmetric

matrix, then $T_A : \mathbb{R}^n \to \mathbb{R}^n$ is a symmetric operator, so let B be an orthonormal basis of $\mathbb{R}^n$ consisting of eigenvectors of T_A (and hence of A). Then P^TAP is diagonal where P is the orthogonal matrix whose columns are the vectors in B (see Theorem 9.2.4).

Similarly, let $T : V \to V$ be a symmetric linear operator on the n-dimensional inner product space V and let B_0 be any convenient orthonormal basis of V. Then an orthonormal basis of eigenvectors of T can be computed from $M_{B_0}(T)$. In fact, if $P^TM_{B_0}(T)P$ is diagonal where P is orthogonal, let $B = \{\mathbf{f}_1, \dots, \mathbf{f}_n\}$ be the vectors in V such that $C_{B_0}(\mathbf{f}_j)$ is column j of P for each j. Then B consists of eigenvectors of T by Theorem 9.3.3, and they are orthonormal because B_0 is orthonormal. Indeed

$$\langle \mathbf{f}_i, \mathbf{f}_j \rangle = C_{B_0}(\mathbf{f}_i) \cdot C_{B_0}(\mathbf{f}_j)$$

holds for all i and j, as the reader can verify. Here is an example.

Example 7.3.4

Let $T : \mathbf{P}_2 \to \mathbf{P}_2$ be given by

$$T\left(a + bx + cx^2\right) = (8a - 2b + 2c) + (-2a + 5b + 4c)x + (2a + 4b + 5c)x^2$$

Using the inner product $\langle a + bx + cx^2, a' + b'x + c'x^2 \rangle = aa' + bb' + cc'$, show that T is symmetric and find an orthonormal basis of $\mathbf{P}_2$ consisting of eigenvectors.

Solution

If $B_0 = \{1, x, x^2\}$, then $M_{B_0}(T) = \begin{bmatrix} 8 & -2 & 2 \\ -2 & 5 & 4 \\ 2 & 4 & 5 \end{bmatrix}$ is symmetric, so T is symmetric. This matrix was analyzed in Example 8.2.5, where it was found that an orthonormal basis of eigenvectors is $\left\{\frac{1}{3}\begin{bmatrix} 1 & 2 & -2 \end{bmatrix}^T, \frac{1}{3}\begin{bmatrix} 2 & 1 & 2 \end{bmatrix}^T, \frac{1}{3}\begin{bmatrix} -2 & 2 & 1 \end{bmatrix}^T\right\}$. Because B_0 is orthonormal, the corresponding orthonormal basis of $\mathbf{P}_2$ is

$$B = \left\{\frac{1}{3}\left(1 + 2x - 2x^2\right), \frac{1}{3}\left(2 + x + 2x^2\right), \frac{1}{3}\left(-2 + 2x + x^2\right)\right\}.$$

7.3E: Orthogonal Diagonalization Exercises

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7.3E: Orthogonal Diagonalization Exercises

Exercise 7.3E.1

In each case, show that T is symmetric by calculating $M_B(T)$ for some orthonormal basis B.

a. $T : \mathbb{R}^3 \to \mathbb{R}^3$; \[T(a, b, c)=(a-2 b,-2 a+2 b+2 c, 2 b-c) \text {; }\nonumber \]; dot product

b. $T : \mathbf{M}_{22} \to \mathbf{M}_{22}$; $T\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} c-a & d-b \\ a+2c & b+2d \end{bmatrix}$; inner product $\left\langle \begin{bmatrix} x & y \\ z & w \end{bmatrix}, \begin{bmatrix} x' & y' \\ z' & w' \end{bmatrix} \right\rangle = xx' + yy' + zz' + ww'$

c. $T : \mathbf{P}_2 \to \mathbf{P}_2; T\left(a + bx + cx^2\right) = (b + c)+ (a + c)x + (a + b)x^2$; inner product $\langle a + bx+ cx^2, a' + b'x + c'x^2\rangle = aa' + bb' + cc'$

Answer available at the end of this section.

Exercise 7.3E.2

Let $T : \mathbb{R}^2 \to \mathbb{R}^2$ be given by

$$T(a, b) = (2a + b, a - b).$$

a. Show that T is symmetric if the dot product is used.

b. Show that T is not symmetric if $\langle \mathbf{x}, \mathbf{y}\rangle = \mathbf{x}A\mathbf{y}^T$, where $A = \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix}$. [Hint: Check that $B = \{(1, 0), (1, -1)\}$ is an orthonormal basis.]

Exercise 7.3E.3

Let $T : \mathbb{R}^2 \to \mathbb{R}^2$ be given by $T(a, b) = (a - b, b - a)$. Use the dot product in $\mathbb{R}^2$.

a. Show that T is symmetric.

b. Show that $M_B(T)$ is not symmetric if the orthogonal basis $B = \{(1, 0), (0, 2)\}$ is used. Why does this not contradict Theorem 10.3.3?

Exercise 7.3E.4

Let V be an n-dimensional inner product space, and let T and S denote symmetric linear operators on V. Show that:

a. The identity operator is symmetric.

b. rT is symmetric for all r in $\mathbb{R}$.

c. $S + T$ is symmetric.

d. If T is invertible, then T^{-1} is symmetric.

e. If $ST = TS$, then ST is symmetric.

Answer available at the end of this section.

Exercise 7.3E.5

In each case, show that T is symmetric and find an orthonormal basis of eigenvectors of T.

a. $T : \mathbb{R}^3 \to \mathbb{R}^3; T(a, b, c) = (2a + 2c, 3b, 2a + 5c)$; use the dot product
b. $T : \mathbb{R}^3 \to \mathbb{R}^3; T(a, b, c) = (7a - b, -a + 7b, 2c)$; use the dot product
c. $T : \mathbf{P}_2 \to \mathbf{P}_2; T\left(a + bx + cx^2\right) = 3b + (3a + 4c)x + 4bx^2$; inner product $\left\langle a + bx + cx^2, a' + b'x + c'x^2 \right\rangle = aa' + bb' + cc'$
d. $T : \mathbf{P}_2 \to \mathbf{P}_2; T\left(a + bx + cx^2\right) = (c - a) + 3bx + (a - c)x^2$; inner product as in part (c)

Answer available at the end of this section.

Exercise 7.3E.6

If A is any $n \times n$ matrix, let $T_A : \mathbb{R}^n \to \mathbb{R}^n$ be given by $T_A(\mathbf{x}) = A\mathbf{x}$. Suppose an inner product on $\mathbb{R}^n$ is given by $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^T P \mathbf{y}$, where P is a positive definite matrix.

a. a. Show that T_A is symmetric if and only if $PA = A^T P$.
b. b. Use part (a) to deduce Example 10.3.3.

Exercise 7.3E.7

Let $T : \mathbf{M}_{22} \to \mathbf{M}_{22}$ be given by $T(X) = AX$, where A is a fixed 2×2 matrix.

a. Compute $M_B(T)$, where

$$B = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}.$$

Note the order!
b. Show that $c_T(x) = [c_A(x)]^2$.
c. If the inner product on $\mathbf{M}_{22}$ is $\langle X, Y \rangle = \operatorname{tr}\left(XY^T\right)$, show that T is symmetric if and only if A is a symmetric matrix.

Answer available at the end of this section.

Exercise 7.3E.8

Let $T : \mathbb{R}^2 \to \mathbb{R}^2$ be given by $T(a, b) = (b - a, a + 2b)$. Show that T is symmetric if the dot product is used in $\mathbb{R}^2$ but that it is not symmetric if the following inner product is used:

$$\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x} A \mathbf{y}^T, A = \begin{bmatrix} 1 & -1 \\ -1 & 2 \end{bmatrix}$$

Exercise 7.3E.9

in block form, where $Q = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$. If $B_0 = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}$, then $M_B(T) = \begin{bmatrix} pQ^T & qQ^T \\ rQ^T & sQ^T \end{bmatrix}$, where $P = \begin{bmatrix} p & q \\ r & s \end{bmatrix}$. Use the fact that $cP = bP^T \Rightarrow \left(c^2 - b^2\right) P = 0$.]

Exercise 7.3E.11

Let $T : V \to W$ be any linear transformation and let $B = \{\mathbf{b}_1, \ldots, \mathbf{b}_n\}$ and $D = \{\mathbf{d}_1, \ldots, \mathbf{d}_m\}$ be bases of V and W, respectively. If W is an inner product space and D is orthogonal, show that

$$M_{DB}(T) = \left[\frac{\langle \mathbf{d}_i, T(\mathbf{b}_j)\rangle}{\|\mathbf{d}_i\|^2}\right]$$

This is a generalization of Theorem 10.3.2.

Exercise 7.3E.12

Let $T : V \to V$ be a linear operator on an inner product space V of finite dimension. Show that the following are equivalent.

1. $\langle \mathbf{v}, T(\mathbf{w})\rangle = -\langle T(\mathbf{v}), \mathbf{w}\rangle$ for all $\mathbf{v}$ and $\mathbf{w}$ in V.
2. $M_B(T)$ is skew-symmetric for every orthonormal basis B.
3. $M_B(T)$ is skew-symmetric for some orthonormal basis B.

Such operators T are called skew-symmetric operators.

Answer available at the end of this section.

Exercise 7.3E.13

Let $T : V \to V$ be a linear operator on an n-dimensional inner product space V.

a. Show that T is symmetric if and only if it satisfies the following two conditions.
   i. $c_T(x)$ factors completely over $\mathbb{R}$.
   ii. If U is a T-invariant subspace of V, then $U^\perp$ is also T-invariant.
b. Using the standard inner product on $\mathbb{R}^2$, show that $T : \mathbb{R}^2 \to \mathbb{R}^2$ with $T(a, b) = (a, a + b)$ satisfies condition (i) and that $S : \mathbb{R}^2 \to \mathbb{R}^2$ with $S(a, b) = (b, -a)$ satisfies condition (ii), but that neither is symmetric. (Example 9.3.4 is useful for S.)

[Hint for part (a): If conditions (i) and (ii) hold, proceed by induction on n. By condition (i), let $\mathbf{e}_1$ be an eigenvector of T. If $U = \mathbb{R}\mathbf{e}_1$, then $U^\perp$ is T-invariant by condition (ii), so show that the restriction of T to $U^\perp$ satisfies conditions (i) and (ii). (Theorem 9.3.1 is helpful for part (i)). Then apply induction to show that V has an orthogonal basis of eigenvectors (as in Theorem 10.3.6)].

Exercise 7.3E.14

Let $B = \{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_n\}$ be an orthonormal basis of an inner product space V. Given $T : V \to V$, define $T' : V \to V$ by $T'(\mathbf{v}) = \langle \mathbf{v}, T(\mathbf{f}_1)\rangle \mathbf{f}_1 + \langle \mathbf{v}, T(\mathbf{f}_2)\rangle \mathbf{f}_2 + \cdots + \langle \mathbf{v}, T(\mathbf{f}_n)\rangle \mathbf{f}_n = \sum_{i=1}^n \langle \mathbf{v}, T(\mathbf{f}_i)\rangle \mathbf{f}_i$

a. Show that $(aT)' = aT'$.
b. Show that $(S + T)' = S' + T'$.
c. Show that $M_B(T')$ is the transpose of $M_B(T)$.
d. Show that $(T')' = T$, using part (c). [Hint: $M_B(S) = M_B(T)$ implies that $S = T$.]
e. Show that $(ST)' = T'S'$, using part (c).
f. Show that T is symmetric if and only if $T = T'$. [Hint: Use the expansion theorem and Theorem 10.3.3.]
g. Show that $T + T'$ and TT' are symmetric, using parts (b) through (e).
h. Show that $T'(\mathbf{v})$ is independent of the choice of orthonormal basis B. [Hint: If $D = \{\mathbf{g}_1, \ldots, \mathbf{g}_n\}$ is also orthonormal, use the fact that $\mathbf{f}_i = \sum_{j=1}^n \langle \mathbf{f}_i, \mathbf{g}_j\rangle \mathbf{g}_j$ for each i.]

Answer available at the end of this section.

Exercise 7.3E.15

Let V be a finite dimensional inner product space. Show that the following conditions are equivalent for a linear operator $T : V \to V$.

a. T is symmetric and $T^2 = T$.
b. $M_B(T) = \begin{bmatrix} I_r & 0 \\ 0 & 0 \end{bmatrix}$ for some orthonormal basis B of V. An operator is called a projection if it satisfies these conditions.
[Hint: If $T^2 = T$ and $T(\mathbf{v}) = \lambda\mathbf{v}$, apply T to get $\lambda\mathbf{v} = \lambda^2\mathbf{v}$. Hence show that 0,1 are the only eigenvalues of T.]

Exercise 7.3E.16

Let V denote a finite dimensional inner product space. Given a subspace U, define $\text{proj}_U : V \to V$ as in Theorem 10.2.7.

a. Show that proj_U is a projection in the sense of Exercise 15.
b. If T is any projection, show that $T = \text{proj}_U$, where $U = \text{im}\, T$. [Hint: Use $T^2 = T$ to show that $V = \text{im}\, T \oplus \ker T$ and $T(\mathbf{u}) = \mathbf{u}$ for all $\mathbf{u}$ in $\text{im}\, T$. Use the fact that T is symmetric to show that $\ker T \subseteq (\text{im}\, T)^\perp$ and hence that these are equal because they have the same dimension.]

Answers

Exercise 7.3E.1

b. $B = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}$; $M_B(T) = \begin{bmatrix} -1 & 0 & 1 & 0 \\ 0 & -1 & 0 & 1 \\ 1 & 0 & 2 & 0 \\ 0 & 1 & 0 & 2 \end{bmatrix}$

Exercise 7.3E.4

b. $\langle \mathbf{v}, \quad (rT)\mathbf{w} \rangle = \langle \mathbf{v}, \quad rT(\mathbf{w}) \rangle = r\langle \mathbf{v}, T(\mathbf{w}) \rangle = r\langle T(\mathbf{v}), \mathbf{w} \rangle = \langle rT(\mathbf{v}), \mathbf{w} \rangle = \langle (rT)(\mathbf{v}), \mathbf{w} \rangle$
d. Given $\mathbf{v}$ and $\mathbf{w}$, write $T^{-1}(\mathbf{v}) = \mathbf{v}_1$ and $T^{-1}(\mathbf{w}) = \mathbf{w}_1$. Then $\langle T^{-1}(\mathbf{v}), \mathbf{w} \rangle = \langle \mathbf{v}_1, T(\mathbf{w}_1) \rangle = \langle T(\mathbf{v}_1), \mathbf{w}_{|1\rangle} \rangle = \langle \mathbf{v}, T^{-1}(\mathbf{w}) \rangle$.

Exercise 7.3E.5

b. If $B_0 = \{(1,0,0), (0,1,0), (0,0,1)\}$, then $M_{B_0}(T) = \begin{bmatrix} 7 & -1 & 0 \\ -1 & 7 & 0 \\ 0 & 0 & 2 \end{bmatrix}$ has an orthonormal basis of eigenvectors $\left\{ \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\}$. Hence an orthonormal basis of eigenvectors of T is $\left\{ \frac{1}{\sqrt{2}}(1,1,0), \frac{1}{\sqrt{2}}(1,-1,0), (0,0,1) \right\}$.
c. If $B_0 = \{1, x, x^2\}$, then $M_{B_0}(T) = \begin{bmatrix} -1 & 0 & 1 \\ 0 & 3 & 0 \\ 1 & 0 & -1 \end{bmatrix}$ has an orthonormal basis of eigenvectors $\left\{ \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \right\}$.
Hence an orthonormal basis of eigenvectors of T is $\left\{ x, \frac{1}{\sqrt{2}}(1+x^2), \frac{1}{\sqrt{2}}(1-x^2) \right\}$.

Exercise 7.3E.7

b. $M_B(T) = \begin{bmatrix} A & 0 \\ 0 & A \end{bmatrix}$, so $c_T(x) = \det \begin{bmatrix} xI_2 - A & 0 \\ 0 & xI_2 - A \end{bmatrix} = [c_A(x)]^2$

Exercise 7.3E.12

(1) ⇒ (2). If $B = \{\mathbf{f}_1, \ldots, \mathbf{f}_n\}$ is an orthonormal basis of V, then $M_B(T) = [a_{ij}]$ where $a_{ij} = \langle \mathbf{f}_i, T(\mathbf{f}_j) \rangle$ by Theorem 10.3.2. If (1) holds, then $a_{ji} = \langle \mathbf{f}_j, T(\mathbf{f}_i) \rangle = -\langle T(\mathbf{f}_j), \mathbf{f}_i \rangle = -\langle \mathbf{f}_i, T(\mathbf{f}_j) \rangle = -a_{ij}$. Hence $[M_V(T)]^T = -M_V(T)$, proving (2).

Exercise 7.3E.14

c. The coefficients in the definition of $T'(\mathbf{f}_j) = \sum_{i=1}^n \langle \mathbf{f}_j, T(\mathbf{f}_i) \rangle \mathbf{f}_i$ are the entries in the j th column $C_B[T'(\mathbf{f}_j)]$ of $M_B(T')$. Hence $M_B(T') = [\langle \mathbf{f}_j, T(\mathbf{f}_j) \rangle]$, and this is the transpose of $M_B(T)$ by Theorem 10.3.2.

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7.4: ISOMETRIES

We saw in Section 2.6 that rotations about the origin and reflections in a line through the origin are linear operators on $\mathbb{R}^2$. Similar geometric arguments (in Section 4.4) establish that, in $\mathbb{R}^3$, rotations about a line through the origin and reflections in a plane through the origin are linear. We are going to give an algebraic proof of these results that is valid in any inner product space. The key observation is that reflections and rotations are distance preserving in the following sense. If V is an inner product space, a transformation $S : V \to V$ (not necessarily linear) is said to be **distance preserving** if the distance between $S(\mathbf{v})$ and $S(\mathbf{w})$ is the same as the distance between $\mathbf{v}$ and $\mathbf{w}$ for all vectors $\mathbf{v}$ and $\mathbf{w}$; more formally, if

$$\|S(\mathbf{v}) - S(\mathbf{w})\| = \|\mathbf{v} - \mathbf{w}\| \quad \text{for all } \mathbf{v} \text{ and } \mathbf{w} \text{ in } V \tag{7.4.1}$$

Distance-preserving maps need not be linear. For example, if $\mathbf{u}$ is any vector in V, the transformation $S_{\mathbf{u}} : V \to V$ defined by $S_{\mathbf{u}}(\mathbf{v}) = \mathbf{v} + \mathbf{u}$ for all $\mathbf{v}$ in V is called **translation** by $\mathbf{u}$, and it is routine to verify that $S_{\mathbf{u}}$ is distance preserving for any $\mathbf{u}$. However, $S_{\mathbf{u}}$ is linear only if $\mathbf{u} = 0$ (since then $S_{\mathbf{u}}(0) = 0$). Remarkably, distance-preserving operators that do fix the origin are necessarily linear.

Lemma 7.4.1

Let V be an inner product space of dimension n, and consider a distance-preserving transformation $S : V \to V$. If $S(\mathbf{0}) = \mathbf{0}$, then S is linear.

We have $\|S(\mathbf{v}) - S(\mathbf{w})\|^2 = \|\mathbf{v} - \mathbf{w}\|^2$ for all $\mathbf{v}$ and $\mathbf{w}$ in V by (7.4.1), which gives

$$\langle S(\mathbf{v}), S(\mathbf{w})\rangle = \langle \mathbf{v}, \mathbf{w}\rangle \quad \text{for all } \mathbf{v} \text{ and } \mathbf{w} \text{ in } V \tag{7.4.2}$$

Now let $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_n\}$ be an orthonormal basis of V. Then $\{S(\mathbf{f}_1), S(\mathbf{f}_2), \dots, S(\mathbf{f}_n)\}$ is orthonormal by (7.4.2) and so is a basis because $dim\mathbf{V} = n$. Now compute:

$$\begin{aligned}\langle S(\mathbf{v}+\mathbf{w}) - S(\mathbf{v}) - S(\mathbf{w}), S(\mathbf{f}_i)\rangle &= \langle S(\mathbf{v}+\mathbf{w}), S(\mathbf{f}_i)\rangle - \langle S(\mathbf{v}), S(\mathbf{f}_i)\rangle - \langle S(\mathbf{w}), S(\mathbf{f}_i)\rangle \\ &= \langle \mathbf{v}+\mathbf{w}, \mathbf{f}_i\rangle - \langle \mathbf{v}, \mathbf{f}_i\rangle - \langle \mathbf{w}, \mathbf{f}_i\rangle \\ &= 0\end{aligned}$$

for each i. It follows from the expansion theorem (Theorem 10.2.4) that $S(\mathbf{v} + \mathbf{w}) - S(\mathbf{v}) - S(\mathbf{w}) = 0$; that is, $S(\mathbf{v} + \mathbf{w}) = S(\mathbf{v}) + S(\mathbf{w})$. A similar argument shows that $S(a\mathbf{v}) = aS(\mathbf{v})$ holds for all a in $\mathbb{R}$ and $\mathbf{v}$ in V, so S is linear after all.

Definition: Isometries

Distance-preserving linear operators are called **isometries**.

It is routine to verify that the composite of two distance-preserving transformations is again distance preserving. In particular the composite of a translation and an isometry is distance preserving. Surprisingly, the converse is true.

Theorem 7.4.1

If V is a finite dimensional inner product space, then every distance-preserving transformation $S : V \to V$ is the composite of a translation and an isometry.

Proof

If $S : V \to V$ is distance preserving, write $S(\mathbf{0}) = \mathbf{u}$ and define $T : V \to V$ by $T(\mathbf{v}) = S(\mathbf{v}) - \mathbf{u}$ for all $\mathbf{v}$ in V. Then $\|T(\mathbf{v}) - T(\mathbf{w})\| = \|\mathbf{v} - \mathbf{w}\|$ for all vectors $\mathbf{v}$ and $\mathbf{w}$ in V as the reader can verify; that is, T is distance preserving. Clearly, $T(\mathbf{0}) = \mathbf{0}$, so it is an isometry by Lemma 10.4.1. Since

$$S(\mathbf{v}) = \mathbf{u} + T(\mathbf{v}) = (S_{\mathbf{u}} \circ T)(\mathbf{v}) \quad \text{for all } \mathbf{v} \text{ in } V$$

we have $S = S_{\mathbf{u}} \circ T$, and the theorem is proved.

In Theorem 10.4.1, $S = S_{\mathbf{u}} \circ T$ factors as the composite of an isometry T followed by a translation $S_{\mathbf{u}}$. More is true: this factorization is unique in that $\mathbf{u}$ and T are uniquely determined by S; and $\mathbf{w} \in V$ exists such that $S = T \circ S_{\mathbf{w}}$ is uniquely the composite of translation by $\mathbf{w}$ followed by the same isometry T (Exercise 10.4.12).

Theorem 10.4.1 focuses our attention on the isometries, and the next theorem shows that, while they preserve distance, they are characterized as those operators that preserve other properties.

Theorem 7.4.2

Let $T : V \to V$ be a linear operator on a finite dimensional inner product space V. The following conditions are equivalent:

1. T is an isometry. & (T preserves distance)
2. $\|T(\mathbf{v})\| = \|\mathbf{v}\|$ for all $\mathbf{v}$ in V. & (T preserves norms)
3. $\langle T(\mathbf{v}), T(\mathbf{w})\rangle = \langle \mathbf{v}, \mathbf{w}\rangle$ for all $\mathbf{v}$ and $\mathbf{w}$ in V. & (T preserves inner products)
4. If $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_n\}$ is an orthonormal basis of V, & & then $\{T(\mathbf{f}_1), T(\mathbf{f}_2), \dots, T(\mathbf{f}_n)\}$ is also an orthonormal basis. & (T preserves orthonormal bases)
5. T carries some orthonormal basis to an orthonormal basis.

Proof

1. $\Rightarrow$ (2). Take $\mathbf{w} = \mathbf{0}$ in (7.4.1).
2. $\Rightarrow$ (3). Since T is linear, (2) gives $\|T(\mathbf{v}) - T(\mathbf{w})\|^2 = \|T(\mathbf{v} - \mathbf{w})\|^2 = \|\mathbf{v} - \mathbf{w}\|^2$. Now (3) follows.
3. $\Rightarrow$ (4). By (3), $\{T(\mathbf{f}_1), T(\mathbf{f}_2), \dots, T(\mathbf{f}_n)\}$ is orthogonal and $\|T(\mathbf{f}_i)\|^2 = \|\mathbf{f}_i\|^2 = 1$. Hence it is a basis because $dim \mathbf{V} = n$.
4. $\Rightarrow$ (5). This needs no proof.
5. $\Rightarrow$ (1). By (5), let $\{\mathbf{f}_1, \dots, \mathbf{f}_n\}$ be an orthonormal basis of V such that$\{T(\mathbf{f}_1), \dots, T(\mathbf{f}_n)\}$ is also orthonormal. Given $\mathbf{v} = v_1\mathbf{f}_1 + \cdots + v_n\mathbf{f}_n$ in V, we have $T(\mathbf{v}) = v_1T(\mathbf{f}_1) + \cdots + v_nT(\mathbf{f}_n)$ so Pythagoras' theorem gives

$$\|T(\mathbf{v})\|^2 = v_1^2 + \cdots + v_n^2 = \|\mathbf{v}\|^2$$

Hence $\|T(\mathbf{v})\| = \|\mathbf{v}\|$ for all $\mathbf{v}$, and (1) follows by replacing $\mathbf{v}$ by $\mathbf{v} - \mathbf{w}$.

□

Before giving examples, we note some consequences of Theorem 10.4.2.

Corollary 7.4.1

Let V be a finite dimensional inner product space.

1. Every isometry of V is an isomorphism.
2. a. $1_V : V \to V$ is an isometry.
   b. The composite of two isometries of V is an isometry.
   c. The inverse of an isometry of V is an isometry.

Proof

(1) is by (4) of Theorem

□

The conditions in part (2) of the corollary assert that the set of isometries of a finite dimensional inner product space forms an algebraic system called a **group**. The theory of groups is well developed, and groups of operators are important in geometry. In fact, geometry itself can be fruitfully viewed as the study of those properties of a vector space that are preserved by a group of invertible linear operators.

Example 7.4.1

Rotations of $\mathbb{R}^2$ about the origin are isometries, as are reflections in lines through the origin: They clearly preserve distance and so are linear by Lemma 7.4.1. Similarly, rotations about lines through the origin and reflections in planes through the origin are isometries of $\mathbb{R}^3$.

Example 7.4.2

Let $T : \mathbf{M}_{nn} \to \mathbf{M}_{nn}$ be the transposition operator: $T(A) = A^T$. Then T is an isometry if the inner product is $\langle A, B\rangle = tr(\mathbf{AB^T}) = \sum_{i,j} a_{ij}b_{ij}$. In fact, T permutes the basis consisting of all matrices with one entry 1 and the other entries 0.

Let $T : \mathbf{M}_{nn} \to \mathbf{M}_{nn}$ be the transposition operator: $T(A) = A^T$. Then T is an isometry if the inner product is

$$\langle A, B\rangle = tr(\mathbf{AB^T}) = \sum_{i,j} a_{ij}b_{ij}.$$

In fact, T permutes the basis consisting of all matrices with one entry 1 and the other entries 0.

The proof of the next result requires the fact (see Theorem 10.4.2) that, if B is an orthonormal basis, then $\langle \mathbf{v}, \mathbf{w}\rangle = C_B(\mathbf{v}) \cdot C_B(\mathbf{w})$ for all vectors $\mathbf{v}$ and $\mathbf{w}$.

Theorem 7.4.3

Let $T : V \to V$ be an operator where V is a finite dimensional inner product space. The following conditions are equivalent.

1. T is an isometry.
2. $M_B(T)$ is an orthogonal matrix for every orthonormal basis B.
3. $M_B(T)$ is an orthogonal matrix for some orthonormal basis B.

Proof

(1) $\Rightarrow$ (2). Let $B = \{\mathbf{e}_1, \dots, \mathbf{e}_n\}$ be an orthonormal basis. Then the jth column of $M_B(T)$ is $C_B[T(\mathbf{e}_j)]$, and we have

$$C_B[T(\mathbf{e}_j)] \cdot C_B[T(\mathbf{e}_k)] = \langle T(\mathbf{e}_j), T(\mathbf{e}_k)\rangle = \langle \mathbf{e}_j, \mathbf{e}_k\rangle$$

using (1). Hence the columns of $M_B(T)$ are orthonormal in $\mathbb{R}^n$, which proves (2).

(2) $\Rightarrow$ (3). This is clear.

(3) $\Rightarrow$ (1). Let $B = \{\mathbf{e}_1, \dots, \mathbf{e}_n\}$ be as in (3). Then, as before,

$$\langle T(\mathbf{e}_j), T(\mathbf{e}_k)\rangle = C_B[T(\mathbf{e}_j)] \cdot C_B[T(\mathbf{e}_k)]$$

so $\{T(\mathbf{e}_1), \dots, T(\mathbf{e}_n)\}$ is orthonormal by (3). Hence Theorem 10.4.2 gives (1).

□

It is important that B is *orthonormal* in Theorem 10.4.3. For example, $T : V \to V$ given by $T(\mathbf{v}) = 2\mathbf{v}$ preserves *orthogonal* sets

but is not an isometry, as is easily checked.

If P is an orthogonal square matrix, then $P^{-1} = P^T$. Taking determinants yields $(\det P)^2 = 1$, so $\det P = \pm 1$. Hence:

Corollary 7.4.2

If $T : V \to V$ is an isometry where V is a finite dimensional inner product space, then $\det T = \pm 1$.

Example 7.4.3

If A is any $n \times n$ matrix, the matrix operator $T_A : \mathbb{R}^n \to \mathbb{R}^n$ is an isometry if and only if A is orthogonal using the dot product in $\mathbb{R}^n$. Indeed, if E is the standard basis of $\mathbb{R}^n$, then $M_E(T_A) = A$ by Theorem 9.2.4.

Rotations and reflections that fix the origin are isometries in $\mathbb{R}^2$ and $\mathbb{R}^3$ (Example 10.4.1); we are going to show that these isometries (and compositions of them in $\mathbb{R}^3$) are the only possibilities. In fact, this will follow from a general structure theorem for isometries. Surprisingly enough, much of the work involves the two–dimensional case.

Theorem 7.4.4

Let $T : V \to V$ be an isometry on the two-dimensional inner product space V. Then there are two possibilities.

Either There is an orthonormal basis B of V such that

$$M_B(T) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}, \ 0 \leq \theta < 2\pi$$

or There is an orthonormal basis B of V such that

$$M_B(T) = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

Furthermore, type (1) occurs if and only if $\det T = 1$, and type (2) occurs if and only if $\det T = -1$.

Proof

The final statement follows from the rest because $\det T = \det[M_B(T)]$ for any basis B. Let $B_0 = \{\mathbf{e}_1, \mathbf{e}_2\}$ be any ordered orthonormal basis of V and write

$$A = M_{B_0}(T) = \begin{bmatrix} a & b \\ c & d \end{bmatrix}; \text{ that is, } \begin{array}{l} T(\mathbf{e}_1) = a\mathbf{e}_1 + c\mathbf{e}_2 \\ T(\mathbf{e}_2) = b\mathbf{e}_1 + d\mathbf{e}_2 \end{array}$$

Then A is orthogonal by Theorem 10.4.3, so its columns (and rows) are orthonormal. Hence

$$a^2 + c^2 = 1 = b^2 + d^2$$

so (a, c) and (d, b) lie on the unit circle. Thus angles θ and φ exist such that

$$\begin{array}{llll} a = \cos\theta, & c = \sin\theta & 0 \leq \theta < 2\pi \\ d = \cos\varphi, & b = \sin\varphi & 0 \leq \varphi < 2\pi \end{array}$$

Then $\sin(\theta + \varphi) = cd + ab = 0$ because the columns of A are orthogonal, so $\theta + \varphi = k\pi$ for some integer k. This gives $d = \cos(k\pi - \theta) = (-1)^k \cos\theta$ and $b = \sin(k\pi - \theta) = (-1)^{k+1} \sin\theta$. Finally

$$A = \begin{bmatrix} \cos\theta & (-1)^{k+1}\sin\theta \\ \sin\theta & (-1)^k\cos\theta \end{bmatrix}$$

If k is even we are in type (1) with $B = B_0$, so assume k is odd. Then $A = \begin{bmatrix} a & c \\ c & -a \end{bmatrix}$. If $a = -1$ and $c = 0$, we are in type (1) with $B = \{\mathbf{e}_2, \mathbf{e}_2\}$. Otherwise A has eigenvalues $\lambda_1 = 1$ and $\lambda_2 = -1$ with corresponding eigenvectors $\mathbf{x}_1 = \begin{bmatrix} 1+a \\ c \end{bmatrix}$ and $\mathbf{x}_2 = \begin{bmatrix} -c \\ 1+a \end{bmatrix}$ as the reader can verify. Write

$$\mathbf{f}_1 = (1+a)\mathbf{e}_1 + c\mathbf{e}_2 \quad \text{and} \quad \mathbf{f}_2 = -c\mathbf{e}_2 + (1+a)\mathbf{e}_2$$

Then $\mathbf{f}_1$ and $\mathbf{f}_2$ are orthogonal (verify) and $C_{B_0}(\mathbf{f}_i) = C_{B_0}(\lambda_i\mathbf{f}_i) = \mathbf{x}_i$ for each i. Moreover

$$C_{B_0}[T(\mathbf{f}_i)] = AC_{B_0}(\mathbf{f}_i) = A\mathbf{x}_i = \lambda_i\mathbf{x}_i = \lambda_i C_{B_0}(\mathbf{f}_i) = C_{B_0}(\lambda_i\mathbf{f}_i)$$

so $T(\mathbf{f}_i) = \lambda_i\mathbf{f}_i$ for each i. Hence $M_B(T) = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$ and we are in type (2) with $B = \left\{\frac{1}{\|\mathbf{f}_1\|}\mathbf{f}_1, \frac{1}{\|\mathbf{f}_2\|}\mathbf{f}_2\right\}$.

□

Corollary 7.4.3

An operator $T : \mathbb{R}^2 \to \mathbb{R}^2$ is an isometry if and only if T is a rotation or a reflection.

In fact, if E is the standard basis of $\mathbb{R}^2$, then the clockwise rotation R_θ about the origin through an angle θ has matrix

$$M_E(R_\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$

(see Theorem 2.2.15). On the other hand, if $S : \mathbb{R}^2 \to \mathbb{R}^2$ is the reflection in a line through the origin (called the **fixed line** of the reflection), let $\mathbf{f}_1$ be a unit vector pointing along the fixed line and let $\mathbf{f}_2$ be a unit vector perpendicular to the fixed line. Then $B = \{\mathbf{f}_1, \mathbf{f}_2\}$ is an orthonormal basis, $S(\mathbf{f}_1) = \mathbf{f}_1$ and $S(\mathbf{f}_2) = -\mathbf{f}_2$, so

$$M_B(S) = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

Thus S is of type 2. Note that, in this case, 1 is an eigenvalue of S, and any eigenvector corresponding to 1 is a direction vector for the fixed line.

Example 7.4.4

In each case, determine whether $T_A : \mathbb{R}^2 \to \mathbb{R}^2$ is a rotation or a reflection, and then find the angle or fixed line:

$$\text{(a) } A = \frac{1}{2}\begin{bmatrix} 1 & \sqrt{3} \\ -\sqrt{3} & 1 \end{bmatrix} \qquad \text{(b) } A = \frac{1}{5}\begin{bmatrix} -3 & 4 \\ 4 & 3 \end{bmatrix}$$

Solution

Both matrices are orthogonal, so (because $M_E(T_A) = A$, where E is the standard basis) T_A is an isometry in both cases. In the first case, $\det A = 1$, so T_A is a counterclockwise rotation through θ, where $\cos\theta = \frac{1}{2}$ and $\sin\theta = -\frac{\sqrt{3}}{2}$. Thus $\theta = -\frac{\pi}{3}$. In (b), $\det A = -1$, so T_A is a reflection in this case. We verify that $\mathbf{d} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ is an eigenvector corresponding to the eigenvalue 1. Hence the fixed line $\mathbb{R}\mathbf{d}$ has equation $y = 2x$.

We now give a structure theorem for isometries. The proof requires three preliminary results, each of interest in its own right.

Lemma 7.4.2

Let $T : V \to V$ be an isometry of a finite dimensional inner product space V. If U is a T-invariant subspace of V, then $U^\perp$ is also T-invariant.

Proof

Let $\mathbf{w}$ lie in $U^\perp$. We are to prove that $T(\mathbf{w})$ is also in $U^\perp$; that is, $\langle T(\mathbf{w}), \mathbf{u}\rangle = 0$ for all $\mathbf{u}$ in U. At this point, observe that the restriction of T to U is an isometry $U \to U$ and so is an isomorphism by the corollary to Theorem 10.4.2. In particular, each $\mathbf{u}$ in U can be written in the form $\mathbf{u} = T(\mathbf{u}_1)$ for some $\mathbf{u}_1$ in U, so

$$\langle T(\mathbf{w}), \mathbf{u}\rangle = \langle T(\mathbf{w}), T(\mathbf{u}_1)\rangle = \langle \mathbf{w}, \mathbf{u}_1\rangle = 0$$

because $\mathbf{w}$ is in $U^\perp$. This is what we wanted.

□

To employ Lemma 10.4.2 above to analyze an isometry $T : V \to V$ when $dim\mathbf{V} = n$, it is necessary to show that a T-invariant subspace U exists such that $U \neq 0$ and $U \neq V$. We will show, in fact, that such a subspace U can always be found of dimension 1 or 2. If T has a real eigenvalue λ then $\mathbb{R}\mathbf{u}$ is T-invariant where $\mathbf{u}$ is any λ-eigenvector. But, in case (1) of Theorem 10.4.4, the eigenvalues of T are $e^{i\theta}$ and $e^{-i\theta}$ (the reader should check this), and these are nonreal if $\theta \neq 0$ and $\theta \neq \pi$. It turns out that every complex eigenvalue λ of T has absolute value 1 (Lemma 10.4.3 below); and that U has a T-invariant subspace of dimension 2 if λ is not real (Lemma 10.4.4).

Lemma 7.4.3

Let $T : V \to V$ be an isometry of the finite dimensional inner product space V. If λ is a complex eigenvalue of T, then $|\lambda| = 1$.

Proof

Choose an orthonormal basis B of V, and let $A = M_B(T)$. Then A is a real orthogonal matrix so, using the standard inner product $\langle \mathbf{x}, \mathbf{y}\rangle = \mathbf{x}^T\overline{\mathbf{y}}$ in $\mathbb{C}$, we get

$$\|A\mathbf{x}\|^2 = (A\mathbf{x})^T(\overline{A\mathbf{x}}) = \mathbf{x}^T A^T\overline{A\mathbf{x}} = \mathbf{x}^T I\mathbf{x} = \|\mathbf{x}\|^2$$

for all $\mathbf{x}$ in $\mathbb{C}^n$. But $A\mathbf{x} = \lambda\mathbf{x}$ for some $\mathbf{x} \neq \mathbf{0}$, whence $\|\mathbf{x}\|^2 = \|\lambda\mathbf{x}\|^2 = |\lambda|^2\|\mathbf{x}\|^2$. This gives $|\lambda| = 1$, as required.

□

Lemma 7.4.4

Let $T : V \to V$ be an isometry of the n-dimensional inner product space V. If T has a nonreal eigenvalue, then V has a two-dimensional T-invariant subspace.

Proof

Let B be an orthonormal basis of V, let $A = M_B(T)$, and (using Lemma 10.4.3) let $\lambda = e^{i\alpha}$ be a nonreal eigenvalue of A, say $A\mathbf{x} = \lambda\mathbf{x}$ where $\mathbf{x} \neq \mathbf{0}$ in $\mathbb{C}^n$. Because A is real, complex conjugation gives $A\overline{\mathbf{x}} = \overline{\lambda}\overline{\mathbf{x}}$, so $\overline{\lambda}$ is also an eigenvalue. Moreover $\lambda \neq \overline{\lambda}$ (λ is nonreal), so $\{\mathbf{x}, \overline{\mathbf{x}}\}$ is linearly independent in $\mathbb{C}^n$ (the argument in the proof of Theorem 5.5.4 works). Now define

$$\mathbf{z}_1 = \mathbf{x} + \overline{\mathbf{x}} \quad \text{and} \quad \mathbf{z}_2 = i(\mathbf{x} - \overline{\mathbf{x}})$$

Then $\mathbf{z}_1$ and $\mathbf{z}_2$ lie in $\mathbb{R}^n$, and $\{\mathbf{z}_1, \mathbf{z}_2\}$ is linearly independent over $\mathbb{R}$ because $\{\mathbf{x}, \overline{\mathbf{x}}\}$ is linearly independent over $\mathbb{C}$. Moreover

$$\mathbf{x} = \frac{1}{2}(\mathbf{z}_1 - i\mathbf{z}_2) \quad \text{and} \quad \overline{\mathbf{x}} = \frac{1}{2}(\mathbf{z}_1 + i\mathbf{z}_2)$$

Now $\lambda + \overline{\lambda} = 2\cos\alpha$ and $\lambda - \overline{\lambda} = 2i\sin\alpha$, and a routine computation gives

$$\begin{aligned} A\mathbf{z}_1 &= \mathbf{z}_1 \cos\alpha + \mathbf{z}_2 \sin\alpha \\ A\mathbf{z}_2 &= -\mathbf{z}_1 \sin\alpha + \mathbf{z}_2 \cos\alpha \end{aligned}$$

Finally, let $\mathbf{e}_1$ and $\mathbf{e}_2$ in V be such that $\mathbf{z}_1 = C_B(\mathbf{e}_1)$ and $\mathbf{z}_2 = C_B(\mathbf{e}_2)$. Then

$$C_B[T(\mathbf{e}_1)] = AC_B(\mathbf{e}_1) = A\mathbf{z}_1 = C_B(\mathbf{e}_1 \cos\alpha + \mathbf{e}_2 \sin\alpha)$$

using Theorem 9.1.2. Because C_B is one-to-one, this gives the first of the following equations (the other is similar):

$$\begin{aligned} T(\mathbf{e}_1) &= \mathbf{e}_1 \cos\alpha + \mathbf{e}_2 \sin\alpha \\ T(\mathbf{e}_2) &= -\mathbf{e}_1 \sin\alpha + \mathbf{e}_2 \cos\alpha \end{aligned}$$

Thus $U = span\{\mathbf{e}_1, \mathbf{e}_2\}$ is T-invariant and two-dimensional.

□

We can now prove the structure theorem for isometries.

Theorem 7.4.5

Let $T : V \to V$ be an isometry of the n-dimensional inner product space V. Given an angle θ, write $R(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$. Then there exists an orthonormal basis B of V such that $M_B(T)$ has one of the following block diagonal forms, classified for convenience by whether n is odd or even:

$$n = 2k+1 \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & R(\theta_1) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & R(\theta_k) \end{bmatrix} \quad \text{or} \quad \begin{bmatrix} -1 & 0 & \cdots & 0 \\ 0 & R(\theta_1) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & R(\theta_k) \end{bmatrix}$$

$$n = 2k \begin{bmatrix} R(\theta_1) & 0 & \cdots & 0 \\ 0 & R(\theta_2) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & R(\theta_k) \end{bmatrix} \quad \text{or} \quad \begin{bmatrix} -1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & R(\theta_1) & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & R(\theta_{k-1}) \end{bmatrix}$$

Proof

We show first, by induction on n, that an orthonormal basis B of V can be found such that $M_B(T)$ is a block diagonal matrix of the following form:

$$M_B(T) = \begin{bmatrix} I_r & 0 & 0 & \cdots & 0 \\ 0 & -I_s & 0 & \cdots & 0 \\ 0 & 0 & R(\theta_1) & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & R(\theta_t) \end{bmatrix}$$

where the identity matrix I_r, the matrix $-I_s$, or the matrices $R(\theta_i)$ may be missing. If $n = 1$ and $V = \mathbb{R}\mathbf{v}$, this holds because $T(\mathbf{v}) = \lambda\mathbf{v}$ and $\lambda = \pm 1$ by Lemma 10.4.3. If $n = 2$, this follows from Theorem 10.4.4. If $n \geq 3$, either T has a real eigenvalue and therefore has a one-dimensional T-invariant subspace $U = \mathbb{R}\mathbf{u}$ for any eigenvector $\mathbf{u}$, or T has no real eigenvalue and therefore has a two-dimensional T-invariant subspace U by Lemma 10.4.4. In either case $U^\perp$ is T-invariant (Lemma 10.4.2) and $dim\mathbf{U}^\perp = n - dim\mathbf{U} < n$. Hence, by induction, let B_1 and B_2 be orthonormal bases of U and $U^\perp$ such that $M_{B_1}(T)$ and $M_{B_2}(T)$ have the form given. Then $B = B_1 \cup B_2$ is an orthonormal basis of V, and $M_B(T)$ has the desired form with a suitable ordering of the vectors in B.

□

Now observe that $R(0) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ and $R(\pi) = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}$. It follows that an even number of 1s or -1s can be written as $R(\theta_1)$ -blocks. Hence, with a suitable reordering of the basis B, the theorem follows.

As in the dimension 2 situation, these possibilities can be given a geometric interpretation when $V = \mathbb{R}^3$ is taken as euclidean space. As before, this entails looking carefully at reflections and rotations in $\mathbb{R}^3$. If $Q : \mathbb{R}^3 \to \mathbb{R}^3$ is any reflection in a plane through the origin (called the **fixed plane** of the reflection), take $\{\mathbf{f}_2, \mathbf{f}_3\}$ to be any orthonormal basis of the fixed plane and take $\mathbf{f}_1$ to be a unit vector perpendicular to the fixed plane. Then $Q(\mathbf{f}_1) = -\mathbf{f}_1$, whereas $Q(\mathbf{f}_2) = \mathbf{f}_2$ and $Q(\mathbf{f}_3) = \mathbf{f}_3$. Hence $B = \{\mathbf{f}_1, \mathbf{f}_2, \mathbf{f}_3\}$ is an orthonormal basis such that

$$M_B(Q) = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Similarly, suppose that $R : \mathbb{R}^3 \to \mathbb{R}^3$ is any rotation about a line through the origin (called the **axis** of the rotation), and let $\mathbf{f}_1$ be a unit vector pointing along the axis, so $R(\mathbf{f}_1) = \mathbf{f}_1$. Now the plane through the origin perpendicular to the axis is an R -invariant subspace of $\mathbb{R}^2$ of dimension 2, and the restriction of R to this plane is a rotation. Hence, by Theorem 10.4.4, there is an orthonormal basis $B_1 = \{\mathbf{f}_2, \mathbf{f}_3\}$ of this plane such that $M_{B_1}(R) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$. But then $B = \{\mathbf{f}_1, \mathbf{f}_2, \mathbf{f}_3\}$ is an orthonormal basis of $\mathbb{R}^3$ such that the matrix of R is

$$M_B(R) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{bmatrix}$$

However, Theorem 10.4.5 shows that there are isometries T in $\mathbb{R}^3$ of a third type: those with a matrix of the form

$$M_B(T) = \begin{bmatrix} -1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{bmatrix}$$

If $B = \{\mathbf{f}_1, \mathbf{f}_2, \mathbf{f}_3\}$, let Q be the reflection in the plane spanned by $\mathbf{f}_2$ and $\mathbf{f}_3$, and let R be the rotation corresponding to θ about the line spanned by $\mathbf{f}_1$. Then $M_B(Q)$ and $M_B(R)$ are as above, and $M_B(Q)M_B(R) = M_B(T)$ as the reader can verify. This means that $M_B(QR) = M_B(T)$ by Theorem 9.2.1, and this in turn implies that $QR = T$ because M_B is one-to-one (see Exercise 9.1.26). A similar argument shows that $RQ = T$, and we have Theorem 10.4.6.

Theorem 7.4.6

If $T : \mathbb{R}^3 \to \mathbb{R}^3$ is an isometry, there are three possibilities.

1. T is a rotation, and $M_B(T) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{bmatrix}$ for some orthonormal basis B.
2. T is a reflection, and $M_B(T) = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ for some orthonormal basis B.

3. $T = QR = RQ$ where Q is a reflection, R is a rotation about an axis perpendicular to the fixed plane of Q and $M_B(T)$ $= \begin{bmatrix} -1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{bmatrix}$ for some orthonormal basis B.

Hence T is a rotation if and only if $\det T = 1$.

Proof

It remains only to verify the final observation that T is a rotation if and only if $\det T = 1$. But clearly $\det T = -1$ in parts (b) and (c).

□

A useful way of analyzing a given isometry $T : \mathbb{R}^3 \to \mathbb{R}^3$ comes from computing the eigenvalues of T. Because the characteristic polynomial of T has degree 3, it must have a real root. Hence, there must be at least one real eigenvalue, and the only possible real eigenvalues are ± 1 by Lemma $7.4.3$. Thus Table ({7{.}4{.}\eatSpaces{1} \endSpaces}\)includes all possibilities.

Table 10.4.1

Eigenvalues of T	Action of T
(1) 1 , no other real eigenvalues	Rotation about the line $\mathbb{R}\mathbf{f}$ where $\mathbf{f}$ is an eigenvector corresponding to 1. [Case (a) of Theorem ({7{.}4{.}\eatSpaces{6} \endSpaces}\).]
(2) -1 , no other real eigenvalues	Rotation about the line $\mathbb{R}\mathbf{f}$ followed by reflection in the plane $(\mathbb{R})^{\perp}$ where $\mathbf{f}$ is an eigenvector corresponding to -1 . [Case (c) of Theorem ({7{.}4{.}\eatSpaces{6} \endSpaces}\).]
(3) -1,1,1	Reflection in the plane $(\mathbb{R}\mathbf{f})^{\perp}$ where $\mathbf{f}$ is an eigenvector corresponding to -1 . [Case (b) of Theorem ({7{.}4{.}\eatSpaces{6} \endSpaces}\).]
(4) 1,-1,-1	This is as in (1) with a rotation of π.
(5) -1,-1,-1	Here T(x) = -x for all x. This is (2) with a rotation of π.
(6) 1,1,1	Here T is the identity isometry.

Example 7.4.5

Analyze the isometry $T : \mathbb{R}^3 \to \mathbb{R}^3$ given by $T \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} y \\ z \\ -x \end{bmatrix}$.

Solution

If B_0 is the standard basis of $\mathbb{R}^3$, then $M_{B_0}(T) = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -1 & 0 & 0 \end{bmatrix}$, so $c_T(x) = x^3 + 1 = (x+1)(x^2 - x + 1)$. This is (2) in Table 10.4.1. Write:

$$\mathbf{f}_1 = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} \quad \mathbf{f}_2 = \frac{1}{\sqrt{6}} \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \quad \mathbf{f}_3 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}$$

Here $\mathbf{f}_1$ is a unit eigenvector corresponding to $\lambda_1 = -1$, so T is a rotation (through an angle θ) about the line $L = \mathbb{R}\mathbf{f}_1$, followed by reflection in the plane U through the origin perpendicular to $\mathbf{f}_1$ (with equation $x - y + z = 0$). Then, $\{\mathbf{f}_1, \mathbf{f}_2\}$ is chosen as an orthonormal basis of U, so $B = \{\mathbf{f}_1, \mathbf{f}_2, \mathbf{f}_3\}$ is an orthonormal basis of $\mathbb{R}^3$ and

$$M_B(T) = \begin{bmatrix} -1 & 0 & 0 \\ 0 & \frac{1}{2} & -\frac{\sqrt{3}}{2} \\ 0 & \frac{\sqrt{3}}{2} & \frac{1}{2} \end{bmatrix}$$

Hence θ is given by $\cos\theta = \frac{1}{2}, \sin\theta = \frac{\sqrt{3}}{2}$, so $\theta = \frac{\pi}{3}$.

Let V be an n-dimensional inner product space. A subspace of V of dimension $n-1$ is called a **hyperplane** in V. Thus the hyperplanes in $\mathbb{R}^3$ and $\mathbb{R}^2$ are, respectively, the planes and lines through the origin. Let $Q : V \to V$ be an isometry with matrix

$$M_B(Q) = \begin{bmatrix} -1 & 0 \\ 0 & I_{n-1} \end{bmatrix}$$

for some orthonormal basis $B = \{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_n\}$. Then $Q(\mathbf{f}_1) = -\mathbf{f}_1$ whereas $Q(\mathbf{u}) = \mathbf{u}$ for each $\mathbf{u}$ in $U = span\{\mathbf{f}_2, \ldots, \mathbf{f}_n\}$. Hence U is called the **fixed hyperplane** of Q, and Q is called **reflection** in U. Note that each hyperplane in V is the fixed hyperplane of a (unique) reflection of V. Clearly, reflections in $\mathbb{R}^2$ and $\mathbb{R}^3$ are reflections in this more general sense.

Continuing the analogy with $\mathbb{R}^2$ and $\mathbb{R}^3$, an isometry $T : V \to V$ is called a **rotation** if there exists an orthonormal basis $\{\mathbf{f}_1, \ldots, \mathbf{f}_n\}$ such that

$$M_B(T) = \begin{bmatrix} I_r & 0 & 0 \\ 0 & R(\theta) & 0 \\ 0 & 0 & I_s \end{bmatrix}$$

in block form, where $R(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$, and where either I_r or I_s (or both) may be missing. If $R(\theta)$ occupies columns i and $i+1$ of $M_B(T)$, and if $W = span\{\mathbf{f}_i, \mathbf{f}_{i+1}\}$, then W is T-invariant and the matrix of $T : W \to W$ with respect to $\{\mathbf{f}_i, \mathbf{f}_{i+1}\}$ is $R(\theta)$. Clearly, if W is viewed as a copy of $\mathbb{R}^2$, then T is a rotation in W. Moreover, $T(\mathbf{u}) = \mathbf{u}$ holds for all vectors $\mathbf{u}$ in the $(n-2)$-dimensional subspace $U = span\{\mathbf{f}_1, \ldots, \mathbf{f}_{i-1}, \mathbf{f}_{i+1}, \ldots, \mathbf{f}_n\}$, and U is called the **fixed axis** of the rotation T. In $\mathbb{R}^3$, the axis of any rotation is a line (one-dimensional), whereas in $\mathbb{R}^2$ the axis is $U = \{\mathbf{0}\}$.

With these definitions, the following theorem is an immediate consequence of Theorem 10.4.5 (the details are left to the reader).

Theorem 7.4.7

Let $T : V \to V$ be an isometry of a finite dimensional inner product space V. Then there exist isometries $T_1, \ldots, T$ such that

$$T = T_k T_{k-1} \cdots T_2 T_1$$

where each T_i is either a rotation or a reflection, at most one is a reflection, and $T_i T_j = T_j T_i$ holds for all i and j. Furthermore, T is a composite of rotations if and only if $\det T = 1$.

7.4E: Isometries Exercises

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7.4E: Isometries Exercises

Throughout these exercises, V denotes a finite dimensional inner product space.

Example 7.4E.1

Exercise 10.4.1 Show that the following linear operators are isometries.

a. $T : \mathbb{C} \to \mathbb{C}; T(z) = \bar{z}; \langle z, w \rangle = \text{re}(z\overline{w})$
b. $T : \mathbb{R}^n \to \mathbb{R}^n; \quad T(a_1, a_2, \ldots, a_n) = (a_n, a_{n-1}, \ldots, a_2, a_1)$; dot product
c. $T : \mathbf{M}_{22} \to \mathbf{M}_{22}; T \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} c & d \\ b & a \end{bmatrix}; \langle A, B \rangle = \text{tr}\,(AB^T)$
d. $T : \mathbb{R}^3 \to \mathbb{R}^3; T(a, b, c) = \frac{1}{9}(2a + 2b - c, 2a + 2c - b, 2b + 2c - a)$; dot product

Example 7.4E.2

Exercise 10.4.2 In each case, show that T is an isometry of $\mathbb{R}^2$, determine whether it is a rotation or a reflection, and find the angle or the fixed line. Use the dot product.

a. $T \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} -a \\ b \end{bmatrix}$
b. $T \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} -a \\ -b \end{bmatrix}$
c. $T \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} b \\ -a \end{bmatrix}$
d. $T \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} -b \\ -a \end{bmatrix}$
e. $T \begin{bmatrix} a \\ b \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} a + b \\ b - a \end{bmatrix}$
f. $T \begin{bmatrix} a \\ b \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} a - b \\ a + b \end{bmatrix}$

Answer available at the end of this section.

Example 7.4E.3

In each case, show that T is an isometry of $\mathbb{R}^3$, determine the type (Theorem 10.4.6), and find the axis of any rotations and the fixed plane of any reflections involved.

a. $T \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} a \\ -b \\ c \end{bmatrix}$
b. $T \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \frac{1}{2} \begin{bmatrix} \sqrt{3}c - a \\ \sqrt{3}a + c \\ 2b \end{bmatrix}$
c. $T \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} b \\ c \\ a \end{bmatrix}$

d. $T\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} a \\ -b \\ -c \end{bmatrix}$

e. $T\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \frac{1}{2}\begin{bmatrix} a+\sqrt{3}b \\ b-\sqrt{3}a \\ 2c \end{bmatrix}$

f. $T\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix} a+c \\ -\sqrt{2}b \\ c-a \end{bmatrix}$

Answer available at the end of this section.

Example 7.4E.4

Let $T : \mathbb{R}^2 \to \mathbb{R}^2$ be an isometry. A vector $\mathbf{x}$ in $\mathbb{R}^2$ is said to be **fixed** by T if $T(\mathbf{x}) = \mathbf{x}$. Let E_1 denote the set of all vectors in $\mathbb{R}^2$ fixed by T. Show that:

a. E_1 is a subspace of $\mathbb{R}^2$.
b. $E_1 = \mathbb{R}^2$ if and only if $T = 1$ is the identity map.
c. $\dim\ \mathbf{E}_1 = 1$ if and only if T is a reflection (about the line E_1).
d. $E_1 = \{0\}$ if and only if T is a rotation ($T \neq 1$)

Example 7.4E.5

Let $T : \mathbb{R}^3 \to \mathbb{R}^3$ be an isometry, and let E_1 be the subspace of all fixed vectors in $\mathbb{R}^3$ (see Exercise 7.4E.4). Show that:

a. $E_1 = \mathbb{R}^3$ if and only if $T = 1$.
b. $\dim\ \mathbf{E}_1 = 2$ if and only if T is a reflection (about the plane E_1).
c. $\dim\ \mathbf{E}_1 = 1$ if and only if T is a rotation ($T \neq 1$) (about the line E_1).
d. $\dim\ \mathbf{E}_1 = 0$ if and only if T is a reflection followed by a (nonidentity) rotation.

Example 7.4E.6

If T is an isometry, show that aT is an isometry if and only if $a = \pm 1$

Answer available at the end of this section.

Example 7.4E.7

Show that every isometry preserves the angle between any pair of nonzero vectors (see Exercise 31 Section 10.1). Must an angle preserving isomorphism be an isometry? Support your answer.

Example 7.4E.8

If $T : V \to V$ is an isometry, show that $T^2 = 1_V$ if and only if the only complex eigenvalues of T are 1 and -1 .

Example 7.4E.9

Let $T : V \to V$ be a linear operator. Show that any two of the following conditions implies the third:

a. T is symmetric.
b. T is an involution ($T^2 = 1_V$).
c. [*Hint*: In all cases, use the definition $\langle \mathbf{v}, T(\mathbf{w})\rangle = \langle T(\mathbf{v}), \mathbf{w}\rangle$ of a symmetric operator. For (1) and (3) $\Rightarrow$ (2), use the fact that, if $\langle T^2(\mathbf{v}) - \mathbf{v}, \mathbf{w}\rangle = 0$ for all $\mathbf{w}$, then $T^2(\mathbf{v}) = \mathbf{v}$.]

Example $7.4E.10$

AIf B and D are any orthonormal bases of V, show that there is an isometry $T : V \to V$ that carries B to D.

Example $7.4E.11$

Show that the following are equivalent for a linear transformation $S : V \to V$ where V is finite dimensional and $S \neq 0$:

a. $\langle S(\mathbf{v}), S(\mathbf{w})\rangle = 0$ whenever $\langle \mathbf{v}, \mathbf{w}\rangle = 0$;
b. $S = aT$ for some isometry $T : V \to V$ and some $a \neq 0$ in $\mathbb{R}$.
c. [*Hint*: Given (1), show that $\|S(\mathbf{e})\| = \|S(\mathbf{f})\|$ for all unit vectors $\mathbf{e}$ and $\mathbf{f}$ in V.]

Example $7.4E.12$

Let $S : V \to V$ be a distance preserving transformation where V is finite dimensional.

a. Show that the factorization in the proof of Theorem $7.4E.1$ is unique. That is, if $S = S_{\mathbf{u}} \circ T$ and $S = S_{\mathbf{u}'} \circ T'$ where $\mathbf{u}$, $\mathbf{u}' \in V$ and T, $T' : V \to V$ are isometries, show that $\mathbf{u} = \mathbf{u}'$ and $T = T'$.
b. If $S = S_{\mathbf{u}} \circ T$, $\mathbf{u} \in V$, T an isometry, show that $\mathbf{w} \in V$ exists such that $S = T \circ S_{\mathbf{w}}$.

Answer available at the end of this section.

Example $7.4E.13$

Define $T : \mathbf{P} \to \mathbf{P}$ by $T(f) = xf(x)$ for all $f \in \mathbf{P}$, and define an inner product on $\mathbf{P}$ as follows: If $f = a_0 + a_1x + a_2x^2 + \cdots$ and $g = b_0 + b_1x + b_2x^2 + \cdots$ are in $\mathbf{P}$, define $\langle f, g\rangle = a_0b_0 + a_1b_1 + a_2b_2 + \cdots$.

a. Show that $\langle\ ,\rangle$ is an inner product on $\mathbf{P}$.
b. Show that T is an isometry of $\mathbf{P}$.
c. Show that T is one-to-one but not onto.

Answers

Example $7.4E.2$

b. Rotation through π
d. Reflection in the line $y = -x$
f. Rotation through $\frac{\pi}{4}$

Example $7.4E.3$

b. $c_T(x) = (x-1)\left(x^2 + \frac{3}{2}x + 1\right)$. If $\mathbf{e} = \left[\begin{array}{cc} 1 & \sqrt{3} \end{array}\ \begin{array}{c} \sqrt{3} \end{array}\right]^T$, then T is a rotation about $\mathbb{R}\mathbf{e}$.\)
d. $c_T(x) = (x+1)(x+1)^2$. Rotation (of π) about the x axis.\)
f. $c_T(x) = (x+1)\left(x^2 - \sqrt{2}x + 1\right)$. Rotation (of $-\frac{\pi}{4}$) about the y axis followed by a reflection in the $x - z$ plane.\)

Example $7.4E.6$

If $\|\mathbf{v}\| = \|(aT)(\mathbf{v})\| = |a|\|T(\mathbf{v})\| = |a|\|\mathbf{v}\|$ for some $\mathbf{v} \neq \mathbf{0}$, then $|a| = 1$ so $a = \pm 1$.

Example $7.4E.12$

b. Assume that $S = S_{\mathbf{u}} \circ T, \mathbf{u} \in V, T$ an isometry of V. Since T is onto (by Theorem 10.4.2), let $\mathbf{u} = T(\mathbf{w})$ where $\mathbf{w} \in V$. Then for any $\mathbf{v} \in V$, we have $(T \circ S_{\mathbf{w}})(\mathbf{v}) = T(\mathbf{w} + \mathbf{v}) = T(\mathbf{w}) + T(\mathbf{w}) = S_{T(\mathbf{w})}(T(\mathbf{v})) = (S_{T(\mathbf{w})} \circ T)(\mathbf{v})$, and it follows that $T \circ S_{\mathbf{w}} = S_{T(\mathbf{w})} \circ T$.

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7.5: AN APPLICATION TO FOURIER APPROXIMATION

If U is an orthogonal basis of a vector space V, the expansion theorem (Theorem 10.2.4) presents a vector $v \in V$ as a linear combination of the vectors in U. Of course this requires that the set U is finite since otherwise the linear combination is an infinite sum and makes no sense in V.

However, given an infinite orthogonal set $U = \{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_n, \ldots\}$, we can use the expansion theorem for $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_n\}$ for each n to get a series of "approximations" $\mathbf{v}_n$ for a given vector $\mathbf{v}$. A natural question is whether these $\mathbf{v}_n$ are getting closer and closer to $\mathbf{v}$ as n increases. This turns out to be a very fruitful idea.

In this section we shall investigate an important orthogonal set in the space $\mathbf{C}[-\pi, \pi]$ of continuous functions on the interval $[-\pi, \pi]$, using the inner product.

$$\langle f, g \rangle = \int_{-\pi}^{\pi} f(x)g(x)dx$$

Of course, calculus will be needed. The orthogonal set in question is

$$\{1, \sin x, \cos x, \sin(2x), \cos(2x), \sin(3x), \cos(3x), \ldots\}$$

Standard techniques of integration give

$$\begin{aligned} \|1\|^2 &= \int_{-\pi}^{\pi} 1^2 dx = 2\pi \\ \|\sin\ kx\|^2 &= \int_{-\pi}^{\pi} \sin^2(kx)dx = \pi \quad \text{for any } k = 1, 2, 3, \ldots \\ \|\cos\ kx\|^2 &= \int_{-\pi}^{\pi} \cos^2(kx)dx = \pi \quad \text{for any } k = 1, 2, 3, \ldots \end{aligned}$$

We leave the verifications to the reader, together with the task of showing that these functions are orthogonal:

$$\langle \sin(kx), \sin(mx) \rangle = 0 = \langle \cos(kx), \cos(mx) \rangle \quad \text{if } k \neq m$$

and

$$\langle \sin(kx), \cos(mx) \rangle = 0 \quad \text{for all } k \geq 0 \text{ and } m \geq 0$$

(Note that $1 = \cos(0x)$, so the constant function 1 is included.)

Now define the following subspace of $\mathbf{C}[-\pi, \pi]$:

$$F_n = span\ \{1, \sin x, \cos x, \sin(2x), \cos(2x), \ldots, \sin(nx), \cos(nx)\}$$

The aim is to use the approximation theorem (Theorem 10.2.8); so, given a function f in $\mathbf{C}[-\pi, \pi]$, define the **Fourier coefficients** of f by

$$\begin{aligned} a_0 &= \frac{\langle f(x), 1 \rangle}{\|1\|^2} = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(x)dx \\ a_k &= \frac{\langle f(x), \cos(kx) \rangle}{\|\cos(kx)\|^2} = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x)\cos(kx)dx \quad k = 1, 2, \ldots \\ b_k &= \frac{\langle f(x), \sin(kx) \rangle}{\|\sin(kx)\|^2} = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x)\sin(kx)dx \quad k = 1, 2, \ldots \end{aligned}$$

Then the approximation theorem (Theorem 10.2.8) gives Theorem 10.5.1.

Theorem 7.5.1

Let f be any continuous real-valued function defined on the interval $[-\pi, \pi]$. If a_0, a_1, ..., and b_0, b_1, ... are the Fourier coefficients of f, then given $n \geq 0$,

$$f_n(x) = a_0 + a_1 \cos x + b_1 \sin x + a_2 \cos(2x) + b_2 \sin(2x) + \cdots + a_n \cos(nx) + b_n \sin(nx)$$

is a function in F_n that is closest to f in the sense that

$$\|f - f_n\| \leq \|f - g\|$$

holds for all functions g in F_n.

The function f_n is called the nth **Fourier approximation** to the function f.

Example 7.5.1

Find the fifth Fourier approximation to the function $f(x)$ defined on $[-\pi, \pi]$ as follows:

$$f(x) = \begin{cases} \pi + x & \text{if } -\pi \leq x < 0 \\ \pi - x & \text{if } 0 \leq x \leq \pi \end{cases}$$

Solution

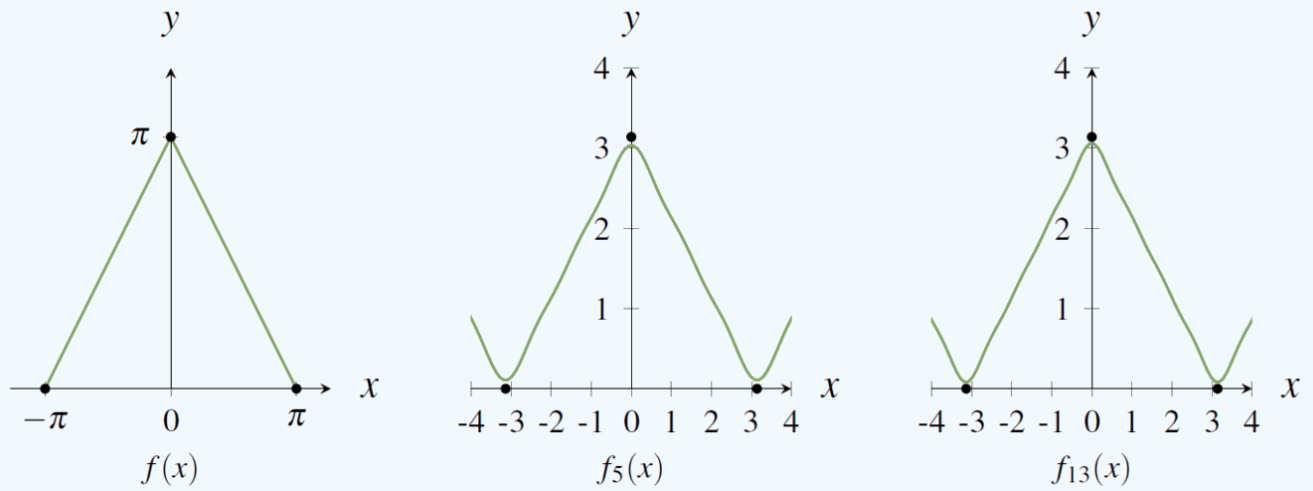
The graph of $y = f(x)$ appears in the top diagram. The Fourier coefficients are computed as follows. The details of the integrations (usually by parts) are omitted.

$$a_0 = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(x)dx = \frac{\pi}{2}$$
$$a_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos(kx)dx = \frac{2}{\pi k^2}[1 - \cos(k\pi)] = \begin{cases} 0 & \text{if } k \text{ is even} \\ \frac{4}{\pi k^2} & \text{if } k \text{ is odd} \end{cases}$$
$$b_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin(kx)dx = 0 \quad \text{for all } k = 1, 2, ...$$

Hence the fifth Fourier approximation is

$$f_5(x) = \frac{\pi}{2} + \frac{4}{\pi} \left\{ \cos x + \frac{1}{3^2} \cos(3x) + \frac{1}{5^2} \cos(5x) \right\}$$

This is plotted in the middle diagram and is already a reasonable approximation to $f(x)$. By comparison, $f_{13}(x)$ is also plotted and the difference is barely noticeable.



We say that a function f is an **even function** if $f(x) = f(-x)$ holds for all x; f is called an **odd function** if $f(-x) = -f(x)$ holds for all x. Examples of even functions are constant functions, the even powers x^2, x^4, ..., and $\cos(kx)$; these functions are characterized by the fact that the graph of $y = f(x)$ is symmetric about the y axis. Examples of odd functions are the odd powers x, x^3, ..., and $\sin(kx)$ where $k > 0$, and the graph of $y = f(x)$ is symmetric about the origin if f is odd. The usefulness of these functions stems from the fact that

$$\begin{array}{ll} \int_{-\pi}^{\pi} f(x)dx = 0 & \text{if } f \text{ is odd} \\ \int_{-\pi}^{\pi} f(x)dx = 2\int_{0}^{\pi} f(x)dx & \text{if } f \text{ is even} \end{array}$$

These facts often simplify the computations of the Fourier coefficients. For example:

1. The Fourier sine coefficients b_k all vanish if f is even.
2. The Fourier cosine coefficients a_k all vanish if f is odd.

This is because $f(x)\sin(kx)$ is odd in the first case and $f(x)\cos(kx)$ is odd in the second case.

The functions 1, $\cos(kx)$, and $\sin(kx)$ that occur in the Fourier approximation for $f(x)$ are all easy to generate as an electrical voltage (when x is time). By summing these signals (with the amplitudes given by the Fourier coefficients), it is possible to produce an electrical signal with (the approximation to) $f(x)$ as the voltage. Hence these Fourier approximations play a fundamental role in electronics.

Finally, the Fourier approximations $f_1, f_2, \ldots$ of a function f get better and better as n increases. The reason is that the subspaces F_n increase:

$$F_1 \subseteq F_2 \subseteq F_3 \subseteq \cdots \subseteq F_n \subseteq \cdots$$

So, because $f_n = \text{proj}F_n f$, we get (see the discussion following Example 10.2.6)

$$\|f - f_1\| \geq \|f - f_2\| \geq \cdots \geq \|f - f_n\| \geq \cdots$$

These numbers $\|f - f_n\|$ approach zero; in fact, we have the following fundamental theorem.

Theorem 7.5.2

Let f be any continuous function in $C[-\pi, \pi]$. Then[1]

$$f_n(x) \text{ approaches } f(x) \text{ for all } x \text{ such that } -\pi < x < \pi.$$

It shows that f has a representation as an infinite series, called the **Fourier series** of f:

$$f(x) = a_0 + a_1 \cos x + b_1 \sin x + a_2 \cos(2x) + b_2 \sin(2x) + \cdots$$

whenever $-\pi < x < \pi$. A full discussion of Theorem 10.5.2 is beyond the scope of this book. This subject had great historical impact on the development of mathematics, and has become one of the standard tools in science and engineering.

Thus the Fourier series for the function f in Example 10.5.1 is

$$f(x) = \frac{\pi}{2} + \frac{4}{\pi}\left\{\cos x + \frac{1}{3^2}\cos(3x) + \frac{1}{5^2}\cos(5x) + \frac{1}{7^2}\cos(7x) + \cdots\right\}$$

Since $f(0) = \pi$ and $\cos(0) = 1$, taking $x = 0$ leads to the series

$$\frac{\pi^2}{8} = 1 + \frac{1}{3^2} + \frac{1}{5^2} + \frac{1}{7^2} + \cdots$$

Example 7.5.2

Expand $f(x) = x$ on the interval $[-\pi, \pi]$ in a Fourier series, and so obtain a series expansion of $\frac{\pi}{4}$.

Solution

Here f is an odd function so all the Fourier cosine coefficients a_k are zero. As to the sine coefficients:

$$b_k = \frac{1}{\pi}\int_{-\pi}^{\pi} x\sin(kx)dx = \frac{2}{k}(-1)^{k+1} \quad \text{for } k \geq 1$$

where we omit the details of the integration by parts. Hence the Fourier series for x is

$$x = 2[\sin x - \frac{1}{2}\sin(2x) + \frac{1}{3}\sin(3x) - \frac{1}{4}\sin(4x) + ...]$$

for $-\pi < x < \pi$. In particular, taking $x = \frac{\pi}{2}$ gives an infinite series for $\frac{\pi}{4}$.

$$\frac{\pi}{4} = 1 - \frac{1}{3} + \frac{1}{5} - \frac{1}{7} + \frac{1}{9} - \cdots$$

Many other such formulas can be proved using Theorem 10.5.2.

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1. The name honors the French mathematician J.B.J. Fourier (1768-1830) who used these techniques in 1822 to investigate heat conduction in solids.

7.5E: An Application to Fourier Approximation Exercises

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7.5E: An Application to Fourier Approximation Exercises

Exercise $7.5E.1$

In each case, find the Fourier approximation f_5 of the given function in $\mathbf{C}[-\pi, \pi]$.

a. $f(x) = \pi - x$

b. $f(x) = |x| = \begin{cases} x & \text{if } 0 \le x \le \pi \\ -x & \text{if } -\pi \le x < 0 \end{cases}$

c. $f(x) = x^2$

d. $f(x) = \begin{cases} 0 & \text{if } -\pi \le x < 0 \\ x & \text{if } 0 \le x \le \pi \end{cases}$

Answer available at the end of this section.

Exercise $7.5E.2$

a. Find f_5 for the even function f on $[-\pi, \pi]$ satisfying $f(x) = x$ for $0 \le x \le \pi$.

b. Find f_6 for the even function f on $[-\pi, \pi]$ satisfying $f(x) = \sin x$ for $0 \le x \le \pi$. [*Hint*: If $k > 1$, $\int \sin x \cos(kx) = \frac{1}{2}\left[\frac{\cos[(k-1)x]}{k-1} - \frac{\cos[(k+1)x]}{k+1}\right]$.]

Answer available at the end of this section.

Exercise $7.5E.3$

a. Prove that $\int_{-\pi}^{\pi} f(x)dx = 0$ if f is odd and that $\int_{-\pi}^{\pi} f(x)dx = 2\int_{0}^{\pi} f(x)dx$ if f is even.

b. Prove that $\frac{1}{2}[f(x) + f(-x)]$ is even and that $\frac{1}{2}[f(x) - f(-x)]$ is odd for any function f. Note that they sum to $f(x)$.

Exercise $7.5E.4$

Show that $\{1, \cos x, \cos(2x), \cos(3x), \ldots\}$ is an orthogonal set in $\mathbf{C}[0, \pi]$ with respect to the inner product $\langle f, g\rangle = \int_{0}^{\pi} f(x)g(x)dx$.

Answer available at the end of this section.

Exercise $7.5E.5$

a. Show that $\frac{\pi^2}{8} = 1 + \frac{1}{3^2} + \frac{1}{5^2} + \cdots$ using Exercise 10.5.1](b).

b. Show that $\frac{\pi^2}{12} = 1 - \frac{1}{2^2} + \frac{1}{3^2} - \frac{1}{4^2} + \cdots$ using Exercise 10.5.1(c).

Answers

Exercise $7.5E.1$

b. $\frac{\pi}{2} - \frac{4}{\pi}\left[\cos x + \frac{\cos 3x}{3^2} + \frac{\cos 5x}{5^2}\right]$

d. $\frac{\pi}{4} + \left[\sin x - \frac{\sin 2x}{2} + \frac{\sin 3x}{3} - \frac{\sin 4x}{4} + \frac{\sin 5x}{5}\right] - \frac{2}{\pi}\left[\cos x + \frac{\cos 3x}{3^2} + \frac{\cos 5x}{5^2}\right]$

Exercise $7.5E.2$

b. $\frac{2}{\pi} - \frac{8}{\pi}\left[\frac{\cos 2x}{2^2 - 1} + \frac{\cos 4x}{4^2 - 1} + \frac{\cos 6x}{6^2 - 1}\right]$

Exercise $7.5E.4$

$\int \cos\ kx\ \cos\ lx\ dx = \frac{1}{2}\left[\frac{\sin[(k+l)x]}{k+l} - \frac{\sin[(k-l)x]}{k-l}\right]_0^{\pi} = 0$ provided that $k \neq l$.

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8: SPECTRAL THEORY

8.1: Eigenvalues and Eigenvectors of a Matrix

Matrix Transformations and Eigenvalues GeoGebra Demo by SKKU-Matrix-Lab

8.2: Diagonalization

8.3: Applications of Spectral Theory

8.4: Orthogonality

8.5: Supplemental Notes - More on Eigenvalues and Intro to Eigenspaces

8.5.1: The Eigenvalue-Eigenvector Equation

8.5.2: Eigenspaces

8.5.3: Eigenvalues and Eigenvectors - Visualizations

8.E: Exercises

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8.1: EIGENVALUES AND EIGENVECTORS OF A MATRIX

Outcomes

A. Describe eigenvalues geometrically and algebraically.
B. Find eigenvalues and eigenvectors for a square matrix.

Spectral Theory refers to the study of eigenvalues and eigenvectors of a matrix. It is of fundamental importance in many areas and is the subject of our study for this chapter.

Definition of Eigenvectors and Eigenvalues

In this section, we will work with the entire set of complex numbers, denoted by $\mathbb{C}$. Recall that the real numbers, $\mathbb{R}$ are contained in the complex numbers, so the discussions in this section apply to both real and complex numbers.

To illustrate the idea behind what will be discussed, consider the following example.

Example 8.1.1: Eigenvectors and Eigenvalues

Let

$$A = \begin{bmatrix} 0 & 5 & -10 \\ 0 & 22 & 16 \\ 0 & -9 & -2 \end{bmatrix}$$

Compute the product AX for

$$X = \begin{bmatrix} -5 \\ -4 \\ 3 \end{bmatrix}, X = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

What do you notice about AX in each of these products?

Solution

First, compute AX for

$$X = \begin{bmatrix} -5 \\ -4 \\ 3 \end{bmatrix}$$

This product is given by

$$AX = \begin{bmatrix} 0 & 5 & -10 \\ 0 & 22 & 16 \\ 0 & -9 & -2 \end{bmatrix} \begin{bmatrix} -5 \\ -4 \\ 3 \end{bmatrix} = \begin{bmatrix} -50 \\ -40 \\ 30 \end{bmatrix} = 10 \begin{bmatrix} -5 \\ -4 \\ 3 \end{bmatrix}$$

In this case, the product AX resulted in a vector which is equal to 10 times the vector X. In other words, $AX = 10X$.

Let's see what happens in the next product. Compute AX for the vector

$$X = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

This product is given by

$$AX = \begin{bmatrix} 0 & 5 & -10 \\ 0 & 22 & 16 \\ 0 & -9 & -2 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = 0 \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

In this case, the product AX resulted in a vector equal to 0 times the vector X, $AX = 0X$.

Perhaps this matrix is such that AX results in kX, for every vector X. However, consider

$$\begin{bmatrix} 0 & 5 & -10 \\ 0 & 22 & 16 \\ 0 & -9 & -2 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -5 \\ 38 \\ -11 \end{bmatrix}$$

In this case, AX did not result in a vector of the form kX for some scalar k.

There is something special about the first two products calculated in Example 8.1.1. Notice that for each, $AX = kX$ where k is some scalar. When this equation holds for some X and k, we call the scalar k an **eigenvalue** of A. We often use the special symbol λ instead of k when referring to eigenvalues. In Example 8.1.1, the values 10 and 0 are eigenvalues for the matrix A and we can label these as $\lambda_1 = 10$ and $\lambda_2 = 0$.

When $AX = \lambda X$ for some $X \neq 0$, we call such an X an **eigenvector** of the matrix A. The eigenvectors of A are associated to an eigenvalue. Hence, if λ_1 is an eigenvalue of A and $AX = \lambda_1 X$, we can label this eigenvector as X_1. Note again that in order to be an eigenvector, X must be nonzero.

There is also a geometric significance to eigenvectors. When you have a **nonzero** vector which, when multiplied by a matrix results in another vector which is parallel to the first or equal to **0**, this vector is called an eigenvector of the matrix. This is the meaning when the vectors are in $\mathbb{R}^n$.

The formal definition of eigenvalues and eigenvectors is as follows.

Definition 8.1.1: Eigenvalues and Eigenvectors

Let A be an $n \times n$ matrix and let $X \in \mathbb{C}^n$ be a **nonzero vector** for which

$$AX = \lambda X \tag{8.1.1}$$

for some scalar λ. Then λ is called an **eigenvalue** of the matrix A and X is called an **eigenvector** of A associated with λ, or a λ-eigenvector of A.

The set of all eigenvalues of an $n \times n$ matrix A is denoted by $\sigma(A)$ and is referred to as the **spectrum** of A.

The eigenvectors of a matrix A are those vectors X for which multiplication by A results in a vector in the same direction or opposite direction to X. Since the zero vector 0 has no direction this would make no sense for the zero vector. As noted above, 0 is never allowed to be an eigenvector.

Let's look at eigenvectors in more detail. Suppose X satisfies (8.1.1). Then

$$AX - \lambda X = 0$$

or

$$(A - \lambda I) X = 0$$

for some $X \neq 0$. Equivalently you could write $(\lambda I - A) X = 0$, which is more commonly used. Hence, when we are looking for eigenvectors, we are looking for nontrivial solutions to this homogeneous system of equations!

Recall that the solutions to a homogeneous system of equations consist of basic solutions, and the linear combinations of those basic solutions. In this context, we call the basic solutions of the equation $(\lambda I - A) X = 0$ **basic eigenvectors**. It follows that any (nonzero) linear combination of basic eigenvectors is again an eigenvector.

Suppose the matrix $(\lambda I - A)$ is invertible, so that $(\lambda I - A)^{-1}$ exists. Then the following equation would be true.

$$\begin{aligned} X &= IX \\ &= \left((\lambda I - A)^{-1} (\lambda I - A) \right) X \\ &= (\lambda I - A)^{-1} ((\lambda I - A) X) \\ &= (\lambda I - A)^{-1} 0 \\ &= 0 \end{aligned} \tag{8.1.2}$$

This claims that $X = 0$. However, we have required that $X \neq 0$. Therefore $(\lambda I - A)$ cannot have an inverse!

Recall that if a matrix is not invertible, then its determinant is equal to 0. Therefore we can conclude that

$$\det (\lambda I - A) = 0 \tag{8.1.3}$$

Note that this is equivalent to $\det (A - \lambda I) = 0$.

The expression $\det (\lambda I - A)$ is a polynomial (in the variable x) called the **characteristic polynomial of** A, and $\det (\lambda I - A) = 0$ is called the **characteristic equation**. For this reason we may also refer to the eigenvalues of A as **characteristic values**, but the former is often used for historical reasons.

The following theorem claims that the roots of the characteristic polynomial are the eigenvalues of A. Thus when [eigen2] holds, A has a nonzero eigenvector.

Theorem 8.1.1: The Existence of an Eigenvector

Let A be an $n \times n$ matrix and suppose $\det (\lambda I - A) = 0$ for some $\lambda \in \mathbb{C}$.
Then λ is an eigenvalue of A and thus there exists a nonzero vector $X \in \mathbb{C}^n$ such that $AX = \lambda X$.

Proof available at the end of this section.

Finding Eigenvectors and Eigenvalues

Now that eigenvalues and eigenvectors have been defined, we will study how to find them for a matrix A.

First, consider the following definition.

Definition 8.1.2: Multiplicity of an Eigenvalue

Let A be an $n \times n$ matrix with characteristic polynomial given by $\det (\lambda I - A)$. Then, the multiplicity of an eigenvalue λ of A is the number of times λ occurs as a root of that characteristic polynomial.

For example, suppose the characteristic polynomial of A is given by $(\lambda - 2)^2$. Solving for the roots of this polynomial, we set $(\lambda - 2)^2 = 0$ and solve for λ. We find that $\lambda = 2$ is a root that occurs twice. Hence, in this case, $\lambda = 2$ is an eigenvalue of A of multiplicity equal to 2.

We will now look at how to find the eigenvalues and eigenvectors for a matrix A in detail. The steps used are summarized in the following procedure.

Procedure 8.1.1: Finding Eigenvalues and Eigenvectors

Let A be an $n \times n$ matrix.

1. First, find the eigenvalues λ of A by solving the equation $\det (\lambda I - A) = 0$.
2. For each λ, find the basic eigenvectors $X \neq 0$ by finding the basic solutions to $(\lambda I - A) X = 0$.

To verify your work, make sure that $AX = \lambda X$ for each λ and associated eigenvector X.

We will explore these steps further in the following example.

Example 8.1.2: Find the Eigenvalues and Eigenvectors

Let $A = \begin{bmatrix} -5 & 2 \\ -7 & 4 \end{bmatrix}$. Find its eigenvalues and eigenvectors.

Solution

We will use Procedure 8.1.1. First we find the eigenvalues of A by solving the equation

$$\det(\lambda I - A) = 0$$

This gives

$$\begin{aligned} \det\left(\lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} -5 & 2 \\ -7 & 4 \end{bmatrix}\right) = 0 \\ \det \begin{bmatrix} \lambda + 5 & -2 \\ 7 & \lambda - 4 \end{bmatrix} = 0 \end{aligned} \tag{8.1.4}$$

Computing the determinant as usual, the result is

$$\lambda^2 + \lambda - 6 = 0$$

Solving this equation, we find that $\lambda_1 = 2$ and $\lambda_2 = -3$.

Now we need to find the basic eigenvectors for each λ. First we will find the eigenvectors for $\lambda_1 = 2$. We wish to find all vectors $X \neq 0$ such that $AX = 2X$. These are the solutions to $(2I - A)X = 0$.

$$\begin{aligned} \left(2 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} -5 & 2 \\ -7 & 4 \end{bmatrix}\right) \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\ \begin{bmatrix} 7 & -2 \\ 7 & -2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \end{aligned} \tag{8.1.5}$$

The augmented matrix for this system and corresponding reduced row-echelon form are given by

$$\begin{bmatrix} 7 & -2 & 0 \\ 7 & -2 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & -\frac{2}{7} & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

The solution is any vector of the form

$$\begin{bmatrix} \frac{2}{7}s \\ s \end{bmatrix} = s \begin{bmatrix} \frac{2}{7} \\ 1 \end{bmatrix}$$

Multiplying this vector by 7 we obtain a simpler description for the solution to this system, given by

$$t \begin{bmatrix} 2 \\ 7 \end{bmatrix}$$

This gives the basic eigenvector for $\lambda_1 = 2$ as

$$\begin{bmatrix} 2 \\ 7 \end{bmatrix}$$

To check, we verify that $AX = 2X$ for this basic eigenvector.

$$\begin{bmatrix} -5 & 2 \\ -7 & 4 \end{bmatrix} \begin{bmatrix} 2 \\ 7 \end{bmatrix} = \begin{bmatrix} 4 \\ 14 \end{bmatrix} = 2 \begin{bmatrix} 2 \\ 7 \end{bmatrix}$$

This is what we wanted, so we know this basic eigenvector is correct.

Next we will repeat this process to find the basic eigenvector for $\lambda_2 = -3$. We wish to find all vectors $X \neq 0$ such that $AX = -3X$. These are the solutions to $((-3)I - A)X = 0$.

$$\begin{aligned} \left((-3)\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} -5 & 2 \\ -7 & 4 \end{bmatrix}\right)\begin{bmatrix} x \\ y \end{bmatrix} &= \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\ \begin{bmatrix} 2 & -2 \\ 7 & -7 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} &= \begin{bmatrix} 0 \\ 0 \end{bmatrix} \end{aligned} \tag{8.1.6}$$

The augmented matrix for this system and corresponding reduced row-echelon form are given by

$$\begin{bmatrix} 2 & -2 & 0 \\ 7 & -7 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & -1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

The solution is any vector of the form

$$\begin{bmatrix} s \\ s \end{bmatrix} = s\begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

This gives the basic eigenvector for $\lambda_2 = -3$ as

$$\begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

To check, we verify that $AX = -3X$ for this basic eigenvector.

$$\begin{bmatrix} -5 & 2 \\ -7 & 4 \end{bmatrix}\begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -3 \\ -3 \end{bmatrix} = -3\begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

This is what we wanted, so we know this basic eigenvector is correct.

The following is an example using Procedure 8.1.1 for a 3×3 matrix.

Example 8.1.3: Find the Eigenvalues and Eigencectors

Find the eigenvalues and eigenvectors for the matrix

$$A = \begin{bmatrix} 5 & -10 & -5 \\ 2 & 14 & 2 \\ -4 & -8 & 6 \end{bmatrix}$$

Solution

We will use Procedure 8.1.1. First we need to find the eigenvalues of A. Recall that they are the solutions of the equation

$$\det(\lambda I - A) = 0$$

In this case the equation is

$$\det\left(\lambda\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} 5 & -10 & -5 \\ 2 & 14 & 2 \\ -4 & -8 & 6 \end{bmatrix}\right) = 0$$

which becomes

$$\det\begin{bmatrix} \lambda - 5 & 10 & 5 \\ -2 & \lambda - 14 & -2 \\ 4 & 8 & \lambda - 6 \end{bmatrix} = 0$$

Using Laplace Expansion, compute this determinant and simplify. The result is the following equation.

$$(\lambda - 5)\left(\lambda^2 - 20\lambda + 100\right) = 0$$

Solving this equation, we find that the eigenvalues are $\lambda_1 = 5, \lambda_2 = 10$ and $\lambda_3 = 10$. Notice that 10 is a root of multiplicity two due to

$$\lambda^2 - 20\lambda + 100 = (\lambda - 10)^2$$

Therefore, $\lambda_2 = 10$ is an eigenvalue of multiplicity two.

Now that we have found the eigenvalues for A, we can compute the eigenvectors.

First we will find the basic eigenvectors for $\lambda_1 = 5$. In other words, we want to find all non-zero vectors X so that $AX = 5X$. This requires that we solve the equation $(5I - A)X = 0$ for X as follows.

$$\left(5\begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix} - \begin{bmatrix}5&-10&-5\\2&14&2\\-4&-8&6\end{bmatrix}\right)\begin{bmatrix}x\\y\\z\end{bmatrix} = \begin{bmatrix}0\\0\\0\end{bmatrix}$$

That is you need to find the solution to

$$\begin{bmatrix}0&10&5\\-2&-9&-2\\4&8&-1\end{bmatrix}\begin{bmatrix}x\\y\\z\end{bmatrix} = \begin{bmatrix}0\\0\\0\end{bmatrix}$$

By now this is a familiar problem. You set up the augmented matrix and row reduce to get the solution. Thus the matrix you must row reduce is

$$\begin{bmatrix}0&10&5&0\\-2&-9&-2&0\\4&8&-1&0\end{bmatrix}$$

The reduced row-echelon form is

$$\begin{bmatrix}1&0&-\frac{5}{4}&0\\0&1&\frac{1}{2}&0\\0&0&0&0\end{bmatrix}$$

and so the solution is any vector of the form

$$\begin{bmatrix}\frac{5}{4}s\\-\frac{1}{2}s\\s\end{bmatrix} = s\begin{bmatrix}\frac{5}{4}\\-\frac{1}{2}\\1\end{bmatrix}$$

where $s \in \mathbb{R}$. If we multiply this vector by 4, we obtain a simpler description for the solution to this system, as given by

$$t\begin{bmatrix}5\\-2\\4\end{bmatrix} \tag{8.1.7}$$

where $t \in \mathbb{R}$. Here, the basic eigenvector is given by

$$X_1 = \begin{bmatrix}5\\-2\\4\end{bmatrix}$$

Notice that we cannot let $t = 0$ here, because this would result in the zero vector and eigenvectors are never equal to $\mathbb{0}$! Other than this value, every other choice of t in (8.1.7) results in an eigenvector.

It is a good idea to check your work! To do so, we will take the original matrix and multiply by the basic eigenvector X_1. We check to see if we get $5X_1$.

$$\begin{bmatrix}5&-10&-5\\2&14&2\\-4&-8&6\end{bmatrix}\begin{bmatrix}5\\-2\\4\end{bmatrix} = \begin{bmatrix}25\\-10\\20\end{bmatrix} = 5\begin{bmatrix}5\\-2\\4\end{bmatrix}$$

This is what we wanted, so we know that our calculations were correct.

Next we will find the basic eigenvectors for $\lambda_2, \lambda_3 = 10$. These vectors are the basic solutions to the equation,

$$\left(10\begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix}-\begin{bmatrix}5&-10&-5\\2&14&2\\-4&-8&6\end{bmatrix}\right)\begin{bmatrix}x\\y\\z\end{bmatrix}=\begin{bmatrix}0\\0\\0\end{bmatrix}$$

That is you must find the solutions to

$$\begin{bmatrix}5&10&5\\-2&-4&-2\\4&8&4\end{bmatrix}\begin{bmatrix}x\\y\\z\end{bmatrix}=\begin{bmatrix}0\\0\\0\end{bmatrix}$$

Consider the augmented matrix

$$\begin{bmatrix}5&10&5&0\\-2&-4&-2&0\\4&8&4&0\end{bmatrix}$$

The reduced row-echelon form for this matrix is

$$\begin{bmatrix}1&2&1&0\\0&0&0&0\\0&0&0&0\end{bmatrix}$$

and so the eigenvectors are of the form

$$\begin{bmatrix}-2s-t\\s\\t\end{bmatrix}=s\begin{bmatrix}-2\\1\\0\end{bmatrix}+t\begin{bmatrix}-1\\0\\1\end{bmatrix}$$

Note that you can't pick t and s both equal to zero because this would result in the zero vector and eigenvectors are never equal to zero.

Here, there are two basic eigenvectors, given by

$$X_2=\begin{bmatrix}-2\\1\\0\end{bmatrix},X_3=\begin{bmatrix}-1\\0\\1\end{bmatrix}$$

Taking any (nonzero) linear combination of X_2 and X_3 will also result in an eigenvector for the eigenvalue $\lambda = 10$. As in the case for $\lambda = 5$, always check your work! For the first basic eigenvector, we can check $AX_2 = 10X_2$ as follows.

$$\begin{bmatrix}5&-10&-5\\2&14&2\\-4&-8&6\end{bmatrix}\begin{bmatrix}-1\\0\\1\end{bmatrix}=\begin{bmatrix}-10\\0\\10\end{bmatrix}=10\begin{bmatrix}-1\\0\\1\end{bmatrix}$$

This is what we wanted. Checking the second basic eigenvector, X_3, is left as an exercise.

It is important to remember that for any eigenvector X, $X \neq 0$. However, it is possible to have eigenvalues equal to zero. This is illustrated in the following example.

Example 8.1.4: A Zero Eigenvalue

Let

$$A=\begin{bmatrix}2&2&-2\\1&3&-1\\-1&1&1\end{bmatrix}$$

Find the eigenvalues and eigenvectors of A.

Solution

First we find the eigenvalues of A. We will do so using Definition 8.1.1.

In order to find the eigenvalues of A, we solve the following equation.

$$\det(\lambda I - A) = \det \begin{bmatrix} \lambda - 2 & -2 & 2 \\ -1 & \lambda - 3 & 1 \\ 1 & -1 & \lambda - 1 \end{bmatrix} = 0$$

This reduces to $\lambda^3 - 6\lambda^2 + 8\lambda = 0$. You can verify that the solutions are $\lambda_1 = 0, \lambda_2 = 2, \lambda_3 = 4$. Notice that while eigenvectors can never equal 0, it is possible to have an eigenvalue equal to 0.

Now we will find the basic eigenvectors. For $\lambda_1 = 0$, we need to solve the equation $(0I - A)X = 0$. This equation becomes $-AX = 0$, and so the augmented matrix for finding the solutions is given by

$$\begin{bmatrix} -2 & -2 & 2 & 0 \\ -1 & -3 & 1 & 0 \\ 1 & -1 & -1 & 0 \end{bmatrix}$$

The reduced row-echelon form is

$$\begin{bmatrix} 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Therefore, the eigenvectors are of the form $t \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$ where $t \neq 0$ and the basic eigenvector is given by

$$X_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

We can verify that this eigenvector is correct by checking that the equation $AX_1 = 0X_1$ holds. The product AX_1 is given by

$$AX_1 = \begin{bmatrix} 2 & 2 & -2 \\ 1 & 3 & -1 \\ -1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

This clearly equals $0X_1$, so the equation holds. Hence, $AX_1 = 0X_1$ and so 0 is an eigenvalue of A.

Computing the other basic eigenvectors is left as an exercise.

In the following sections, we examine ways to simplify this process of finding eigenvalues and eigenvectors by using properties of special types of matrices.

Eigenvalues and Eigenvectors for Special Types of Matrices

There are three special kinds of matrices which we can use to simplify the process of finding eigenvalues and eigenvectors. Throughout this section, we will discuss similar matrices, elementary matrices, as well as triangular matrices.

We begin with a definition.

Definition 8.1.3: Similar Matrices

Let A and B be $n \times n$ matrices. Suppose there exists an invertible matrix P such that

$$A = P^{-1}BP$$

Then A and B are called **similar matrices**.

It turns out that we can use the concept of similar matrices to help us find the eigenvalues of matrices. Consider the following lemma.

Lemma 8.1.1: Similar Matrices and Eigenvalues

Let A and B be similar matrices, so that $A = P^{-1}BP$ where A, B are $n \times n$ matrices and P is invertible. Then A, B have the same eigenvalues.

Proof available at the end of this section.

Note that this proof also demonstrates that the eigenvectors of A and B will (generally) be *different*. We see in the proof that $AX = \lambda X$, while $B(PX) = \lambda(PX)$. Therefore, for an eigenvalue λ, A will have the eigenvector X while B will have the eigenvector PX.

The second special type of matrices we discuss in this section is elementary matrices. Recall from Definition 2.8.1 that an elementary matrix E is obtained by applying one row operation to the identity matrix.

It is possible to use elementary matrices to simplify a matrix before searching for its eigenvalues and eigenvectors. This is illustrated in the following example.

Example 8.1.5: Simplify Using Elementary Matrices

Find the eigenvalues for the matrix

$$A = \begin{bmatrix} 33 & 105 & 105 \\ 10 & 28 & 30 \\ -20 & -60 & -62 \end{bmatrix}$$

Solution

This matrix has big numbers and therefore we would like to simplify as much as possible before computing the eigenvalues.

We will do so using row operations. First, add 2 times the second row to the third row. To do so, left multiply A by $E(2,2)$. Then right multiply A by the inverse of $E(2,2)$ as illustrated.

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 2 & 1 \end{bmatrix} \begin{bmatrix} 33 & 105 & 105 \\ 10 & 28 & 30 \\ -20 & -60 & -62 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -2 & 1 \end{bmatrix} = \begin{bmatrix} 33 & -105 & 105 \\ 10 & -32 & 30 \\ 0 & 0 & -2 \end{bmatrix}$$

By Lemma 8.1.1, the resulting matrix has the same eigenvalues as A where here, the matrix $E(2,2)$ plays the role of P.

We do this step again, as follows. In this step, we use the elementary matrix obtained by adding -3 times the second row to the first row.

$$\begin{bmatrix} 1 & -3 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 33 & -105 & 105 \\ 10 & -32 & 30 \\ 0 & 0 & -2 \end{bmatrix} \begin{bmatrix} 1 & 3 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 3 & 0 & 15 \\ 10 & -2 & 30 \\ 0 & 0 & -2 \end{bmatrix} \tag{8.1.8}$$

Again by Lemma 8.1.1, this resulting matrix has the same eigenvalues as A. At this point, we can easily find the eigenvalues. Let

$$B = \begin{bmatrix} 3 & 0 & 15 \\ 10 & -2 & 30 \\ 0 & 0 & -2 \end{bmatrix}$$

Then, we find the eigenvalues of B (and therefore of A) by solving the equation $\det(\lambda I - B) = 0$. You should verify that this equation becomes

$$(\lambda+2)(\lambda+2)(\lambda-3)=0$$

Solving this equation results in eigenvalues of $\lambda_1=-2, \lambda_2=-2$, and $\lambda_3=3$. Therefore, these are also the eigenvalues of A.

Through using elementary matrices, we were able to create a matrix for which finding the eigenvalues was easier than for A. At this point, you could go back to the original matrix A and solve $(\lambda I-A)X=0$ to obtain the eigenvectors of A.

Notice that when you multiply on the right by an elementary matrix, you are doing the column operation defined by the elementary matrix. In (8.1.8) multiplication by the elementary matrix on the right merely involves taking three times the first column and adding to the second. Thus, without referring to the elementary matrices, the transition to the new matrix in (8.1.8) can be illustrated by

$$\begin{bmatrix} 33 & -105 & 105 \\ 10 & -32 & 30 \\ 0 & 0 & -2 \end{bmatrix} \rightarrow \begin{bmatrix} 3 & -9 & 15 \\ 10 & -32 & 30 \\ 0 & 0 & -2 \end{bmatrix} \rightarrow \begin{bmatrix} 3 & 0 & 15 \\ 10 & -2 & 30 \\ 0 & 0 & -2 \end{bmatrix}$$

The third special type of matrix we will consider in this section is the triangular matrix. Recall Definition 3.1.6 which states that an upper (lower) triangular matrix contains all zeros below (above) the main diagonal. Remember that finding the determinant of a triangular matrix is a simple procedure of taking the product of the entries on the main diagonal.. It turns out that there is also a simple way to find the eigenvalues of a triangular matrix.

In the next example we will demonstrate that the eigenvalues of a triangular matrix are the entries on the main diagonal.

Example 8.1.6: Eigenvalues for a Triangular Matrix

Let $A=\begin{bmatrix} 1 & 2 & 4 \\ 0 & 4 & 7 \\ 0 & 0 & 6 \end{bmatrix}$. Find the eigenvalues of A.

Solution

We need to solve the equation $\det(\lambda I-A)=0$ as follows

$$\det(\lambda I-A)=\det\begin{bmatrix} \lambda-1 & -2 & -4 \\ 0 & \lambda-4 & -7 \\ 0 & 0 & \lambda-6 \end{bmatrix}=(\lambda-1)(\lambda-4)(\lambda-6)=0 \tag{8.1.9}$$

Solving the equation $(\lambda-1)(\lambda-4)(\lambda-6)=0$ for λ results in the eigenvalues $\lambda_1=1, \lambda_2=4$ and $\lambda_3=6$. Thus the eigenvalues are the entries on the main diagonal of the original matrix.

The same result is true for lower triangular matrices. For any triangular matrix, the eigenvalues are equal to the entries on the main diagonal. To find the eigenvectors of a triangular matrix, we use the usual procedure.

In the next section, we explore an important process involving the eigenvalues and eigenvectors of a matrix.

Answers

Theorem 8.1.1: The Existence of an Eigenvector

For A an $n\times n$ matrix, the method of Laplace Expansion demonstrates that $\det(\lambda I-A)$ is a polynomial of degree n. As such, the equation (8.1.3) has a solution $\lambda\in\mathbb{C}$ by the Fundamental Theorem of Algebra. The fact that λ is an eigenvalue is left as an exercise.

Lemma 8.1.1: Similar Matrices and Eigenvalues

We need to show two things. First, we need to show that if $A=P^{-1}BP$, then A and B have the same eigenvalues. Secondly, we show that if A and B have the same eigenvalues, then $A=P^{-1}BP$.

Here is the proof of the first statement. Suppose $A=P^{-1}BP$ and λ is an eigenvalue of A, that is $AX=\lambda X$ for some $X\neq 0$. Then

$$P^{-1}BPX=\lambda X$$

and so

$$BPX=\lambda PX$$

Since P is one to one and $X\neq 0$, it follows that $PX\neq 0$. Here, PX plays the role of the eigenvector in this equation. Thus λ is also an eigenvalue of B. One can

similarly verify that any eigenvalue of B is also an eigenvalue of A, and thus both matrices have the same eigenvalues as desired.

Proving the second statement is similar and is left as an exercise.

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8.2: Diagonalization

Outcomes

A. Determine when it is possible to diagonalize a matrix.
B. When possible, diagonalize a matrix.

Similarity and Diagonalization

We begin this section by recalling the definition of similar matrices. Recall that if A, B are two $n \times n$ matrices, then they are **similar** if and only if there exists an invertible matrix P such that

$$A = P^{-1}BP$$

In this case we write $A \sim B$. The concept of similarity is an example of an **equivalence relation**.

Lemma 8.2.1: Similarity is an Equivalence Relation

Similarity is an equivalence relation, i.e. for $n \times n$ matrices A, B, and C,

1. $A \sim A$ (reflexive)
2. If $A \sim B$, then $B \sim A$ (symmetric)
3. If $A \sim B$ and $B \sim C$, then $A \sim C$ (transitive)

Proof available at the end of this section.

Another important concept necessary to this section is the trace of a matrix. Consider the definition.

Definition 8.2.1: Trace of a Matrix

If $A = [a_{ij}]$ is an $n \times n$ matrix, then the trace of A is

$$\text{trace}(A) = \sum_{i=1}^{n} a_{ii}.$$

In words, the trace of a matrix is the sum of the entries on the main diagonal.

Lemma 8.2.2: Properties of Trace

For $n \times n$ matrices A and B, and any $k \in \mathbb{R}$,

1. $\text{trace}(A + B) = \text{trace}(A) + \text{trace}(B)$
2. $\text{trace}(kA) = k \cdot \text{trace}(A)$
3. $\text{trace}(AB) = \text{trace}(BA)$

The following theorem includes a reference to the characteristic polynomial of a matrix. Recall that for any $n \times n$ matrix A, the characteristic polynomial of A is $c_A(x) = \det(xI - A)$.

Theorem 8.2.1: Properties of Similar Matrices

If A and B are $n \times n$ matrices and $A \sim B$, then

1. $\det(A) = \det(B)$
2. $\text{rank}(A) = \text{rank}(B)$
3. $\text{trace}(A) = \text{trace}(B)$
4. $c_A(x) = c_B(x)$
5. A and B have the same eigenvalues

We now proceed to the main concept of this section. When a matrix is similar to a diagonal matrix, the matrix is said to be diagonalizable. We define a diagonal matrix D as a matrix containing a zero in every entry except those on the main diagonal. More precisely, if d_{ij} is the ij^{th} entry of a diagonal matrix D, then $d_{ij} = 0$ unless $i = j$. Such matrices look like the following.

$$D = \begin{bmatrix} * & & 0 \\ & \ddots & \\ 0 & & * \end{bmatrix}$$

where $*$ is a number which might not be zero.

The following is the formal definition of a diagonalizable matrix.

Definition 8.2.2: Diagonalizable

Let A be an $n \times n$ matrix. Then A is said to be **diagonalizable** if there exists an invertible matrix P such that

$$P^{-1}AP = D$$

where D is a diagonal matrix.

Notice that the above equation can be rearranged as $A = PDP^{-1}$. Suppose we wanted to compute A^{100}. By diagonalizing A first it suffices to then compute $\left(PDP^{-1}\right)^{100}$, which reduces to $PD^{100}P^{-1}$. This last computation is much simpler than A^{100}. While this process is described in detail later, it provides motivation for diagonalization.

Diagonalizing a Matrix

The most important theorem about diagonalizability is the following major result.

Theorem 8.2.2: Eigenvectors and Diagonalizable Matrices

An $n \times n$ matrix A is diagonalizable if and only if there is an invertible matrix P given by

$$P = \begin{bmatrix} X_1 & X_2 & \cdots & X_n \end{bmatrix}$$

where the X_k are eigenvectors of A.

Moreover if A is diagonalizable, the corresponding eigenvalues of A are the diagonal entries of the diagonal matrix D.

Proof available at the end of this section.

Notice that because the matrix P defined above is invertible it follows that the set of eigenvectors of A, $\{X_1, X_2, \cdots, X_n\}$, form a basis of $\mathbb{R}^n$.

We demonstrate the concept given in the above theorem in the next example. Note that not only are the columns of the matrix P formed by eigenvectors, but P must be invertible so must consist of a wide variety of eigenvectors. We achieve this by using basic eigenvectors for the columns of P.

Example 8.2.1: Diagonalize a Matrix

Let

$$A = \begin{bmatrix} 2 & 0 & 0 \\ 1 & 4 & -1 \\ -2 & -4 & 4 \end{bmatrix}$$

Find an invertible matrix P and a diagonal matrix D such that $P^{-1}AP = D$.

Solution

By Theorem 8.2.2 we use the eigenvectors of A as the columns of P, and the corresponding eigenvalues of A as the diagonal entries of D.

First, we will find the eigenvalues of A. To do so, we solve $\det(\lambda I - A) = 0$ as follows.

$$\det\left(\lambda \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} 2 & 0 & 0 \\ 1 & 4 & -1 \\ -2 & -4 & 4 \end{bmatrix}\right) = 0$$

This computation is left as an exercise, and you should verify that the eigenvalues are $\lambda_1 = 2, \lambda_2 = 2$, and $\lambda_3 = 6$.

Next, we need to find the eigenvectors. We first find the eigenvectors for $\lambda_1, \lambda_2 = 2$. Solving $(2I - A)X = 0$ to find the eigenvectors, we find that the eigenvectors are

$$t \begin{bmatrix} -2 \\ 1 \\ 0 \end{bmatrix} + s \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

where t, s are scalars. Hence there are two basic eigenvectors which are given by

$$X_1 = \begin{bmatrix} -2 \\ 1 \\ 0 \end{bmatrix}, X_2 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

You can verify that the basic eigenvector for $\lambda_3 = 6$ is $X_3 = \begin{bmatrix} 0 \\ 1 \\ -2 \end{bmatrix}$

Then, we construct the matrix P as follows.

$$P = \begin{bmatrix} X_1 & X_2 & X_3 \end{bmatrix} = \begin{bmatrix} -2 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & -2 \end{bmatrix}$$

That is, the columns of P are the basic eigenvectors of A. Then, you can verify that

$$P^{-1} = \begin{bmatrix} -\frac{1}{4} & \frac{1}{2} & \frac{1}{4} \\ \frac{1}{2} & 1 & \frac{1}{2} \\ \frac{1}{4} & \frac{1}{2} & -\frac{1}{4} \end{bmatrix}$$

Thus,

$$\begin{aligned} P^{-1}AP &= \begin{bmatrix} -\frac{1}{4} & \frac{1}{2} & \frac{1}{4} \\ \frac{1}{2} & 1 & \frac{1}{2} \\ \frac{1}{4} & \frac{1}{2} & -\frac{1}{4} \end{bmatrix} \begin{bmatrix} 2 & 0 & 0 \\ 1 & 4 & -1 \\ -2 & -4 & 4 \end{bmatrix} \begin{bmatrix} -2 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & -2 \end{bmatrix} \\ &= \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 6 \end{bmatrix} \end{aligned} \tag{8.2.1}$$

You can see that the result here is a diagonal matrix where the entries on the main diagonal are the eigenvalues of A. We expected this based on Theorem 8.2.2. Notice that eigenvalues on the main diagonal *must* be in the same order as the corresponding eigenvectors in P.

Consider the next important theorem.

Theorem 8.2.3: Linearly Independent Eigenvectors

Let A be an $n \times n$ matrix, and suppose that A has distinct eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_m$. For each i, let X_i be a λ_i-eigenvector of A. Then $\{X_1, X_2, \ldots, X_m\}$ is linearly independent.

The corollary that follows from this theorem gives a useful tool in determining if A is diagonalizable.

Corollary 8.2.1: Distinct Eigenvalues

Let A be an $n \times n$ matrix and suppose it has n distinct eigenvalues. Then it follows that A is diagonalizable.

It is possible that a matrix A cannot be diagonalized. In other words, we cannot find an invertible matrix P so that $P^{-1}AP = D$.

Consider the following example.

Example 8.2.2: A Matrix which cannot be Diagonalized

Let

$$A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$$

If possible, find an invertible matrix P and diagonal matrix D so that $P^{-1}AP = D$.

Solution

Through the usual procedure, we find that the eigenvalues of A are $\lambda_1 = 1, \lambda_2 = 1$. To find the eigenvectors, we solve the equation $(\lambda I - A)\, X = 0$. The matrix $(\lambda I - A)$ is given by

$$\begin{bmatrix} \lambda - 1 & -1 \\ 0 & \lambda - 1 \end{bmatrix}$$

Substituting in $\lambda = 1$, we have the matrix

$$\begin{bmatrix} 1 - 1 & -1 \\ 0 & 1 - 1 \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix}$$

Then, solving the equation $(\lambda I - A)\, X = 0$ involves carrying the following augmented matrix to its reduced row-echelon form.

$$\begin{bmatrix} 0 & -1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 0 & -1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Then the eigenvectors are of the form

$$t \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

and the basic eigenvector is

$$X_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

In this case, the matrix A has one eigenvalue of multiplicity two, but only one basic eigenvector. In order to diagonalize A, we need to construct an invertible 2×2 matrix P. However, because A only has one basic eigenvector, we cannot construct this P. Notice that if we were to use X_1 as both columns of P, P would not be invertible. For this reason, we cannot repeat eigenvectors in P.

Hence this matrix cannot be diagonalized.

The idea that a matrix may not be diagonalizable suggests that conditions exist to determine when it is possible to diagonalize a matrix. We saw earlier in Corollary 8.2.1 that an $n \times n$ matrix with n distinct eigenvalues is diagonalizable. It turns out that there are other useful diagonalizability tests.

First we need the following definition.

Definition 8.2.3: Eigenspace

Let A be an $n \times n$ matrix and $\lambda \in \mathbb{R}$. The eigenspace of A corresponding to λ, written $E_\lambda(A)$ is the set of all eigenvectors corresponding to λ.

In other words, the eigenspace $E_\lambda(A)$ is all X such that $AX = \lambda X$. Notice that this set can be written $E_\lambda(A) = \text{null}(\lambda I - A)$, showing that $E_\lambda(A)$ is a subspace of $\mathbb{R}^n$.

Recall that the multiplicity of an eigenvalue λ is the number of times that it occurs as a root of the characteristic polynomial.

Consider now the following lemma.

Lemma 8.2.3: Dimension of the Eigenspace

If A is an $n \times n$ matrix, then

$$\dim(E_\lambda(A)) \leq m$$

where λ is an eigenvalue of A of multiplicity m.

This result tells us that if λ is an eigenvalue of A, then the number of linearly independent λ-eigenvectors is never more than the multiplicity of λ. We now use this fact to provide a useful diagonalizability condition.

Theorem 8.2.4: Diagonalizability Condition

Let A be an $n \times n$ matrix A. Then A is diagonalizable if and only if for each eigenvalue λ of A, $\dim(E_\lambda(A))$ is equal to the multiplicity of λ.

Complex Eigenvalues

In some applications, a matrix may have eigenvalues which are complex numbers. For example, this often occurs in differential equations. These questions are approached in the same way as above.

Consider the following example.

Example 8.2.3: A Real Matrix with Complex Eigenvalues

Let

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & -1 \\ 0 & 1 & 2 \end{bmatrix}$$

Find the eigenvalues and eigenvectors of A.

Solution

We will first find the eigenvalues as usual by solving the following equation.

$$\det\left(\lambda \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & -1 \\ 0 & 1 & 2 \end{bmatrix}\right) = 0$$

This reduces to $(\lambda - 1)(\lambda^2 - 4\lambda + 5) = 0$. The solutions are $\lambda_1 = 1, \lambda_2 = 2 + i$ and $\lambda_3 = 2 - i$.

There is nothing new about finding the eigenvectors for $\lambda_1 = 1$ so this is left as an exercise.

Consider now the eigenvalue $\lambda_2 = 2 + i$. As usual, we solve the equation $(\lambda I - A) X = 0$ as given by

$$\left((2+i) \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & -1 \\ 0 & 1 & 2 \end{bmatrix}\right) X = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

In other words, we need to solve the system represented by the augmented matrix

$$\begin{bmatrix} 1+i & 0 & 0 & 0 \\ 0 & i & 1 & 0 \\ 0 & -1 & i & 0 \end{bmatrix}$$

We now use our row operations to solve the system. Divide the first row by $(1 + i)$ and then take $-i$ times the second row and add to the third row. This yields

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & i & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Now multiply the second row by $-i$ to obtain the reduced row-echelon form, given by

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & -i & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Therefore, the eigenvectors are of the form

$$t \begin{bmatrix} 0 \\ i \\ 1 \end{bmatrix}$$

and the basic eigenvector is given by

$$X_2 = \begin{bmatrix} 0 \\ i \\ 1 \end{bmatrix}$$

As an exercise, verify that the eigenvectors for $\lambda_3 = 2 - i$ are of the form

$$t \begin{bmatrix} 0 \\ -i \\ 1 \end{bmatrix}$$

Hence, the basic eigenvector is given by

$$X_3 = \begin{bmatrix} 0 \\ -i \\ 1 \end{bmatrix}$$

As usual, be sure to check your answers! To verify, we check that $AX_3 = (2-i)\,X_3$ as follows.

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & -1 \\ 0 & 1 & 2 \end{bmatrix} \begin{bmatrix} 0 \\ -i \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ -1-2i \\ 2-i \end{bmatrix} = (2-i) \begin{bmatrix} 0 \\ -i \\ 1 \end{bmatrix}$$

Therefore, we know that this eigenvector and eigenvalue are correct.

Notice that in Example 8.2.3, two of the eigenvalues were given by $\lambda_2 = 2+i$ and $\lambda_3 = 2-i$. You may recall that these two complex numbers are **conjugates**. It turns out that whenever a matrix containing real entries has a complex eigenvalue λ, it also has an eigenvalue equal to $\overline{\lambda}$, the conjugate of λ.

Answers

Lemma 8.2.1**: Similarity is an Equivalence Relation**

It is clear that $A \sim A$, taking $P = I$.

Now, if $A \sim B$, then for some P invertible,

$$A = P^{-1}BP$$

and so

$$PAP^{-1} = B$$

But then

$$\left(P^{-1}\right)^{-1} AP^{-1} = B$$

which shows that $B \sim A$.

Now suppose $A \sim B$ and $B \sim C$. Then there exist invertible matrices P, Q such that

$$A = P^{-1}BP,\ B = Q^{-1}CQ$$

Then,

$$A = P^{-1}\left(Q^{-1}CQ\right)P = (QP)^{-1}C\,(QP)$$

showing that A is similar to C.

Theorem 8.2.2**: Eigenvectors and Diagonalizable Matrices**

Suppose P is given as above as an invertible matrix whose columns are eigenvectors of A. Then P^{-1} is of the form

$$P^{-1} = \begin{bmatrix} W_1^T \\ W_2^T \\ \vdots \\ W_n^T \end{bmatrix}$$

where $W_k^T X_j = \delta_{kj}$, which is the Kronecker's symbol defined by

$$\delta_{ij} = \begin{cases} 1 \text{ if } i = j \\ 0 \text{ if } i \neq j \end{cases}$$

Then

$$\begin{aligned} P^{-1}AP &= \begin{bmatrix} W_1^T \\ W_2^T \\ \vdots \\ W_n^T \end{bmatrix} \begin{bmatrix} AX_1 & AX_2 & \cdots & AX_n \end{bmatrix} \\ &= \begin{bmatrix} W_1^T \\ W_2^T \\ \vdots \\ W_n^T \end{bmatrix} \begin{bmatrix} \lambda_1 X_1 & \lambda_2 X_2 & \cdots & \lambda_n X_n \end{bmatrix} \\ &= \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix} \end{aligned} \tag{8.2.2}$$

Conversely, suppose A is diagonalizable so that $P^{-1}AP = D$. Let

$$P = \begin{bmatrix} X_1 & X_2 & \cdots & X_n \end{bmatrix}$$

where the columns are the X_k and

$$D = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix}$$

Then

$$AP = PD = \begin{bmatrix} X_1 & X_2 & \cdots & X_n \end{bmatrix} \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix}$$

and so

$$\begin{bmatrix} AX_1 & AX_2 & \cdots & AX_n \end{bmatrix} = \begin{bmatrix} \lambda_1 X_1 & \lambda_2 X_2 & \cdots & \lambda_n X_n \end{bmatrix}$$

showing the X_k are eigenvectors of A and the λ_k are eigenvectors.

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8.3: Applications of Spectral Theory

Outcomes

A. Use diagonalization to find a high power of a matrix.
B. Use diagonalization to solve dynamical systems.

Raising a Matrix to a High Power

Suppose we have a matrix A and we want to find A^{50}. One could try to multiply A with itself 50 times, but this is computationally extremely intensive (try it!). However diagonalization allows us to compute high powers of a matrix relatively easily. Suppose A is diagonalizable, so that $P^{-1}AP = D$. We can rearrange this equation to write $A = PDP^{-1}$.

Now, consider A^2. Since $A = PDP^{-1}$, it follows that

$$A^2 = \left(PDP^{-1}\right)^2 = PDP^{-1}PDP^{-1} = PD^2P^{-1}$$

Similarly,

$$A^3 = \left(PDP^{-1}\right)^3 = PDP^{-1}PDP^{-1}PDP^{-1} = PD^3P^{-1}$$

In general,

$$A^n = \left(PDP^{-1}\right)^n = PD^nP^{-1}$$

Therefore, we have reduced the problem to finding D^n. In order to compute D^n, then because D is diagonal we only need to raise every entry on the main diagonal of D to the power of n.

Through this method, we can compute large powers of matrices. Consider the following example.

Example 8.3.1: Raising a Matrix to a High Power

Let $A = \begin{bmatrix} 2 & 1 & 0 \\ 0 & 1 & 0 \\ -1 & -1 & 1 \end{bmatrix}$. Find A^{50}.

Solution

We will first diagonalize A. The steps are left as an exercise and you may wish to verify that the eigenvalues of A are $\lambda_1 = 1, \lambda_2 = 1$, and $\lambda_3 = 2$.

The basic eigenvectors corresponding to $\lambda_1, \lambda_2 = 1$ are

$$X_1 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, X_2 = \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix}$$

The basic eigenvector corresponding to $\lambda_3 = 2$ is

$$X_3 = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

Now we construct P by using the basic eigenvectors of A as the columns of P. Thus

$$P = \begin{bmatrix} X_1 & X_2 & X_3 \end{bmatrix} = \begin{bmatrix} 0 & -1 & -1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}$$

Then also

$$P^{-1} = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 0 \\ -1 & -1 & 0 \end{bmatrix}$$

which you may wish to verify.

Then,

$$\begin{aligned} P^{-1}AP &= \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 0 \\ -1 & -1 & 0 \end{bmatrix} \begin{bmatrix} 2 & 1 & 0 \\ 0 & 1 & 0 \\ -1 & -1 & 1 \end{bmatrix} \begin{bmatrix} 0 & -1 & -1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \\ &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} \\ &= D \end{aligned} \tag{8.3.1}$$

Now it follows by rearranging the equation that

$$A = PDP^{-1} = \begin{bmatrix} 0 & -1 & -1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 0 \\ -1 & -1 & 0 \end{bmatrix}$$

Therefore,

$$\begin{aligned} A^{50} &= PD^{50}P^{-1} \\ &= \begin{bmatrix} 0 & -1 & -1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}^{50} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 0 \\ -1 & -1 & 0 \end{bmatrix} \end{aligned} \tag{8.3.2}$$

By our discussion above, D^{50} is found as follows.

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}^{50} = \begin{bmatrix} 1^{50} & 0 & 0 \\ 0 & 1^{50} & 0 \\ 0 & 0 & 2^{50} \end{bmatrix}$$

It follows that

$$\begin{aligned} A^{50} &= \begin{bmatrix} 0 & -1 & -1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1^{50} & 0 & 0 \\ 0 & 1^{50} & 0 \\ 0 & 0 & 2^{50} \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 0 \\ -1 & -1 & 0 \end{bmatrix} \\ &= \begin{bmatrix} 2^{50} & -1+2^{50} & 0 \\ 0 & 1 & 0 \\ 1-2^{50} & 1-2^{50} & 1 \end{bmatrix} \end{aligned} \tag{8.3.3}$$

Through diagonalization, we can efficiently compute a high power of A. Without this, we would be forced to multiply this by hand!

The next section explores another interesting application of diagonalization.

Raising a Symmetric Matrix to a High Power

We already have seen how to use matrix diagonalization to compute powers of matrices. This requires computing eigenvalues of the matrix A, and finding an invertible matrix of eigenvectors P such that $P^{-1}AP$ is diagonal. In this section we will see that if the matrix A is symmetric (see Definition 2.5.2), then we can actually find such a matrix P that is an orthogonal matrix of eigenvectors.

Thus P^{-1} is simply its transpose P^T, and P^TAP is diagonal. When this happens we say that A is **orthogonally diagonalizable**

In fact this happens if and only if A is a symmetric matrix as shown in the following important theorem.

Theorem 8.3.1: Principal Axis Theorem

The following conditions are equivalent for an $n \times n$ matrix A:

1. A is symmetric.
2. A has an orthonormal set of eigenvectors.
3. A is orthogonally diagonalizable.

Proof available at the end of this section.

We demonstrate this in the following example.

Example 8.3.2: Orthogonal Diagonalization of a Symmetric Matrix

Let $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{3}{2} & \frac{1}{2} \\ 0 & \frac{1}{2} & \frac{3}{2} \end{bmatrix}$. Find an orthogonal matrix P such that P^TAP is a diagonal matrix.

Solution

In this case, verify that the eigenvalues are 2 and 1. First we will find an eigenvector for the eigenvalue 2. This involves row reducing the following augmented matrix.

$$\begin{bmatrix} 2-1 & 0 & 0 & 0 \\ 0 & 2-\frac{3}{2} & -\frac{1}{2} & 0 \\ 0 & -\frac{1}{2} & 2-\frac{3}{2} & 0 \end{bmatrix}$$

The reduced row-echelon form is

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

and so an eigenvector is

$$\begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

Finally to obtain an eigenvector of length one (unit eigenvector) we simply divide this vector by its length to yield:

$$\begin{bmatrix} 0 \\ \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

Next consider the case of the eigenvalue 1. To obtain basic eigenvectors, the matrix which needs to be row reduced in this case is

$$\begin{bmatrix} 1-1 & 0 & 0 & 0 \\ 0 & 1-\frac{3}{2} & -\frac{1}{2} & 0 \\ 0 & -\frac{1}{2} & 1-\frac{3}{2} & 0 \end{bmatrix}$$

The reduced row-echelon form is

$$\begin{bmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Therefore, the eigenvectors are of the form

$$\begin{bmatrix} s \\ -t \\ t \end{bmatrix}$$

Note that all these vectors are automatically orthogonal to eigenvectors corresponding to the first eigenvalue. This follows from the fact that A is symmetric, as mentioned earlier.

We obtain basic eigenvectors

$$\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \text{ and } \begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix}$$

Since they are themselves orthogonal (by luck here) we do not need to use the Gram-Schmidt process and instead simply normalize these vectors to obtain

$$\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \text{ and } \begin{bmatrix} 0 \\ -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

An orthogonal matrix P to orthogonally diagonalize A is then obtained by letting these basic vectors be the columns.

$$P = \begin{bmatrix} 0 & 1 & 0 \\ -\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \end{bmatrix}$$

We verify this works. $P^T AP$ is of the form

$$\begin{bmatrix} 0 & -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{3}{2} & \frac{1}{2} \\ 0 & \frac{1}{2} & \frac{3}{2} \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ -\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

which is the desired diagonal matrix.

We can now apply this technique to efficiently compute high powers of a symmetric matrix.

Example 8.3.3: Powers of a Symmetric Matrix

Let $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{3}{2} & \frac{1}{2} \\ 0 & \frac{1}{2} & \frac{3}{2} \end{bmatrix}$. Compute A^7.

Solution

We found in Example 8.3.2 that $P^T AP = D$ is diagonal, where

$$P = \begin{bmatrix} 0 & 1 & 0 \\ -\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \text{ and } D = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

Thus $A = PDP^T$ and $A^7 = PDP^T \ PDP^T \ \cdots PDP^T = PD^7P^T$ which gives:

$$\begin{aligned} A^7 &= \begin{bmatrix} 0 & 1 & 0 \\ -\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}^7 \begin{bmatrix} 0 & -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \\ &= \begin{bmatrix} 0 & 1 & 0 \\ -\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2^7 \end{bmatrix} \begin{bmatrix} 0 & -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \\ &= \begin{bmatrix} 0 & 1 & 0 \\ -\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 0 & -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 1 & 0 & 0 \\ 0 & \frac{2^7}{\sqrt{2}} & \frac{2^7}{\sqrt{2}} \end{bmatrix} \\ &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{2^7+1}{2} & \frac{2^7-1}{2} \\ 0 & \frac{2^7-1}{2} & \frac{2^7+1}{2} \end{bmatrix} \end{aligned}$$

Markov Matrices

There are applications of great importance which feature a special type of matrix. Matrices whose columns consist of non-negative numbers that sum to one are called **Markov matrices**. An important application of Markov matrices is in population migration, as illustrated in the following definition.

Definition 8.3.1: Migration Matrices

Let m locations be denoted by the numbers $1, 2, \cdots, m$. Suppose it is the case that each year the proportion of residents in location j which move to location i is a_{ij}. Also suppose no one escapes or emigrates from without these m locations. This last assumption requires $\sum_i a_{ij} = 1$, and means that the matrix A, such that $A = [a_{ij}]$, is a Markov matrix. In this context, A is also called a **migration matrix**.

Consider the following example which demonstrates this situation.

Example 8.3.4: Migration Matrix

Let A be a Markov matrix given by

$$A = \begin{bmatrix} .4 & .2 \\ .6 & .8 \end{bmatrix}$$

Verify that A is a Markov matrix and describe the entries of A in terms of population migration.

Solution

The columns of A are comprised of non-negative numbers which sum to 1. Hence, A is a Markov matrix.

Now, consider the entries a_{ij} of A in terms of population. The entry $a_{11} = .4$ is the proportion of residents in location one which stay in location one in a given time period. Entry $a_{21} = .6$ is the proportion of residents in location 1 which move to location 2 in the same time period. Entry $a_{12} = .2$ is the proportion of residents in location 2 which move to location 1. Finally, entry $a_{22} = .8$ is the proportion of residents in location 2 which stay in location 2 in this time period.

Considered as a Markov matrix, these numbers are usually identified with probabilities. Hence, we can say that the probability that a resident of location one will stay in location one in the time period is $.4$.

Observe that in Example 8.3.4 if there was initially say 15 thousand people in location 1 and 10 thousands in location 2, then after one year there would be $.4 \times 15 + .2 \times 10 = 8$ thousands people in location 1 the following year, and similarly there would be $.6 \times 15 + .8 \times 10 = 17$ thousands people in location 2 the following year.

More generally let $X_n = [x_{1n} \cdots x_{mn}]^T$ where x_{in} is the population of location i at time period n. We call X_n the **state vector at period** n. In particular, we call X_0 the initial state vector. Letting A be the migration matrix, we compute the population in each location i one time period later by AX_n. In order to find the population of location i after k years, we compute the i^{th} component of $A^k X$. This discussion is summarized in the following theorem.

Theorem 8.3.2: State Vector

Let A be the migration matrix of a population and let X_n be the vector whose entries give the population of each location at time period n. Then X_n is the state vector at period n and it follows that

$$X_{n+1} = AX_n$$

The sum of the entries of X_n will equal the sum of the entries of the initial vector X_0. Since the columns of A sum to 1, this sum is preserved for every multiplication by A as demonstrated below.

$$\sum_i \sum_j a_{ij} x_j = \sum_j x_j \left(\sum_i a_{ij} \right) = \sum_j x_j$$

Consider the following example.

Example 8.3.5: Using a Migration Matrix

Consider the migration matrix

$$A = \begin{bmatrix} .6 & 0 & .1 \\ .2 & .8 & 0 \\ .2 & .2 & .9 \end{bmatrix}$$

for locations $1, 2,$ and 3. Suppose initially there are 100 residents in location 1, 200 in location 2 and 400 in location 3. Find the population in the three locations after $1, 2,$ and 10 units of time.

Solution

Using Theorem 8.3.2 we can find the population in each location using the equation $X_{n+1} = AX_n$. For the population after 1 unit, we calculate $X_1 = AX_0$ as follows.

$$\begin{aligned} X_1 &= AX_0 \\ \begin{bmatrix} x_{11} \\ x_{21} \\ x_{31} \end{bmatrix} &= \begin{bmatrix} .6 & 0 & .1 \\ .2 & .8 & 0 \\ .2 & .2 & .9 \end{bmatrix} \begin{bmatrix} 100 \\ 200 \\ 400 \end{bmatrix} \\ &= \begin{bmatrix} 100 \\ 180 \\ 420 \end{bmatrix} \end{aligned} \tag{8.3.4}$$

Therefore after one time period, location 1 has 100 residents, location 2 has 180, and location 3 has 420. Notice that the **total** population is unchanged, it simply migrates within the given locations. We find the locations after two time periods in the same way.

$$\begin{aligned} X_2 &= AX_1 \\ \begin{bmatrix} x_{12} \\ x_{22} \\ x_{32} \end{bmatrix} &= \begin{bmatrix} .6 & 0 & .1 \\ .2 & .8 & 0 \\ .2 & .2 & .9 \end{bmatrix} \begin{bmatrix} 100 \\ 180 \\ 420 \end{bmatrix} \\ &= \begin{bmatrix} 102 \\ 164 \\ 434 \end{bmatrix} \end{aligned} \tag{8.3.5}$$

We could progress in this manner to find the populations after 10 time periods. However from our above discussion, we can simply calculate $(A^n X_0)_i$, where n denotes the number of time periods which have passed. Therefore, we compute the populations in each location after 10 units of time as follows.

$$\begin{aligned} X_{10} &= A^{10} X_0 \\ \begin{bmatrix} x_{110} \\ x_{210} \\ x_{310} \end{bmatrix} &= \begin{bmatrix} .6 & 0 & .1 \\ .2 & .8 & 0 \\ .2 & .2 & .9 \end{bmatrix}^{10} \begin{bmatrix} 100 \\ 200 \\ 400 \end{bmatrix} \\ &= \begin{bmatrix} 115.085\,829\,22 \\ 120.130\,672\,44 \\ 464.783\,498\,34 \end{bmatrix} \end{aligned} \tag{8.3.6}$$

Since we are speaking about populations, we would need to round these numbers to provide a logical answer. Therefore, we can say that after 10 units of time, there will be 115 residents in location one, 120 in location two, and 465 in location three.

A second important application of Markov matrices is the concept of random walks. Suppose a walker has m locations to choose from, denoted $1, 2, \cdots, m$. Let a_{ij} refer to the probability that the person will travel **to** location i **from** location j. Again, this requires that

$$\sum_{i=1}^{k} a_{ij} = 1$$

In this context, the vector $X_n = [x_{1n} \cdots x_{mn}]^T$ contains the probabilities x_{in} the walker ends up in location $i, 1 \leq i \leq m$ at time n.

Example 8.3.6: Random Walks

Suppose three locations exist, referred to as locations $1, 2$ and 3. The Markov matrix of probabilities $A = [a_{ij}]$ is given by

$$\begin{bmatrix} 0.4 & 0.1 & 0.5 \\ 0.4 & 0.6 & 0.1 \\ 0.2 & 0.3 & 0.4 \end{bmatrix}$$

If the walker starts in location 1, calculate the probability that he ends up in location 3 at time $n = 2$.

Solution

Since the walker begins in location 1, we have

$$X_0 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

The goal is to calculate x_{32}. To do this we calculate X_2, using $X_{n+1} = AX_n$.

$$\begin{aligned} X_1 &= AX_0 \\ &= \begin{bmatrix} 0.4 & 0.1 & 0.5 \\ 0.4 & 0.6 & 0.1 \\ 0.2 & 0.3 & 0.4 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \\ &= \begin{bmatrix} 0.4 \\ 0.4 \\ 0.2 \end{bmatrix} \end{aligned} \tag{8.3.7}$$

$$\begin{aligned} X_2 &= AX_1 \\ &= \begin{bmatrix} 0.4 & 0.1 & 0.5 \\ 0.4 & 0.6 & 0.1 \\ 0.2 & 0.3 & 0.4 \end{bmatrix} \begin{bmatrix} 0.4 \\ 0.4 \\ 0.2 \end{bmatrix} \\ &= \begin{bmatrix} 0.3 \\ 0.42 \\ 0.28 \end{bmatrix} \end{aligned} \tag{8.3.8}$$

This gives the probabilities that our walker ends up in locations 1, 2, and 3. For this example we are interested in location 3, with a probability on 0.28.

Returning to the context of migration, suppose we wish to know how many residents will be in a certain location after a very long time. It turns out that if some power of the migration matrix has all positive entries, then there is a vector X_s such that $A^n X_0$ approaches X_s as n becomes very large. Hence as more time passes and n increases, $A^n X_0$ will become closer to the vector X_s.

Consider Theorem 8.3.2. Let n increase so that X_n approaches X_s. As X_n becomes closer to X_s, so too does X_{n+1}. For sufficiently large n, the statement $X_{n+1} = AX_n$ can be written as $X_s = AX_s$.

This discussion motivates the following theorem.

Theorem 8.3.3: Steady State Vector

Let A be a migration matrix. Then there exists a **steady state vector** written X_s such that

$$X_s = AX_s$$

where X_s has positive entries which have the same sum as the entries of X_0.

As n increases, the state vectors X_n will approach X_s.

Note that the condition in Theorem 8.3.3 can be written as $(I - A)X_s = 0$, representing a homogeneous system of equations.

Consider the following example. Notice that it is the same example as the Example 8.3.5 but here it will involve a longer time frame.

Example 8.3.7: Populations over the Long Run

Consider the migration matrix

$$A = \begin{bmatrix} .6 & 0 & .1 \\ .2 & .8 & 0 \\ .2 & .2 & .9 \end{bmatrix}$$

for locations $1, 2,$ and 3. Suppose initially there are 100 residents in location 1, 200 in location 2 and 400 in location 4. Find the population in the three locations after a long time.

Solution

By Theorem 8.3.3 the steady state vector X_s can be found by solving the system $(I - A)X_s = 0$.

Thus we need to find a solution to

$$\left(\begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix}-\begin{bmatrix}.6&0&.1\\.2&.8&0\\.2&.2&.9\end{bmatrix}\right)\begin{bmatrix}x_{1s}\\x_{2s}\\x_{3s}\end{bmatrix}=\begin{bmatrix}0\\0\\0\end{bmatrix}$$

The augmented matrix and the resulting reduced row-echelon form are given by

$$\begin{bmatrix}0.4&0&-0.1&0\\-0.2&0.2&0&0\\-0.2&-0.2&0.1&0\end{bmatrix}\to\cdots\to\begin{bmatrix}1&0&-0.25&0\\0&1&-0.25&0\\0&0&0&0\end{bmatrix}$$

Therefore, the eigenvectors are

$$t\begin{bmatrix}0.25\\0.25\\1\end{bmatrix}$$

The initial vector X_0 is given by

$$\begin{bmatrix}100\\200\\400\end{bmatrix}$$

Now all that remains is to choose the value of t such that

$$0.25t+0.25t+t=100+200+400$$

Solving this equation for t yields $t=\frac{1400}{3}$. Therefore the population in the long run is given by

$$\frac{1400}{3}\begin{bmatrix}0.25\\0.25\\1\end{bmatrix}=\begin{bmatrix}116.666\,666\,666\,666\,7\\116.666\,666\,666\,666\,7\\466.666\,666\,666\,666\,7\end{bmatrix}$$

Again, because we are working with populations, these values need to be rounded. The steady state vector X_s is given by

$$\begin{bmatrix}117\\117\\466\end{bmatrix}$$

We can see that the numbers we calculated in Example 8.3.5 for the populations after the 10^{th} unit of time are not far from the long term values.

Consider another example.

Example 8.3.8: Populations After a Long Time

Suppose a migration matrix is given by

$$A=\begin{bmatrix}\frac{1}{5}&\frac{1}{2}&\frac{1}{5}\\\frac{1}{4}&\frac{1}{4}&\frac{1}{2}\\\frac{11}{20}&\frac{1}{4}&\frac{3}{10}\end{bmatrix}$$

Find the comparison between the populations in the three locations after a long time.

Solution

In order to compare the populations in the long term, we want to find the steady state vector X_s. Solve

$$\left(\begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix}-\begin{bmatrix}\frac{1}{5}&\frac{1}{2}&\frac{1}{5}\\\frac{1}{4}&\frac{1}{4}&\frac{1}{2}\\\frac{11}{20}&\frac{1}{4}&\frac{3}{10}\end{bmatrix}\right)\begin{bmatrix}x_{1s}\\x_{2s}\\x_{3s}\end{bmatrix}=\begin{bmatrix}0\\0\\0\end{bmatrix}$$

The augmented matrix and the resulting reduced row-echelon form are given by

$$\begin{bmatrix}\frac{4}{5}&-\frac{1}{2}&-\frac{1}{5}&0\\-\frac{1}{4}&\frac{3}{4}&-\frac{1}{2}&0\\-\frac{11}{20}&-\frac{1}{4}&\frac{7}{10}&0\end{bmatrix}\to\cdots\to\begin{bmatrix}1&0&-\frac{16}{19}&0\\0&1&-\frac{18}{19}&0\\0&0&0&0\end{bmatrix}$$

and so an eigenvector is

$$\begin{bmatrix}16\\18\\19\end{bmatrix}$$

Therefore, the proportion of population in location 2 to location 1 is given by $\frac{18}{16}$. The proportion of population 3 to location 2 is given by $\frac{19}{18}$.

Eigenvalues of Markov Matrices

The following is an important proposition.

Proposition 8.3.1: Eigenvalues of a Migration Matrix

Let $A=[a_{ij}]$ be a migration matrix. Then 1 is always an eigenvalue for A.

Proof available at the end of this section.

Dynamical Systems

The migration matrices discussed above give an example of a discrete dynamical system. We call them discrete because they involve discrete values taken at a sequence of points rather than on a continuous interval of time.

An example of a situation which can be studied in this way is a predator prey model. Consider the following model where x is the number of prey and y the number of predators in a certain area at a certain time. These are functions of $n\in\mathbb{N}$ where $n=1,2,\cdots$ are the ends of intervals of time which may be of interest in the problem. In other words, $x(n)$ is the number of prey at the end of the n^{th} interval of time. An example of this situation may be modeled by the following equation

$$\begin{bmatrix}x(n+1)\\y(n+1)\end{bmatrix}=\begin{bmatrix}2&-3\\1&4\end{bmatrix}\begin{bmatrix}x(n)\\y(n)\end{bmatrix}$$

This says that from time period n to $n+1$, x increases if there are more x and decreases as there are more y. In the context of this example, this means that as the number of predators increases, the number of prey decreases. As for y, it increases if there are more y and also if there are more x.

This is an example of a matrix recurrence which we define now.

Definition 8.3.2: Matrix Recurrence

Suppose a dynamical system is given by

$$\begin{aligned}x_{n+1}&=ax_n+by_n\\y_{n+1}&=cx_n+dy_n\end{aligned}\tag{8.3.9}$$

This system can be expressed as $V_{n+1} = AV_n$ where $V_n = \begin{bmatrix} x_n \\ y_n \end{bmatrix}$ and $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$.

In this section, we will examine how to find solutions to a dynamical system given certain initial conditions. This process involves several concepts previously studied, including matrix diagonalization and Markov matrices. The procedure is given as follows. Recall that when diagonalized, we can write $A^n = PD^nP^{-1}$.

Procedure 8.3.1: Solving a Dynamical System

Suppose a dynamical system is given by

$$\begin{aligned} x_{n+1} &= ax_n + by_n \\ y_{n+1} &= cx_n + dy_n \end{aligned} \tag{8.3.10}$$

Given initial conditions x_0 and y_0, the solutions to the system are found as follows:

1. Express the dynamical system in the form $V_{n+1} = AV_n$.
2. Diagonalize A to be written as $A = PDP^{-1}$.
3. Then $V_n = PD^nP^{-1}V_0$ where V_0 is the vector containing the initial conditions.
4. If given specific values for n, substitute into this equation. Otherwise, find a general solution for n.

We will now consider an example in detail.

Example 8.3.9: Solutions of a Discrete Dynamical System

Suppose a dynamical system is given by

$$\begin{aligned} x_{n+1} &= 1.5x_n - 0.5y_n \\ y_{n+1} &= 1.0x_n \end{aligned} \tag{8.3.11}$$

Express this system as a matrix recurrence and find solutions to the dynamical system for initial conditions $x_0 = 20, y_0 = 10$.

Solution

First, we express the system as a matrix recurrence.

$$\begin{aligned} V_{n+1} &= AV_n \\ \begin{bmatrix} x(n+1) \\ y(n+1) \end{bmatrix} &= \begin{bmatrix} 1.5 & -0.5 \\ 1.0 & 0 \end{bmatrix} \begin{bmatrix} x(n) \\ y(n) \end{bmatrix} \end{aligned} \tag{8.3.12}$$

Then

$$A = \begin{bmatrix} 1.5 & -0.5 \\ 1.0 & 0 \end{bmatrix}$$

You can verify that the eigenvalues of A are 1 and $.5$. By diagonalizing, we can write A in the form

$$P^{-1}DP = \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & .5 \end{bmatrix} \begin{bmatrix} 2 & -1 \\ -1 & 1 \end{bmatrix}$$

Now given an initial condition

$$V_0 = \begin{bmatrix} x_0 \\ y_0 \end{bmatrix}$$

the solution to the dynamical system is given by

$$
\begin{aligned}
V_n &= PD^nP^{-1}V_0 \\
\begin{bmatrix} x(n) \\ y(n) \end{bmatrix} &= \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & .5 \end{bmatrix}^n \begin{bmatrix} 2 & -1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} \\
&= \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & (.5)^n \end{bmatrix} \begin{bmatrix} 2 & -1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} \\
&= \begin{bmatrix} y_0\left((.5)^n - 1\right) - x_0\left((.5)^n - 2\right) \\ y_0\left(2\,(.5)^n - 1\right) - x_0\left(2\,(.5)^n - 2\right) \end{bmatrix}
\end{aligned} \tag{8.3.13}
$$

If we let n become arbitrarily large, this vector approaches

$$\begin{bmatrix} 2x_0 - y_0 \\ 2x_0 - y_0 \end{bmatrix}$$

Thus for large n,

$$\begin{bmatrix} x(n) \\ y(n) \end{bmatrix} \approx \begin{bmatrix} 2x_0 - y_0 \\ 2x_0 - y_0 \end{bmatrix}$$

Now suppose the initial condition is given by

$$\begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \begin{bmatrix} 20 \\ 10 \end{bmatrix}$$

Then, we can find solutions for various values of n. Here are the solutions for values of n between 1 and 5

$$n = 1 : \begin{bmatrix} 25.0 \\ 20.0 \end{bmatrix}, n = 2 : \begin{bmatrix} 27.5 \\ 25.0 \end{bmatrix}, n = 3 : \begin{bmatrix} 28.75 \\ 27.5 \end{bmatrix}$$

$$n = 4 : \begin{bmatrix} 29.375 \\ 28.75 \end{bmatrix}, n = 5 : \begin{bmatrix} 29.688 \\ 29.375 \end{bmatrix}$$

Notice that as n increases, we approach the vector given by

$$\begin{bmatrix} 2x_0 - y_0 \\ 2x_0 - y_0 \end{bmatrix} = \begin{bmatrix} 2\,(20) - 10 \\ 2\,(20) - 10 \end{bmatrix} = \begin{bmatrix} 30 \\ 30 \end{bmatrix}$$

These solutions are graphed in the following figure.

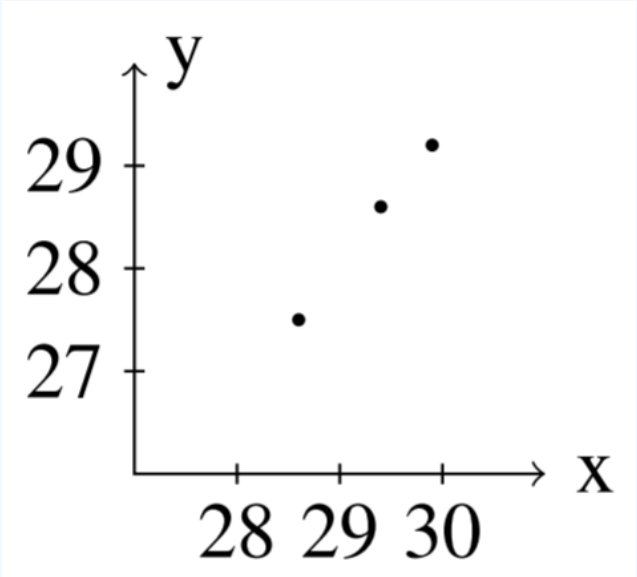


Figure 8.3.1

The following example demonstrates another system which exhibits some interesting behavior. When we graph the solutions, it is

possible for the ordered pairs to spiral around the origin.

Example 8.3.10: Finding Solutions to a Dynamical System

Suppose a dynamical system is of the form

$$\begin{bmatrix} x(n+1) \\ y(n+1) \end{bmatrix} = \begin{bmatrix} 0.7 & 0.7 \\ -0.7 & 0.7 \end{bmatrix} \begin{bmatrix} x(n) \\ y(n) \end{bmatrix}$$

Find solutions to the dynamical system for given initial conditions.

Solution

Let

$$A = \begin{bmatrix} 0.7 & 0.7 \\ -0.7 & 0.7 \end{bmatrix}$$

To find solutions, we must diagonalize A. You can verify that the eigenvalues of A are complex and are given by $\lambda_1 = .7 + .7i$ and $\lambda_2 = .7 - .7i$. The eigenvector for $\lambda_1 = .7 + .7i$ is

$$\begin{bmatrix} 1 \\ i \end{bmatrix}$$

and that the eigenvector for $\lambda_2 = .7 - .7i$ is

$$\begin{bmatrix} 1 \\ -i \end{bmatrix}$$

Thus the matrix A can be written in the form

$$\begin{bmatrix} 1 & 1 \\ i & -i \end{bmatrix} \begin{bmatrix} .7+.7i & 0 \\ 0 & .7-.7i \end{bmatrix} \begin{bmatrix} \frac{1}{2} & -\frac{1}{2}i \\ \frac{1}{2} & \frac{1}{2}i \end{bmatrix}$$

and so,

$$\begin{aligned} V_n &= PD^nP^{-1}V_0 \\ \begin{bmatrix} x(n) \\ y(n) \end{bmatrix} &= \begin{bmatrix} 1 & 1 \\ i & -i \end{bmatrix} \begin{bmatrix} (.7+.7i)^n & 0 \\ 0 & (.7-.7i)^n \end{bmatrix} \begin{bmatrix} \frac{1}{2} & -\frac{1}{2}i \\ \frac{1}{2} & \frac{1}{2}i \end{bmatrix} \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} \end{aligned} \tag{8.3.14}$$

The explicit solution is given by

$$\begin{bmatrix} x_0\left(\frac{1}{2}(0.7-0.7i)^n + \frac{1}{2}(0.7+0.7i)^n\right) + y_0\left(\frac{1}{2}i(0.7-0.7i)^n - \frac{1}{2}i(0.7+0.7i)^n\right) \\ y_0\left(\frac{1}{2}(0.7-0.7i)^n + \frac{1}{2}(0.7+0.7i)^n\right) - x_0\left(\frac{1}{2}i(0.7-0.7i)^n - \frac{1}{2}i(0.7+0.7i)^n\right) \end{bmatrix}$$

Suppose the initial condition is

$$\begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \begin{bmatrix} 10 \\ 10 \end{bmatrix}$$

Then one obtains the following sequence of values which are graphed below by letting $n = 1, 2, \cdots, 20$

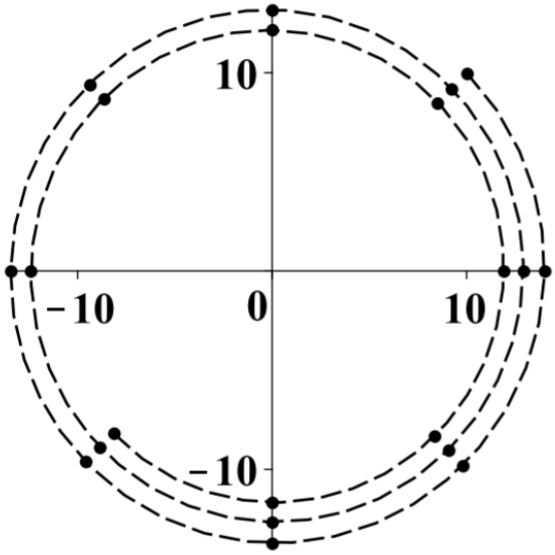


Figure 8.3.2

In this picture, the dots are the values and the dashed line is to help to picture what is happening.

These points are getting gradually closer to the origin, but they are circling the origin in the clockwise direction as they do so. As n increases, the vector $\begin{bmatrix} x(n) \\ y(n) \end{bmatrix}$ approaches $\begin{bmatrix} 0 \\ 0 \end{bmatrix}$

This type of behavior along with complex eigenvalues is typical of the deviations from an equilibrium point in the Lotka Volterra system of differential equations which is a famous model for predator-prey interactions. These differential equations are given by

$$\begin{aligned} x' &= x(a - by) \\ y' &= -y(c - dx) \end{aligned} \tag{8.3.15}$$

where a, b, c, d are positive constants. For example, you might have X be the population of moose and Y the population of wolves on an island.

Note that these equations make logical sense. The top says that the rate at which the moose population increases would be aX if there were no predators Y. However, this is modified by multiplying instead by $(a - bY)$ because if there are predators, these will militate against the population of moose. The more predators there are, the more pronounced is this effect. As to the predator equation, you can see that the equations predict that if there are many prey around, then the rate of growth of the predators would seem to be high. However, this is modified by the term $-cY$ because if there are many predators, there would be competition for the available food supply and this would tend to decrease Y'.

The behavior near an equilibrium point, which is a point where the right side of the differential equations equals zero, is of great interest. In this case, the equilibrium point is

$$x = \frac{c}{d}, y = \frac{a}{b}$$

Then one defines new variables according to the formula

$$x + \frac{c}{d} = x, \ y = y + \frac{a}{b}$$

In terms of these new variables, the differential equations become

$$\begin{aligned} x' &= \left(x + \frac{c}{d}\right)\left(a - b\left(y + \frac{a}{b}\right)\right) \\ y' &= -\left(y + \frac{a}{b}\right)\left(c - d\left(x + \frac{c}{d}\right)\right) \end{aligned} \tag{8.3.16}$$

Multiplying out the right sides yields

$$\begin{aligned} x' &= -bxy - b\frac{c}{d}y \\ y' &= dxy + \frac{a}{b}dx \end{aligned} \tag{8.3.17}$$

The interest is for x, y small and so these equations are essentially equal to

$$x' = -b\frac{c}{d}y,\ y' = \frac{a}{b}dx$$

Replace x' with the difference quotient $\frac{x(t+h)-x(t)}{h}$ where h is a small positive number and y' with a similar difference quotient. For example one could have h correspond to one day or even one hour. Thus, for h small enough, the following would seem to be a good approximation to the differential equations.

$$\begin{aligned} x\left(t+h\right) &= x\left(t\right) - hb\frac{c}{d}y \\ y\left(t+h\right) &= y\left(t\right) + h\frac{a}{b}dx \end{aligned} \tag{8.3.18}$$

Let $1, 2, 3, \cdots$ denote the ends of discrete intervals of time having length h chosen above. Then the above equations take the form

$$\begin{bmatrix} x\left(n+1\right) \\ y\left(n+1\right) \end{bmatrix} = \begin{bmatrix} 1 & -\frac{hbc}{d} \\ \frac{had}{b} & 1 \end{bmatrix} \begin{bmatrix} x\left(n\right) \\ y\left(n\right) \end{bmatrix}$$

Note that the eigenvalues of this matrix are always complex.

We are not interested in time intervals of length h for h very small. Instead, we are interested in much longer lengths of time. Thus, replacing the time interval with mh,

$$\begin{bmatrix} x\left(n+m\right) \\ y\left(n+m\right) \end{bmatrix} = \begin{bmatrix} 1 & -\frac{hbc}{d} \\ \frac{had}{b} & 1 \end{bmatrix}^m \begin{bmatrix} x\left(n\right) \\ y\left(n\right) \end{bmatrix}$$

For example, if $m = 2$, you would have

$$\begin{bmatrix} x\left(n+2\right) \\ y\left(n+2\right) \end{bmatrix} = \begin{bmatrix} 1-ach^2 & -2b\frac{c}{d}h \\ 2\frac{a}{b}dh & 1-ach^2 \end{bmatrix} \begin{bmatrix} x\left(n\right) \\ y\left(n\right) \end{bmatrix}$$

Note that most of the time, the eigenvalues of the new matrix will be complex.

You can also notice that the upper right corner will be negative by considering higher powers of the matrix. Thus letting $1, 2, 3, \cdots$ denote the ends of discrete intervals of time, the desired discrete dynamical system is of the form

$$\begin{bmatrix} x\left(n+1\right) \\ y\left(n+1\right) \end{bmatrix} = \begin{bmatrix} a & -b \\ c & d \end{bmatrix} \begin{bmatrix} x\left(n\right) \\ y\left(n\right) \end{bmatrix}$$

where a, b, c, d are positive constants and the matrix will likely have complex eigenvalues because it is a power of a matrix which has complex eigenvalues.

You can see from the above discussion that if the eigenvalues of the matrix used to define the dynamical system are less than 1 in absolute value, then the origin is stable in the sense that as $n \to \infty$, the solution converges to the origin. If either eigenvalue is larger than 1 in absolute value, then the solutions to the dynamical system will usually be unbounded, unless the initial condition is chosen very carefully. The next example exhibits the case where one eigenvalue is larger than 1 and the other is smaller than 1.

The following example demonstrates a familiar concept as a dynamical system.

Example 8.3.11: The Fibonacci Sequence

The Fibonacci sequence is the sequence given by

$$1, 1, 2, 3, 5, \cdots$$

which is defined recursively in the form

$$x\left(0\right) = 1 = x\left(1\right),\ x\left(n+2\right) = x\left(n+1\right) + x\left(n\right)$$

Show how the Fibonacci Sequence can be considered a dynamical system.

Solution

This sequence is extremely important in the study of reproducing rabbits. It can be considered as a dynamical system as follows. Let $y(n) = x(n+1)$. Then the above recurrence relation can be written as

$$\begin{bmatrix} x(n+1) \\ y(n+1) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x(n) \\ y(n) \end{bmatrix}, \quad \begin{bmatrix} x(0) \\ y(0) \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Let

$$A = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix}$$

The eigenvalues of the matrix A are $\lambda_1 = \frac{1}{2} - \frac{1}{2}\sqrt{5}$ and $\lambda_2 = \frac{1}{2}\sqrt{5} + \frac{1}{2}$. The corresponding eigenvectors are, respectively,

$$X_1 = \begin{bmatrix} -\frac{1}{2}\sqrt{5} - \frac{1}{2} \\ 1 \end{bmatrix}, X_2 = \begin{bmatrix} \frac{1}{2}\sqrt{5} - \frac{1}{2} \\ 1 \end{bmatrix}$$

You can see from a short computation that one of the eigenvalues is smaller than 1 in absolute value while the other is larger than 1 in absolute value. Now, diagonalizing A gives us

$$\begin{bmatrix} \frac{1}{2}\sqrt{5} - \frac{1}{2} & -\frac{1}{2}\sqrt{5} - \frac{1}{2} \\ 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \frac{1}{2}\sqrt{5} - \frac{1}{2} & -\frac{1}{2}\sqrt{5} - \frac{1}{2} \\ 1 & 1 \end{bmatrix}$$
$$= \begin{bmatrix} \frac{1}{2}\sqrt{5} + \frac{1}{2} & 0 \\ 0 & \frac{1}{2} - \frac{1}{2}\sqrt{5} \end{bmatrix}$$

Then it follows that for a given initial condition, the solution to this dynamical system is of the form

$$\begin{bmatrix} x(n) \\ y(n) \end{bmatrix} = \begin{bmatrix} \frac{1}{2}\sqrt{5} - \frac{1}{2} & -\frac{1}{2}\sqrt{5} - \frac{1}{2} \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \left(\frac{1}{2}\sqrt{5} + \frac{1}{2}\right)^n & 0 \\ 0 & \left(\frac{1}{2} - \frac{1}{2}\sqrt{5}\right)^n \end{bmatrix} \cdot \begin{bmatrix} \frac{1}{5}\sqrt{5} & \frac{1}{10}\sqrt{5} + \frac{1}{2} \\ -\frac{1}{5}\sqrt{5} & \frac{1}{5}\sqrt{5}\left(\frac{1}{2}\sqrt{5} - \frac{1}{2}\right) \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \tag{8.3.19}$$

It follows that

$$x(n) = \left(\frac{1}{2}\sqrt{5} + \frac{1}{2}\right)^n \left(\frac{1}{10}\sqrt{5} + \frac{1}{2}\right) + \left(\frac{1}{2} - \frac{1}{2}\sqrt{5}\right)^n \left(\frac{1}{2} - \frac{1}{10}\sqrt{5}\right)$$

Here is a picture of the ordered pairs $(x(n), y(n))$ for $n = 0, 1, \cdots, n$.

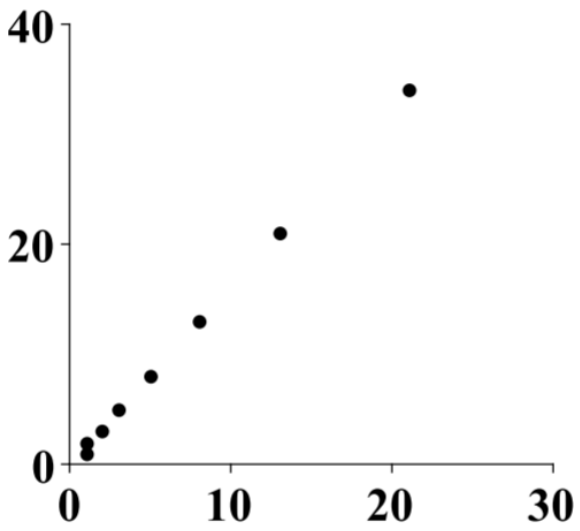


Figure 8.3.3

There is so much more that can be said about dynamical systems. It is a major topic of study in differential equations and what is given above is just an introduction.

The Matrix Exponential

The goal of this section is to use the concept of the matrix exponential to solve first order linear differential equations. We begin by proving the matrix exponential.

Suppose A is a diagonalizable matrix. Then the **matrix exponential**, written e^A, can be easily defined. Recall that if D is a diagonal matrix, then

$$P^{-1}AP = D$$

D is of the form

$$\begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix} \tag{8.3.20}$$

and it follows that

$$D^m = \begin{bmatrix} \lambda_1^m & & 0 \\ & \ddots & \\ 0 & & \lambda_n^m \end{bmatrix}$$

Since A is diagonalizable,

$$A = PDP^{-1}$$

and

$$A^m = PD^mP^{-1}$$

Recall why this is true.

$$A = PDP^{-1}$$

and so

$$\begin{aligned} A^m &= \overbrace{PDP^{-1}PDP^{-1}PDP^{-1}\cdots PDP^{-1}}^{\text{m times}} \\ &= PD^mP^{-1} \end{aligned} \tag{8.3.21}$$

We now will examine what is meant by the matrix exponental e^A. Begin by formally writing the following power series for e^A:

$$e^A = \sum_{k=0}^{\infty} \frac{A^k}{k!} = \sum_{k=0}^{\infty} \frac{PD^kP^{-1}}{k!} = P\left(\sum_{k=0}^{\infty} \frac{D^k}{k!}\right)P^{-1}$$

If D is given above in (8.3.20), the above sum is of the form

$$P\left(\sum_{k=0}^{\infty} \begin{bmatrix} \frac{1}{k!}\lambda_1^k & & 0 \\ & \ddots & \\ 0 & & \frac{1}{k!}\lambda_n^k \end{bmatrix}\right)P^{-1}$$

This can be rearranged as follows:

$$\begin{aligned} e^A &= P\begin{bmatrix} \sum_{k=0}^{\infty}\frac{1}{k!}\lambda_1^k & & 0 \\ & \ddots & \\ 0 & & \sum_{k=0}^{\infty}\frac{1}{k!}\lambda_n^k \end{bmatrix}P^{-1} \\ &= P\begin{bmatrix} e^{\lambda_1} & & 0 \\ & \ddots & \\ 0 & & e^{\lambda_n} \end{bmatrix}P^{-1} \end{aligned}$$

This justifies the following theorem.

Theorem 8.3.4: The Matrix Exponential

Let A be a diagonalizable matrix, with eigenvalues $\lambda_1, ..., \lambda_n$and corresponding matrix of eigenvectors P. Then the matrix exponential, e^A, is given by

$$e^A = P \begin{bmatrix} e^{\lambda_1} & & 0 \\ & \ddots & \\ 0 & & e^{\lambda_n} \end{bmatrix} P^{-1}$$

Example 8.3.12: Compute e^A for a Matrix A

Let

$$A = \begin{bmatrix} 2 & -1 & -1 \\ 1 & 2 & 1 \\ -1 & 1 & 2 \end{bmatrix}$$

Find e^A.

Solution

The eigenvalues work out to be $1, 2, 3$ and eigenvectors associated with these eigenvalues are

$$\begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix} \leftrightarrow 1, \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix} \leftrightarrow 2, \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \leftrightarrow 3$$

Then let

$$D = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix}, P = \begin{bmatrix} 0 & -1 & -1 \\ -1 & -1 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

and so

$$P^{-1} = \begin{bmatrix} 1 & 0 & 1 \\ -1 & -1 & -1 \\ 0 & 1 & 1 \end{bmatrix}$$

Then the matrix exponential is

$$e^{At} = \begin{bmatrix} 0 & -1 & -1 \\ -1 & -1 & 0 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} e^1 & 0 & 0 \\ 0 & e^2 & 0 \\ 0 & 0 & e^3 \end{bmatrix} \begin{bmatrix} 1 & 0 & 1 \\ -1 & -1 & -1 \\ 0 & 1 & 1 \end{bmatrix}$$

$$\begin{bmatrix} e^2 & e^2 - e^3 & e^2 - e^3 \\ e^2 - e & e^2 & e^2 - e \\ -e^2 + e & -e^2 + e^3 & -e^2 + e + e^3 \end{bmatrix}$$

The matrix exponential is a useful tool to solve autonomous systems of first order linear differential equations. These are equations which are of the form

$$X' = AX, X(0) = C$$

where A is a diagonalizable $n \times n$ matrix and C is a constant vector. X is a vector of functions in one variable, t:

$$X = X(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_n(t) \end{bmatrix}$$

Then X' refers to the first derivative of X and is given by

$$X' = X'(t) = \begin{bmatrix} x_1'(t) \\ x_2'(t) \\ \vdots \\ x_n'(t) \end{bmatrix}, \; x_i'(t) = \text{the derivative of } x_i(t)$$

Then it turns out that the solution to the above system of equations is $X(t) = e^{At}C$. To see this, suppose A is diagonalizable so that

$$A = P \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix} P^{-1}$$

Then

$$e^{At} = P \begin{bmatrix} e^{\lambda_1 t} & & \\ & \ddots & \\ & & e^{\lambda_n t} \end{bmatrix} P^{-1}$$

$$e^{At}C = P \begin{bmatrix} e^{\lambda_1 t} & & \\ & \ddots & \\ & & e^{\lambda_n t} \end{bmatrix} P^{-1}C$$

Differentiating $e^{At}C$ yields

$$\begin{aligned} X' = \left(e^{At}C\right)' &= P \begin{bmatrix} \lambda_1 e^{\lambda_1 t} & & \\ & \ddots & \\ & & \lambda_n e^{\lambda_n t} \end{bmatrix} P^{-1}C \\ &= P \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix} \begin{bmatrix} e^{\lambda_1 t} & & \\ & \ddots & \\ & & e^{\lambda_n t} \end{bmatrix} P^{-1}C \\ &= P \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix} P^{-1} P \begin{bmatrix} e^{\lambda_1 t} & & \\ & \ddots & \\ & & e^{\lambda_n t} \end{bmatrix} P^{-1}C \\ &= A\left(e^{At}C\right) = AX \end{aligned} \tag{8.3.22}$$

Therefore $X = X(t) = e^{At}C$ is a solution to $X' = AX$.

To prove that $X(0) = C$ if $X(t) = e^{At}C$:

$$X(0) = e^{A0}C = P \begin{bmatrix} 1 & & \\ & \ddots & \\ & & 1 \end{bmatrix} P^{-1}C = C$$

Example 8.3.13: Solving an Initial Value Problem

Solve the initial value problem

$$\begin{bmatrix} x \\ y \end{bmatrix}' = \begin{bmatrix} 0 & -2 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}, \; \begin{bmatrix} x(0) \\ y(0) \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Solution

The matrix is diagonalizable and can be written as

$$A = PDP^{-1}$$
$$\begin{bmatrix} 0 & -2 \\ 1 & 3 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ -\frac{1}{2} & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 2 & 2 \\ -1 & -2 \end{bmatrix} \tag{8.3.23}$$

Therefore, the matrix exponential is of the form

$$e^{At} = \begin{bmatrix} 1 & 1 \\ -\frac{1}{2} & -1 \end{bmatrix} \begin{bmatrix} e^t & 0 \\ 0 & e^{2t} \end{bmatrix} \begin{bmatrix} 2 & 2 \\ -1 & -2 \end{bmatrix}$$

The solution to the initial value problem is

$$\begin{aligned} X(t) &= e^{At}C \\ \begin{bmatrix} x(t) \\ y(t) \end{bmatrix} &= \begin{bmatrix} 1 & 1 \\ -\frac{1}{2} & -1 \end{bmatrix} \begin{bmatrix} e^t & 0 \\ 0 & e^{2t} \end{bmatrix} \begin{bmatrix} 2 & 2 \\ -1 & -2 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} 4e^t - 3e^{2t} \\ 3e^{2t} - 2e^t \end{bmatrix} \end{aligned} \tag{8.3.24}$$

We can check that this works:

$$\begin{aligned} \begin{bmatrix} x(0) \\ y(0) \end{bmatrix} &= \begin{bmatrix} 4e^0 - 3e^{2(0)} \\ 3e^{2(0)} - 2e^0 \end{bmatrix} \\ &= \begin{bmatrix} 1 \\ 1 \end{bmatrix} \end{aligned} \tag{8.3.25}$$

Lastly,

$$X' = \begin{bmatrix} 4e^t - 3e^{2t} \\ 3e^{2t} - 2e^t \end{bmatrix}' = \begin{bmatrix} 4e^t - 6e^{2t} \\ 6e^{2t} - 2e^t \end{bmatrix}$$

and

$$AX = \begin{bmatrix} 0 & -2 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} 4e^t - 3e^{2t} \\ 3e^{2t} - 2e^t \end{bmatrix} = \begin{bmatrix} 4e^t - 6e^{2t} \\ 6e^{2t} - 2e^t \end{bmatrix}$$

which is the same thing. Thus this is the solution to the initial value problem.

Answers

Theorem 8.3.1**: Principal Axis Theorem**

The complete proof is beyond this course, but to give an idea assume that A has an orthonormal set of eigenvectors, and let P consist of these eigenvectors as columns. Then $P^{-1} = P^T$, and $P^TAP = D$ a diagonal matrix. But then $A = PDP^T$, and

$$A^T = (PDP^T)^T = (P^T)^T D^T P^T = PDP^T = A$$

so A is symmetric.

Now given a symmetric matrix A, one shows that eigenvectors corresponding to different eigenvalues are always orthogonal. So it suffices to apply the Gram-Schmidt process on the set of basic eigenvectors of each eigenvalue to obtain an orthonormal set of eigenvectors.

Proposition 8.3.1**: Eigenvalues of a Migration Matrix**

Remember that the determinant of a matrix always equals that of its transpose. Therefore,

$$\det(\lambda I - A) = \det\left((\lambda I - A)^T\right) = \det(\lambda I - A^T)$$

because $I^T = I$. Thus the characteristic equation for A is the same as the characteristic equation for A^T. Consequently, A and A^T have the same eigenvalues. We will show that 1 is an eigenvalue for A^T and then it will follow that 1 is an eigenvalue for A.

Remember that for a migration matrix, $\sum_i a_{ij} = 1$. Therefore, if $A^T = [b_{ij}]$ with $b_{ij} = a_{ji}$, it follows that

$$\sum_j b_{ij} = \sum_j a_{ji} = 1$$

Therefore, from matrix multiplication,

$$A^T \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} = \begin{bmatrix} \sum_j b_{ij} \\ \vdots \\ \sum_j b_{ij} \end{bmatrix} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$$

Notice that this shows that $\begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$ is an eigenvector for A^T corresponding to the eigenvalue, $\lambda = 1$. As explained above, this shows that $\lambda = 1$ is an eigenvalue for

A because A and A^T have the same eigenvalues.

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8.4: Orthogonality

Orthogonal Diagonalization

We begin this section by recalling some important definitions. Recall from Definition 4.11.4 that non-zero vectors are called orthogonal if their dot product equals 0. A set is orthonormal if it is orthogonal and each vector is a unit vector.

An orthogonal matrix U, from Definition 4.11.7, is one in which $UU^T = I$. In other words, the transpose of an orthogonal matrix is equal to its inverse. A key characteristic of orthogonal matrices, which will be essential in this section, is that the columns of an orthogonal matrix form an orthonormal set.

We now recall another important definition.

Definition 8.4.1: Symmetric and Skew Symmetric Matrices

A real $n \times n$ matrix A, is **symmetric** if $A^T = A$. If $A = -A^T$, then A is called **skew symmetric.**

Before proving an essential theorem, we first examine the following lemma which will be used below.

Lemma 8.4.1: The Dot Product

Let $A = (a_{ij})$ be a real symmetric $n \times n$ matrix, and let $\vec{x}, \vec{y} \in \mathbb{R}^n$. Then

$$A\vec{x} \cdot \vec{y} = \vec{x} \cdot A\vec{y}$$

Proof available at the end of this section.

We can now prove that the eigenvalues of a real symmetric matrix are real numbers. Consider the following important theorem.

Theorem 8.4.1: Orthogonal Eigenvectors

Let A be a real symmetric matrix. Then the eigenvalues of A are real numbers and eigenvectors corresponding to distinct eigenvalues are orthogonal.

Proof available at the end of this section.

The following theorem is proved in a similar manner.

Theorem 8.4.2: Eigenvalues of Skew Symmetric Matrix

The eigenvalues of a real skew symmetric matrix are either equal to 0 or are pure imaginary numbers.

Proof available at the end of this section.

Consider the following example.

Example 8.4.1: Eigenvalues of a Skew Symmetric Matrix

Let $A = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$. Find its eigenvalues.

Solution

First notice that A is skew symmetric. By Theorem 8.4.2, the eigenvalues will either equal 0 or be pure imaginary. The eigenvalues of A are obtained by solving the usual equation

$$\det(\lambda I - A) = \det \begin{bmatrix} \lambda & 1 \\ -1 & \lambda \end{bmatrix} = \lambda^2 + 1 = 0$$

Hence the eigenvalues are $\pm i$, pure imaginary.

Consider the following example.

Example 8.4.2: Eigenvalues of a Symmetric Matrix

Let $A = \begin{bmatrix} 1 & 2 \\ 2 & 3 \end{bmatrix}$. Find its eigenvalues.

Solution

First, notice that A is symmetric. By Theorem 8.4.1, the eigenvalues will all be real. The eigenvalues of A are obtained by solving the usual equation

$$\det(\lambda I - A) = \det \begin{bmatrix} \lambda - 1 & -2 \\ -2 & \lambda - 3 \end{bmatrix} = \lambda^2 - 4\lambda - 1 = 0$$

The eigenvalues are given by $\lambda_1 = 2 + \sqrt{5}$ and $\lambda_2 = 2 - \sqrt{5}$ which are both real.

Recall that a diagonal matrix $D = (d_{ij})$ is one in which $d_{ij} = 0$ whenever $i \neq j$. In other words, all numbers not on the main diagonal are equal to zero.

Consider the following important theorem.

Theorem 8.4.3: Orthogonal Diagonalization

Let A be a real symmetric matrix. Then there exists an orthogonal matrix U such that

$$U^T A U = D$$

where D is a diagonal matrix. Moreover, the diagonal entries of D are the eigenvalues of A.

We can use this theorem to diagonalize a symmetric matrix, using orthogonal matrices. Consider the following corollary.

Corollary 8.4.1: Orthonormal Set of Eigenvectors

If A is a real $n \times n$ symmetric matrix, then there exists an orthonormal set of eigenvectors, $\{\vec{u}_1, \cdots, \vec{u}_n\}$.

Proof available at the end of this section.

Definition 8.4.2: Principal Axes

Let A be an $n \times n$ matrix. Then the principal axes of A is a set of orthonormal eigenvectors of A.

In the next example, we examine how to find such a set of orthonormal eigenvectors.

Example 8.4.3: Find an Orthonormal Set of Eigenvectors

Find an orthonormal set of eigenvectors for the symmetric matrix

$$A = \begin{bmatrix} 17 & -2 & -2 \\ -2 & 6 & 4 \\ -2 & 4 & 6 \end{bmatrix}$$

Solution

Recall Procedure 7.1.1 for finding the eigenvalues and eigenvectors of a matrix. You can verify that the eigenvalues are $18, 9, 2$. First find the eigenvector for 18 by solving the equation $(18I - A)X = 0$. The appropriate augmented matrix is given by

$$\begin{bmatrix} 18-17 & 2 & 2 & 0 \\ 2 & 18-6 & -4 & 0 \\ 2 & -4 & 18-6 & 0 \end{bmatrix}$$

The reduced row-echelon form is

$$\begin{bmatrix} 1 & 0 & 4 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Therefore an eigenvector is

$$\begin{bmatrix} -4 \\ 1 \\ 1 \end{bmatrix}$$

Next find the eigenvector for $\lambda = 9$. The augmented matrix and resulting reduced row-echelon form are

$$\begin{bmatrix} 9-17 & 2 & 2 & 0 \\ 2 & 9-6 & -4 & 0 \\ 2 & -4 & 9-6 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & -\frac{1}{2} & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Thus an eigenvector for $\lambda = 9$ is

$$\begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix}$$

Finally find an eigenvector for $\lambda = 2$. The appropriate augmented matrix and reduced row-echelon form are

$$\begin{bmatrix} 2-17 & 2 & 2 & 0 \\ 2 & 2-6 & -4 & 0 \\ 2 & -4 & 2-6 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Thus an eigenvector for $\lambda = 2$ is

$$\begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix}$$

The set of eigenvectors for A is given by

$$\left\{ \begin{bmatrix} -4 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix} \right\}$$

You can verify that these eigenvectors form an orthogonal set. By dividing each eigenvector by its magnitude, we obtain an orthonormal set:

$$\left\{ \frac{1}{\sqrt{18}} \begin{bmatrix} -4 \\ 1 \\ 1 \end{bmatrix}, \frac{1}{3} \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix}, \frac{1}{\sqrt{2}} \begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix} \right\}$$

Consider the following example.

Example 8.4.4: Repeated Eigenvalues

Find an orthonormal set of three eigenvectors for the matrix

$$A = \begin{bmatrix} 10 & 2 & 2 \\ 2 & 13 & 4 \\ 2 & 4 & 13 \end{bmatrix}$$

Solution

You can verify that the eigenvalues of A are 9 (with multiplicity two) and 18 (with multiplicity one). Consider the eigenvectors corresponding to $\lambda = 9$. The appropriate augmented matrix and reduced row-echelon form are given by

$$\begin{bmatrix} 9-10 & -2 & -2 & 0 \\ -2 & 9-13 & -4 & 0 \\ -2 & -4 & 9-13 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 2 & 2 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

and so eigenvectors are of the form

$$\begin{bmatrix} -2y-2z \\ y \\ z \end{bmatrix}$$

We need to find two of these which are orthogonal. Let one be given by setting $z = 0$ and $y = 1$, giving $\begin{bmatrix} -2 \\ 1 \\ 0 \end{bmatrix}$.

In order to find an eigenvector orthogonal to this one, we need to satisfy

$$\begin{bmatrix} -2 \\ 1 \\ 0 \end{bmatrix} \cdot \begin{bmatrix} -2y-2z \\ y \\ z \end{bmatrix} = 5y + 4z = 0$$

The values $y = -4$ and $z = 5$ satisfy this equation, giving another eigenvector corresponding to $\lambda = 9$ as

$$\begin{bmatrix} -2(-4) - 2(5) \\ (-4) \\ 5 \end{bmatrix} = \begin{bmatrix} -2 \\ -4 \\ 5 \end{bmatrix}$$

Next find the eigenvector for $\lambda = 18$. The augmented matrix and the resulting reduced row-echelon form are given by

$$\begin{bmatrix} 18-10 & -2 & -2 & 0 \\ -2 & 18-13 & -4 & 0 \\ -2 & -4 & 18-13 & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & -\frac{1}{2} & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

and so an eigenvector is

$$\begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix}$$

Dividing each eigenvector by its length, the orthonormal set is

$$\left\{ \frac{1}{\sqrt{5}} \begin{bmatrix} -2 \\ 1 \\ 0 \end{bmatrix}, \frac{\sqrt{5}}{15} \begin{bmatrix} -2 \\ -4 \\ 5 \end{bmatrix}, \frac{1}{3} \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} \right\}$$

In the above solution, the repeated eigenvalue implies that there would have been many other orthonormal bases which could have been obtained. While we chose to take $z = 0, y = 1$, we could just as easily have taken $y = 0$ or even $y = z = 1$. Any such change would have resulted in a different orthonormal set.

Recall the following definition.

Definition 8.4.3: Diagonalizable

An $n \times n$ matrix A is said to be **non defective** or **diagonalizable** if there exists an invertible matrix P such that $P^{-1}AP = D$ where D is a diagonal matrix.

As indicated in Theorem 8.4.3 if A is a real symmetric matrix, there exists an orthogonal matrix U such that $U^T AU = D$ where D is a diagonal matrix. Therefore, every symmetric matrix is diagonalizable because if U is an orthogonal matrix, it is invertible and its inverse is U^T. In this case, we say that A is **orthogonally diagonalizable**. Therefore every symmetric matrix is in fact orthogonally diagonalizable. The next theorem provides another way to determine if a matrix is orthogonally diagonalizable.

Theorem 8.4.4: Orthogonally Diagonalizable

Let A be an $n \times n$ matrix. Then A is orthogonally diagonalizable if and only if A has an orthonormal set of eigenvectors.

Recall from Corollary 8.4.1 that every symmetric matrix has an orthonormal set of eigenvectors. In fact these three conditions are equivalent.

In the following example, the orthogonal matrix U will be found to orthogonally diagonalize a matrix.

Example 8.4.5: Diagonalize a Symmetric Matrix

Let $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{3}{2} & \frac{1}{2} \\ 0 & \frac{1}{2} & \frac{3}{2} \end{bmatrix}$. Find an orthogonal matrix U such that $U^T AU$ is a diagonal matrix.

Solution

In this case, the eigenvalues are 2 (with multiplicity one) and 1 (with multiplicity two). First we will find an eigenvector for the eigenvalue 2. The appropriate augmented matrix and resulting reduced row-echelon form are given by

$$\begin{bmatrix} 2-1 & 0 & 0 & 0 \\ 0 & 2-\frac{3}{2} & -\frac{1}{2} & 0 \\ 0 & -\frac{1}{2} & 2-\frac{3}{2} & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

and so an eigenvector is

$$\begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

However, it is desired that the eigenvectors be unit vectors and so dividing this vector by its length gives

$$\begin{bmatrix} 0 \\ \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

Next find the eigenvectors corresponding to the eigenvalue equal to 1. The appropriate augmented matrix and resulting reduced row-echelon form are given by:

$$\begin{bmatrix} 1-1 & 0 & 0 & 0 \\ 0 & 1-\frac{3}{2} & -\frac{1}{2} & 0 \\ 0 & -\frac{1}{2} & 1-\frac{3}{2} & 0 \end{bmatrix} \to \cdots \to \begin{bmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Therefore, the eigenvectors are of the form

$$\begin{bmatrix} s \\ -t \\ t \end{bmatrix}$$

Two of these which are orthonormal are $\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$, choosing $s = 1$ and $t = 0$, and $\begin{bmatrix} 0 \\ -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$, letting $s = 0$, $t = 1$ and normalizing the resulting vector.

To obtain the desired orthogonal matrix, we let the orthonormal eigenvectors computed above be the columns.

$$\begin{bmatrix} 0 & 1 & 0 \\ -\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \end{bmatrix}$$

To verify, compute $U^T AU$ as follows:

$$U^T AU = \begin{bmatrix} 0 & -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{3}{2} & \frac{1}{2} \\ 0 & \frac{1}{2} & \frac{3}{2} \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ -\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \end{bmatrix}$$
$$= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} = D$$

the desired diagonal matrix. Notice that the eigenvectors, which construct the columns of U, are in the same order as the eigenvalues in D.

We conclude this section with a Theorem that generalizes earlier results.

Theorem 8.4.5: Triangulation of a Matrix

Let A be an $n \times n$ matrix. If A has n real eigenvalues, then an orthogonal matrix U can be found to result in the upper triangular matrix $U^T AU$.

triangulation

This Theorem provides a useful Corollary.

Corollary 8.4.2: Determinant and Trace

Let A be an $n \times n$ matrix with eigenvalues $\lambda_1, \cdots, \lambda_n$. Then it follows that $\det(A)$ is equal to the product of the λ_i, while $trace(A)$ is equal to the sum of the λ_i.

Proof available at the end of this section.

The Singular Value Decomposition

We begin this section with an important definition.

Definition 8.4.4: Singular Values

Let A be an $m \times n$ matrix. The singular values of A are the square roots of the positive eigenvalues of $A^T A$.

Singular Value Decomposition (SVD) can be thought of as a generalization of orthogonal diagonalization of a symmetric matrix to an arbitrary $m \times n$ matrix. This decomposition is the focus of this section.

The following is a useful result that will help when computing the SVD of matrices.

Proposition 8.4.1: Same Nonzero Eigenvalues

Let A be an $m \times n$ matrix. Then $A^T A$ and AA^T have the same **nonzero eigenvalues.**

Proof available at the end of this section.

Given an $m \times n$ matrix A, we will see how to express A as a product

$$A = U\Sigma V^T$$

where

- U is an $m \times m$ orthogonal matrix whose columns are eigenvectors of AA^T.
- V is an $n \times n$ orthogonal matrix whose columns are eigenvectors of $A^T A$.
- Σ is an $m \times n$ matrix whose only nonzero values lie on its main diagonal, and are the singular values of A.

How can we find such a decomposition? We are aiming to decompose A in the following form:

$$A = U \begin{bmatrix} \sigma & 0 \\ 0 & 0 \end{bmatrix} V^T$$

where σ is of the form

$$\sigma = \begin{bmatrix} \sigma_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_k \end{bmatrix}$$

Thus $A^T = V \begin{bmatrix} \sigma & 0 \\ 0 & 0 \end{bmatrix} U^T$ and it follows that

$$A^T A = V \begin{bmatrix} \sigma & 0 \\ 0 & 0 \end{bmatrix} U^T U \begin{bmatrix} \sigma & 0 \\ 0 & 0 \end{bmatrix} V^T = V \begin{bmatrix} \sigma^2 & 0 \\ 0 & 0 \end{bmatrix} V^T$$

and so $A^T AV = V \begin{bmatrix} \sigma^2 & 0 \\ 0 & 0 \end{bmatrix}$. Similarly, $AA^T U = U \begin{bmatrix} \sigma^2 & 0 \\ 0 & 0 \end{bmatrix}$. Therefore, you would find an orthonormal basis of eigenvectors for AA^T make them the columns of a matrix such that the corresponding eigenvalues are decreasing. This gives U. You could

then do the same for A^TA to get V.

We formalize this discussion in the following theorem.

Theorem 8.4.6: Singular Value Decomposition

Let A be an $m \times n$ matrix. Then there exist orthogonal matrices U and V of the appropriate size such that $A = U\Sigma V^T$ where Σ is of the form

$$\Sigma = \begin{bmatrix} \sigma & 0 \\ 0 & 0 \end{bmatrix}$$

and σ is of the form

$$\sigma = \begin{bmatrix} \sigma_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_k \end{bmatrix}$$

for the σ_i the singular values of A.

Proof available at the end of this section.

The singular value decomposition has as an immediate corollary which is given in the following interesting result.

Corollary 8.4.3: Rank and Singular Values

Let A be an $m \times n$ matrix. Then the rank of A and A^Tequals the number of singular values.

Let's compute the Singular Value Decomposition of a simple matrix.

Example 8.4.6: Singular Value Decomposition

Let $A = \begin{bmatrix} 1 & -1 & 3 \\ 3 & 1 & 1 \end{bmatrix}$. Find the Singular Value Decomposition (SVD) of A.

Solution

To begin, we compute AA^T and A^TA.

$$AA^T = \begin{bmatrix} 1 & -1 & 3 \\ 3 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 3 \\ -1 & 1 \\ 3 & 1 \end{bmatrix} = \begin{bmatrix} 11 & 5 \\ 5 & 11 \end{bmatrix}.$$

$$A^TA = \begin{bmatrix} 1 & 3 \\ -1 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 & 3 \\ 3 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 10 & 2 & 6 \\ 2 & 2 & -2 \\ 6 & -2 & 10 \end{bmatrix}.$$

Since AA^T is 2×2 while A^TA is 3×3, and AA^T and A^TA have the same *nonzero* eigenvalues (by Proposition 8.4.1), we compute the characteristic polynomial $c_{AA^T}(x)$ (because it's easier to compute than $c_{A^TA}(x)$).

$$\begin{aligned} c_{AA^T}(x) = \det(xI - AA^T) &= \begin{vmatrix} x-11 & -5 \\ -5 & x-11 \end{vmatrix} \\ &= (x-11)^2 - 25 \\ &= x^2 - 22x + 121 - 25 \\ &= x^2 - 22x + 96 \\ &= (x-16)(x-6) \end{aligned} \tag{8.4.1}$$

Therefore, the eigenvalues of AA^T are $\lambda_1 = 16$ and $\lambda_2 = 6$.

The eigenvalues of A^TA are $\lambda_1 = 16$, $\lambda_2 = 6$, and $\lambda_3 = 0$, and the singular values of A are $\sigma_1 = \sqrt{16} = 4$ and $\sigma_2 = \sqrt{6}$. By convention, we list the eigenvalues (and corresponding singular values) in non increasing order (i.e., from largest to smallest).

To find the matrix V:

To construct the matrix V we need to find eigenvectors for A^TA. Since the eigenvalues of AA^T are distinct, the corresponding eigenvectors are orthogonal, and we need only normalize them.

$\lambda_1 = 16$: solve $(16I - A^TA)Y = 0$.

$$\begin{bmatrix} 6 & -2 & -6 & 0 \\ -2 & 14 & 2 & 0 \\ -6 & 2 & 6 & 0 \end{bmatrix} \to \begin{bmatrix} 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \text{ so } Y = \begin{bmatrix} t \\ 0 \\ t \end{bmatrix} = t \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, t \in \mathbb{R}.$$

$\lambda_2 = 6$: solve $(6I - A^TA)Y = 0$.

$$\begin{bmatrix} -4 & -2 & -6 & 0 \\ -2 & 4 & 2 & 0 \\ -6 & 2 & -4 & 0 \end{bmatrix} \to \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \text{ so } Y = \begin{bmatrix} -s \\ -s \\ s \end{bmatrix} = s \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix}, s \in \mathbb{R}.$$

$\lambda_3 = 0$: solve $(-A^TA)Y = 0$.

$$\begin{bmatrix} -10 & -2 & -6 & 0 \\ -2 & -2 & 2 & 0 \\ -6 & 2 & -10 & 0 \end{bmatrix} \to \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & -2 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \text{ so } Y = \begin{bmatrix} -r \\ 2r \\ r \end{bmatrix} = r \begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix}, r \in \mathbb{R}.$$

Let

$$V_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, V_2 = \frac{1}{\sqrt{3}} \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix}, V_3 = \frac{1}{\sqrt{6}} \begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix}.$$

Then

$$V = \frac{1}{\sqrt{6}} \begin{bmatrix} \sqrt{3} & -\sqrt{2} & -1 \\ 0 & -\sqrt{2} & 2 \\ \sqrt{3} & \sqrt{2} & 1 \end{bmatrix}.$$

Also,

$$\Sigma = \begin{bmatrix} 4 & 0 & 0 \\ 0 & \sqrt{6} & 0 \end{bmatrix},$$

and we use A, V^T, and Σ to find U.

Since V is orthogonal and $A = U\Sigma V^T$, it follows that $AV = U\Sigma$. Let $V = \begin{bmatrix} V_1 & V_2 & V_3 \end{bmatrix}$, and let $U = \begin{bmatrix} U_1 & U_2 \end{bmatrix}$, where U_1 and U_2 are the two columns of U.

Then we have

$$\begin{aligned} A \begin{bmatrix} V_1 & V_2 & V_3 \end{bmatrix} &= \begin{bmatrix} U_1 & U_2 \end{bmatrix} \Sigma \\ \begin{bmatrix} AV_1 & AV_2 & AV_3 \end{bmatrix} &= \begin{bmatrix} \sigma_1 U_1 + 0U_2 & 0U_1 + \sigma_2 U_2 & 0U_1 + 0U_2 \end{bmatrix} \\ &= \begin{bmatrix} \sigma_1 U_1 & \sigma_2 U_2 & 0 \end{bmatrix} \end{aligned} \tag{8.4.2}$$

which implies that $AV_1 = \sigma_1 U_1 = 4U_1$ and $AV_2 = \sigma_2 U_2 = \sqrt{6}U_2$.

Thus,

$$U_1 = \frac{1}{4}AV_1 = \frac{1}{4}\begin{bmatrix} 1 & -1 & 3 \\ 3 & 1 & 1 \end{bmatrix}\frac{1}{\sqrt{2}}\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} = \frac{1}{4\sqrt{2}}\begin{bmatrix} 4 \\ 4 \end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 \\ 1 \end{bmatrix},$$

and

$$U_2 = \frac{1}{\sqrt{6}}AV_2 = \frac{1}{\sqrt{6}}\begin{bmatrix} 1 & -1 & 3 \\ 3 & 1 & 1 \end{bmatrix}\frac{1}{\sqrt{3}}\begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix} = \frac{1}{3\sqrt{2}}\begin{bmatrix} 3 \\ -3 \end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 \\ -1 \end{bmatrix}.$$

Therefore,

$$U = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix},$$

and

$$\begin{aligned} A &= \begin{bmatrix} 1 & -1 & 3 \\ 3 & 1 & 1 \end{bmatrix} \\ &= \left(\frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}\right)\begin{bmatrix} 4 & 0 & 0 \\ 0 & \sqrt{6} & 0 \end{bmatrix}\left(\frac{1}{\sqrt{6}}\begin{bmatrix} \sqrt{3} & 0 & \sqrt{3} \\ -\sqrt{2} & -\sqrt{2} & \sqrt{2} \\ -1 & 2 & 1 \end{bmatrix}\right). \end{aligned} \tag{8.4.3}$$

Here is another example.

Example 8.4.7: Finding the SVD

Find an SVD for $A = \begin{bmatrix} -1 \\ 2 \\ 2 \end{bmatrix}$.

Solution

Since A is 3×1, A^TA is a 1×1 matrix whose eigenvalues are easier to find than the eigenvalues of the 3×3 matrix AA^T.

$$A^TA = \begin{bmatrix} -1 & 2 & 2 \end{bmatrix}\begin{bmatrix} -1 \\ 2 \\ 2 \end{bmatrix} = \begin{bmatrix} 9 \end{bmatrix}.$$

Thus A^TA has eigenvalue $\lambda_1 = 9$, and the eigenvalues of AA^T are $\lambda_1 = 9$, $\lambda_2 = 0$, and $\lambda_3 = 0$. Furthermore, A has only one singular value, $\sigma_1 = 3$.

To find the matrix V: To do so we find an eigenvector for A^TA and normalize it. In this case, finding a unit eigenvector is trivial: $V_1 = \begin{bmatrix} 1 \end{bmatrix}$, and

$$V = \begin{bmatrix} 1 \end{bmatrix}.$$

Also, $\Sigma = \begin{bmatrix} 3 \\ 0 \\ 0 \end{bmatrix}$, and we use A, V^T, and Σ to find U.

Now $AV = U\Sigma$, with $V = \begin{bmatrix} V_1 \end{bmatrix}$, and $U = \begin{bmatrix} U_1 & U_2 & U_3 \end{bmatrix}$, where U_1, U_2, and U_3 are the columns of U. Thus

$$\begin{aligned} A\begin{bmatrix} V_1 \end{bmatrix} &= \begin{bmatrix} U_1 & U_2 & U_3 \end{bmatrix}\Sigma \\ \begin{bmatrix} AV_1 \end{bmatrix} &= \begin{bmatrix} \sigma_1U_1 + 0U_2 + 0U_3 \end{bmatrix} \\ &= \begin{bmatrix} \sigma_1U_1 \end{bmatrix} \end{aligned} \tag{8.4.4}$$

This gives us $AV_1 = \sigma_1U_1 = 3U_1$, so

$$U_1 = \frac{1}{3}AV_1 = \frac{1}{3}\begin{bmatrix} -1 \\ 2 \\ 2 \end{bmatrix}\begin{bmatrix} 1 \end{bmatrix} = \frac{1}{3}\begin{bmatrix} -1 \\ 2 \\ 2 \end{bmatrix}.$$

The vectors U_2 and U_3 are eigenvectors of AA^T corresponding to the eigenvalue $\lambda_2 = \lambda_3 = 0$. Instead of solving the system $(0I - AA^T)X = 0$ and then using the Gram-Schmidt process on the resulting set of two basic eigenvectors, the following approach may be used.

Find vectors U_2 and U_3 by first extending $\{U_1\}$ to a basis of $\mathbb{R}^3$, then using the Gram-Schmidt algorithm to orthogonalize the basis, and finally normalizing the vectors.

Starting with $\{3U_1\}$ instead of $\{U_1\}$ makes the arithmetic a bit easier. It is easy to verify that

$$\left\{\begin{bmatrix} -1 \\ 2 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}\right\}$$

is a basis of $\mathbb{R}^3$. Set

$$E_1 = \begin{bmatrix} -1 \\ 2 \\ 2 \end{bmatrix}, X_2 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, X_3 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix},$$

and apply the Gram-Schmidt algorithm to $\{E_1, X_2, X_3\}$.

This gives us

$$E_2 = \begin{bmatrix} 4 \\ 1 \\ 1 \end{bmatrix} \text{ and } E_3 = \begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix}.$$

Therefore,

$$U_2 = \frac{1}{\sqrt{18}}\begin{bmatrix} 4 \\ 1 \\ 1 \end{bmatrix}, U_3 = \frac{1}{\sqrt{2}}\begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix},$$

and

$$U = \begin{bmatrix} -\frac{1}{3} & \frac{4}{\sqrt{18}} & 0 \\ \frac{2}{3} & \frac{1}{\sqrt{18}} & \frac{1}{\sqrt{2}} \\ \frac{2}{3} & \frac{1}{\sqrt{18}} & -\frac{1}{\sqrt{2}} \end{bmatrix}.$$

Finally,

$$A = \begin{bmatrix} -1 \\ 2 \\ 2 \end{bmatrix} = \begin{bmatrix} -\frac{1}{3} & \frac{4}{\sqrt{18}} & 0 \\ \frac{2}{3} & \frac{1}{\sqrt{18}} & \frac{1}{\sqrt{2}} \\ \frac{2}{3} & \frac{1}{\sqrt{18}} & -\frac{1}{\sqrt{2}} \end{bmatrix}\begin{bmatrix} 3 \\ 0 \\ 0 \end{bmatrix}\begin{bmatrix} 1 \end{bmatrix}.$$

Consider another example.

Example 8.4.8: Find the SVD

Find a singular value decomposition for the matrix

$$A = \begin{bmatrix} \frac{2}{5}\sqrt{2}\sqrt{5} & \frac{4}{5}\sqrt{2}\sqrt{5} & 0 \\ \frac{2}{5}\sqrt{2}\sqrt{5} & \frac{4}{5}\sqrt{2}\sqrt{5} & 0 \end{bmatrix}$$

Solution

First consider A^TA

$$\begin{bmatrix} \frac{16}{5} & \frac{32}{5} & 0 \\ \frac{32}{5} & \frac{64}{5} & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

What are some eigenvalues and eigenvectors? Some computing shows these are

$$\left\{ \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} -\frac{2}{5}\sqrt{5} \\ \frac{1}{5}\sqrt{5} \\ 0 \end{bmatrix} \right\} \leftrightarrow 0, \left\{ \begin{bmatrix} \frac{1}{5}\sqrt{5} \\ \frac{2}{5}\sqrt{5} \\ 0 \end{bmatrix} \right\} \leftrightarrow 16$$

Thus the matrix V is given by

$$V = \begin{bmatrix} \frac{1}{5}\sqrt{5} & -\frac{2}{5}\sqrt{5} & 0 \\ \frac{2}{5}\sqrt{5} & \frac{1}{5}\sqrt{5} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Next consider AA^T

$$\begin{bmatrix} 8 & 8 \\ 8 & 8 \end{bmatrix}$$

Eigenvectors and eigenvalues are

$$\left\{ \begin{bmatrix} -\frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} \end{bmatrix} \right\} \leftrightarrow 0, \left\{ \begin{bmatrix} \frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} \end{bmatrix} \right\} \leftrightarrow 16$$

Thus you can let U be given by

$$U = \begin{bmatrix} \frac{1}{2}\sqrt{2} & -\frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} & \frac{1}{2}\sqrt{2} \end{bmatrix}$$

Lets check this. $U^TAV =$

$$\begin{bmatrix} \frac{1}{2}\sqrt{2} & \frac{1}{2}\sqrt{2} \\ -\frac{1}{2}\sqrt{2} & \frac{1}{2}\sqrt{2} \end{bmatrix} \begin{bmatrix} \frac{2}{5}\sqrt{2}\sqrt{5} & \frac{4}{5}\sqrt{2}\sqrt{5} & 0 \\ \frac{2}{5}\sqrt{2}\sqrt{5} & \frac{4}{5}\sqrt{2}\sqrt{5} & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{5}\sqrt{5} & -\frac{2}{5}\sqrt{5} & 0 \\ \frac{2}{5}\sqrt{5} & \frac{1}{5}\sqrt{5} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 4 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

This illustrates that if you have a good way to find the eigenvectors and eigenvalues for a Hermitian matrix which has nonnegative eigenvalues, then you also have a good way to find the singular value decomposition of an arbitrary matrix.

Positive Definite Matrices

Positive definite matrices are often encountered in applications such mechanics and statistics.

We begin with a definition.

Definition 8.4.5: Positive Definite Matrix

Let A be an $n \times n$ symmetric matrix. Then A is positive definite if all of its eigenvalues are positive.

The relationship between a negative definite matrix and positive definite matrix is as follows.

Lemma 8.4.2: Negative Definite Matrix

An $n \times n$ matrix A is negative definite if and only if $-A$ is positive definite

Consider the following lemma.

Lemma 8.4.3: Positive Definite Matrix and Invertibility

If A is positive definite, then it is invertible.

Proof available at the end of this section.

Notice that this lemma implies that if a matrix A is positive definite, then $\det(A) > 0$.

The following theorem provides another characterization of positive definite matrices. It gives a useful test for verifying if a matrix is positive definite.

Theorem 8.4.7: Positive Definite Matrix

Let A be a symmetric matrix. Then A is positive definite if and only if $\vec{x}^T A\vec{x}$ is positive for all nonzero $\vec{x} \in \mathbb{R}^n$.

Proof available at the end of this section.

There are some other very interesting consequences which result from a matrix being positive definite. First one can note that the property of being positive definite is transferred to each of the principal submatrices which we will now define.

Definition 8.4.6: The Submatrix A_k

Let A be an $n \times n$ matrix. Denote by A_k the $k \times k$ matrix obtained by deleting the $k+1, \cdots, n$ columns and the $k+1, \cdots, n$ rows from A. Thus $A_n = A$ and A_k is the $k \times k$ submatrix of A which occupies the upper left corner of A.

Lemma 8.4.4: Positive Definite and Submatrices

Let A be an $n \times n$ positive definite matrix. Then each submatrix A_k is also positive definite.

Proof available at the end of this section.

There is yet another way to recognize whether a matrix is positive definite which is described in terms of these submatrices. We state the result, the proof of which can be found in more advanced texts.

Theorem 8.4.8: Positive Matrix and Determinant of A_k

Let A be a symmetric matrix. Then A is positive definite if and only if $\det(A_k)$ is greater than 0 for every submatrix A_k, $k = 1, \cdots, n$.

Proof available at the end of this section.

Corollary 8.4.4: Symmetric and Negative Definite Matrix

Let A be symmetric. Then A is negative definite if and only if

$$(-1)^k \det(A_k) > 0$$

for every $k = 1, \cdots, n$.

Proof available at the end of this section.

The Cholesky Factorization

Another important theorem is the existence of a specific factorization of positive definite matrices. It is called the Cholesky Factorization and factors the matrix into the product of an upper triangular matrix and its transpose.

Theorem 8.4.9: Cholesky Factorization

Let A be a positive definite matrix. Then there exists an upper triangular matrix U whose main diagonal entries are positive, such that A can be written

$$A = U^T U$$

This factorization is unique.

The process for finding such a matrix U relies on simple row operations.

Procedure 8.4.1: Finding the Cholesky Factorization

Let A be a positive definite matrix. The matrix U that creates the Cholesky Factorization can be found through two steps.

1. Using only type 3 elementary row operations (multiples of rows added to other rows) put A in upper triangular form. Call this matrix $\hat{U}$. Then $\hat{U}$ has positive entries on the main diagonal.
2. Divide each row of $\hat{U}$ by the square root of the diagonal entry in that row. The result is the matrix U.

Of course you can always verify that your factorization is correct by multiplying U and U^T to ensure the result is the original matrix A.

Consider the following example.

Example 8.4.9: Cholesky Factorization

Show that $A = \begin{bmatrix} 9 & -6 & 3 \\ -6 & 5 & -3 \\ 3 & -3 & 6 \end{bmatrix}$ is positive definite, and find the Cholesky factorization of A.

Solution

First we show that A is positive definite. By Theorem 8.4.8 it suffices to show that the determinant of each submatrix is positive.

$$A_1 = \begin{bmatrix} 9 \end{bmatrix} \text{ and } A_2 = \begin{bmatrix} 9 & -6 \\ -6 & 5 \end{bmatrix},$$

so $\det(A_1) = 9$ and $\det(A_2) = 9$. Since $\det(A) = 36$, it follows that A is positive definite.

Now we use Procedure 8.4.1 to find the Cholesky Factorization. Row reduce (using only type 3 row operations) until an upper triangular matrix is obtained.

$$\begin{bmatrix} 9 & -6 & 3 \\ -6 & 5 & -3 \\ 3 & -3 & 6 \end{bmatrix} \rightarrow \begin{bmatrix} 9 & -6 & 3 \\ 0 & 1 & -1 \\ 0 & -1 & 5 \end{bmatrix} \rightarrow \begin{bmatrix} 9 & -6 & 3 \\ 0 & 1 & -1 \\ 0 & 0 & 4 \end{bmatrix}$$

Now divide the entries in each row by the square root of the diagonal entry in that row, to give

$$U = \begin{bmatrix} 3 & -2 & 1 \\ 0 & 1 & -1 \\ 0 & 0 & 2 \end{bmatrix}$$

You can verify that $U^T U = A$.

Example 8.4.10: Cholesky Factorization

Let A be a positive definite matrix given by

$$\begin{bmatrix} 3 & 1 & 1 \\ 1 & 4 & 2 \\ 1 & 2 & 5 \end{bmatrix}$$

Determine its Cholesky factorization.

Solution

You can verify that A is in fact positive definite.

To find the Cholesky factorization we first row reduce to an upper triangular matrix.

$$\begin{bmatrix} 3 & 1 & 1 \\ 1 & 4 & 2 \\ 1 & 2 & 5 \end{bmatrix} \rightarrow \begin{bmatrix} 3 & 1 & 1 \\ 0 & \frac{11}{3} & \frac{5}{3} \\ 0 & \frac{5}{3} & \frac{14}{5} \end{bmatrix} \rightarrow \begin{bmatrix} 3 & 1 & 1 \\ 0 & \frac{11}{3} & \frac{5}{3} \\ 0 & 0 & \frac{43}{11} \end{bmatrix}$$

Now divide the entries in each row by the square root of the diagonal entry in that row and simplify.

$$U = \begin{bmatrix} \sqrt{3} & \frac{1}{3}\sqrt{3} & \frac{1}{3}\sqrt{3} \\ 0 & \frac{1}{3}\sqrt{3}\sqrt{11} & \frac{5}{33}\sqrt{3}\sqrt{11} \\ 0 & 0 & \frac{1}{11}\sqrt{11}\sqrt{43} \end{bmatrix}$$

QR Factorization

In this section, a reliable factorization of matrices is studied. Called the QR factorization of a matrix, it *always* exists. While much can be said about the QR factorization, this section will be limited to real matrices. Therefore we assume the dot product used below is the usual dot product. We begin with a definition.

Definition 8.4.7: QRFactorization

Let A be a real $m \times n$ matrix. Then a QR factorization of A consists of two matrices, Q orthogonal and R upper triangular, such that $A = QR$.

qrfactorization

The following theorem claims that such a factorization exists.

Theorem 8.4.10: Existence of QRFactorization

Let A be any real $m \times n$ matrix with linearly independent columns. Then there exists an orthogonal matrix Q and an upper triangular matrix R having non-negative entries on the main diagonal such that

$$A = QR$$

The procedure for obtaining the QR factorization for any matrix A is as follows.

Procedure 8.4.2: QRFactorization

Let A be an $m \times n$ matrix given by $A = \begin{bmatrix} A_1 & A_2 & \cdots & A_n \end{bmatrix}$ where the A_i are the linearly independent columns of A.

1. Apply the Gram-Schmidt Process 4.11.1 to the columns of A, writing B_i for the resulting columns.
2. Normalize the B_i, to find $C_i = \frac{1}{B_i} B_i$.
3. Construct the orthogonal matrix Q as $Q = \begin{bmatrix} C_1 & C_2 & \cdots & C_n \end{bmatrix}$.
4. Construct the upper triangular matrix R as

$$R = \begin{bmatrix} B_1 & A_2 \cdot C_1 & A_3 \cdot C_1 & \cdots & A_n \cdot C_1 \\ 0 & B_2 & A_3 \cdot C_2 & \cdots & A_n \cdot C_2 \\ 0 & 0 & B_3 & \cdots & A_n \cdot C_3 \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & B_n \end{bmatrix}$$

5. Finally, write $A = QR$ where Q is the orthogonal matrix and R is the upper triangular matrix obtained above.

Notice that Q is an orthogonal matrix as the C_i form an orthonormal set. Since $B_i > 0$ for all i (since the length of a vector is always positive), it follows that R is an upper triangular matrix with positive entries on the main diagonal.

Consider the following example.

Example 8.4.11: Finding a QRFactorization

Let

$$A = \begin{bmatrix} 1 & 2 \\ 0 & 1 \\ 1 & 0 \end{bmatrix}$$

Find an orthogonal matrix Q and upper triangular matrix R such that $A = QR$.

Solution

First, observe that A_1, A_2, the columns of A, are linearly independent. Therefore we can use the Gram-Schmidt Process to create a corresponding orthogonal set $\{B_1, B_2\}$ as follows:

$$\begin{aligned} B_1 = A_1 &= \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \\ B_2 = A_2 - \frac{A_2 \cdot B_1}{B_1^2} B_1 &= \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} - \frac{2}{2} \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix} \end{aligned} \tag{8.4.5}$$

Normalize each vector to create the set $\{C_1, C_2\}$ as follows:

$$\begin{aligned} C_1 &= \frac{1}{B_1} B_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \\ C_2 &= \frac{1}{B_2} B_2 = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix} \end{aligned} \tag{8.4.6}$$

Now construct the orthogonal matrix Q as

$$\begin{aligned} Q &= \begin{bmatrix} C_1 & C_2 & \cdots & C_n \end{bmatrix} \\ &= \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{3}} \\ 0 & \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{3}} \end{bmatrix} \end{aligned} \tag{8.4.7}$$

Finally, construct the upper triangular matrix R as

$$\begin{aligned} R &= \begin{bmatrix} B_1 & A_2 \cdot C_1 \\ 0 & B_2 \end{bmatrix} \\ &= \begin{bmatrix} \sqrt{2} & \sqrt{2} \\ 0 & \sqrt{3} \end{bmatrix} \end{aligned} \tag{8.4.8}$$

It is left to the reader to verify that $A = QR$.

The QR Factorization and Eigenvalues

The QR factorization of a matrix has a very useful application. It turns out that it can be used repeatedly to estimate the eigenvalues of a matrix. Consider the following procedure.

Procedure 8.4.3: Using the QR Factorization to Estimate Eigenvalues

Let A be an invertible matrix. Define the matrices $A_1, A_2, \cdots$ as follows:

1. $A_1 = A$ factored as $A_1 = Q_1 R_1$
2. $A_2 = R_1 Q_1$ factored as $A_2 = Q_2 R_2$
3. $A_3 = R_2 Q_2$ factored as $A_3 = Q_3 R_3$

Continue in this manner, where in general $A_k = Q_k R_k$ and $A_{k+1} = R_k Q_k$.

Then it follows that this sequence of A_i converges to an upper triangular matrix which is similar to A. Therefore the eigenvalues of A can be approximated by the entries on the main diagonal of this upper triangular matrix.

Power Methods

While the QR algorithm can be used to compute eigenvalues, there is a useful and fairly elementary technique for finding the eigenvector and associated eigenvalue nearest to a given complex number which is called the *shifted inverse power method*. It tends to work extremely well provided you start with something which is fairly close to an eigenvalue.

Power methods are based the consideration of powers of a given matrix. Let $\{\vec{x}_1, \cdots, \vec{x}_n\}$ be a basis of eigenvectors for $\mathbb{C}^n$ such that $A\vec{x}_n = \lambda_n \vec{x}_n$. Now let $\vec{u}_1$ be some nonzero vector. Since $\{\vec{x}_1, \cdots, \vec{x}_n\}$ is a basis, there exists unique scalars, c_i such that

$$\vec{u}_1 = \sum_{k=1}^{n} c_k \vec{x}_k$$

Assume you have not been so unlucky as to pick $\vec{u}_1$ in such a way that $c_n = 0$. Then let $A\vec{u}_k = \vec{u}_{k+1}$ so that

$$\vec{u}_m = A^m \vec{u}_1 = \sum_{k=1}^{n-1} c_k \lambda_k^m \vec{x}_k + \lambda_n^m c_n \vec{x}_n. \tag{8.4.9}$$

For large m the last term, $\lambda_n^m c_n \vec{x}_n$, determines quite well the direction of the vector on the right. This is because $|\lambda_n|$ is larger than $|\lambda_k|$ for $k < n$ and so for a large m, the sum, $\sum_{k=1}^{n-1} c_k \lambda_k^m \vec{x}_k$, on the right is fairly insignificant. Therefore, for large m, $\vec{u}_m$ is essentially a multiple of the eigenvector $\vec{x}_n$, the one which goes with λ_n. The only problem is that there is no control of the size of the vectors $\vec{u}_m$. You can fix this by scaling. Let S_2 denote the entry of $A\vec{u}_1$ which is largest in absolute value. We call this a **scaling factor**. Then $\vec{u}_2$ will not be just $A\vec{u}_1$ but $A\vec{u}_1/S_2$. Next let S_3 denote the entry of $A\vec{u}_2$ which has largest absolute value and define $\vec{u}_3 \equiv A\vec{u}_2/S_3$. Continue this way. The scaling just described does not destroy the relative insignificance of the term involving a sum in (8.4.9). Indeed it amounts to nothing more than changing the units of length. Also note that from this scaling procedure, the absolute value of the largest element of $\vec{u}_k$ is always equal to 1. Therefore, for large m,

$$\vec{u}_m = \frac{\lambda_n^m c_n \vec{x}_n}{S_2 S_3 \cdots S_m} + (\text{relatively insignificant term}).$$

Therefore, the entry of $A\vec{u}_m$ which has the largest absolute value is essentially equal to the entry having largest absolute value of

$$A\left(\frac{\lambda_n^m c_n \vec{x}_n}{S_2 S_3 \cdots S_m}\right) = \frac{\lambda_n^{m+1} c_n \vec{x}_n}{S_2 S_3 \cdots S_m} \approx \lambda_n \vec{u}_m$$

and so for large m, it must be the case that $\lambda_n \approx S_{m+1}$. This suggests the following procedure.

Procedure 8.4.4: Finding the Largest Eigenvalue with its Eigenvector

1. Start with a vector $\vec{u}_1$ which you hope has a component in the direction of $\vec{x}_n$. The vector $(1, \cdots, 1)^T$ is usually a pretty good choice.
2. If $\vec{u}_k$ is known,
$$\vec{u}_{k+1} = \frac{A\vec{u}_k}{S_{k+1}}$$
where S_{k+1} is the entry of $A\vec{u}_k$ which has largest absolute value.
3. When the scaling factors, S_k are not changing much, S_{k+1} will be close to the eigenvalue and $\vec{u}_{k+1}$ will be close to an eigenvector.
4. Check your answer to see if it worked well.

The shifted inverse power method involves finding the eigenvalue closest to a given complex number along with the associated eigenvalue. If μ is a complex number and you want to find λ which is closest to μ, you could consider the eigenvalues and eigenvectors of $(A - \mu I)^{-1}$. Then $A\vec{x} = \lambda\vec{x}$ if and only if

$$(A - \mu I)\vec{x} = (\lambda - \mu)\vec{x}$$

If and only if

$$\frac{1}{\lambda - \mu}\vec{x} = (A - \mu I)^{-1}\vec{x}$$

Thus, if λ is the closest eigenvalue of A to μ then out of all eigenvalues of $(A - \mu I)^{-1}$, you would have $\frac{1}{\lambda - \mu}$ would be the largest. Thus all you have to do is apply the power method to $(A - \mu I)^{-1}$ and the eigenvector you get will be the eigenvector which corresponds to λ where λ is the closest to μ of all eigenvalues of A. You could use the eigenvector to determine this directly.

Example 8.4.12: Finding Eigenvalue and Eigenvector

Find the eigenvalue and eigenvector for

$$\begin{bmatrix} 3 & 2 & 1 \\ -2 & 0 & -1 \\ -2 & -2 & 0 \end{bmatrix}$$

which is closest to $.9 + .9i$.

Solution

$$\left(\begin{bmatrix} 3 & 2 & 1 \\ -2 & 0 & -1 \\ -2 & -2 & 0 \end{bmatrix} - (.9 + .9i) \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \right)^{-1}$$

$$= \begin{bmatrix} -0.619\,19 - 10.545i & -5.524\,9 - 4.972\,4i & -0.370\,57 - 5.821\,3i \\ 5.524\,9 + 4.972\,4i & 5.276\,2 + 0.248\,62i & 2.762\,4 + 2.486\,2i \\ 0.741\,14 + 11.643i & 5.524\,9 + 4.972\,4i & 0.492\,52 + 6.918\,9i \end{bmatrix}$$

Then pick an initial guess an multiply by this matrix raised to a large power.

$$= \begin{bmatrix} -0.619\,19 - 10.545i & -5.524\,9 - 4.972\,4i & -0.370\,57 - 5.821\,3i \\ 5.524\,9 + 4.972\,4i & 5.276\,2 + 0.248\,62i & 2.762\,4 + 2.486\,2i \\ 0.741\,14 + 11.643i & 5.524\,9 + 4.972\,4i & 0.492\,52 + 6.918\,9i \end{bmatrix}^{15} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

This equals

$$\begin{bmatrix} 1.562\,9 \times 10^{13} - 3.899\,3 \times 10^{12}i \\ -5.864\,5 \times 10^{12} + 9.764\,2 \times 10^{12}i \\ -1.562\,9 \times 10^{13} + 3.899\,9 \times 10^{12}i \end{bmatrix}$$

Now divide by an entry to make the vector have reasonable size. This yields

$$\begin{bmatrix} -0.999\,99 - 3.614\,0 \times 10^{-5}i \\ 0.499\,99 - 0.499\,99i \\ 1.0 \end{bmatrix}$$

which is close to

$$\begin{bmatrix} -1 \\ 0.5 - 0.5i \\ 1.0 \end{bmatrix}$$

Then

$$\begin{bmatrix} 3 & 2 & 1 \\ -2 & 0 & -1 \\ -2 & -2 & 0 \end{bmatrix} \begin{bmatrix} -1 \\ 0.5 - 0.5i \\ 1.0 \end{bmatrix} = \begin{bmatrix} -1.0 - 1.0i \\ 1.0 \\ 1.0 + 1.0i \end{bmatrix}$$

Now to determine the eigenvalue, you could just take the ratio of corresponding entries. Pick the two corresponding entries which have the largest absolute values. In this case, you would get the eigenvalue is $1 + i$ which happens to be the exact eigenvalue. Thus an eigenvector and eigenvalue are

$$\begin{bmatrix} -1 \\ 0.5 - 0.5i \\ 1.0 \end{bmatrix}, 1 + i$$

Usually it won't work out so well but you can still find what is desired. Thus, once you have obtained approximate eigenvalues using the QR algorithm, you can find the eigenvalue more exactly along with an eigenvector associated with it by using the shifted inverse power method.

Quadratic Forms

One of the applications of orthogonal diagonalization is that of quadratic forms and graphs of level curves of a quadratic form. This section has to do with rotation of axes so that with respect to the new axes, the graph of the level curve of a quadratic form is oriented parallel to the coordinate axes. This makes it much easier to understand. For example, we all know that $x_1^2 + x_2^2 = 1$ represents the equation in two variables whose graph in $\mathbb{R}^2$ is a circle of radius 1. But how do we know what the graph of the equation $5x_1^2 + 4x_1x_2 + 3x_2^2 = 1$ represents?

We first formally define what is meant by a quadratic form. In this section we will work with only *real* quadratic forms, which means that the coefficients will all be real numbers.

Definition 8.4.8: Quadratic Form

A **quadratic form** is a polynomial of degree two in n variables $x_1, x_2, \cdots, x_n$, written as a linear combination of x_i^2 terms and x_ix_j terms.

Consider the quadratic form $q = a_{11}x_1^2 + a_{22}x_2^2 + \cdots + a_{nn}x_n^2 + a_{12}x_1x_2 + \cdots$. We can write $\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$ as the vector whose entries are the variables contained in the quadratic form.

Similarly, let $A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}$ be the matrix whose entries are the coefficients of x_i^2 and x_ix_j from q. Note that the matrix A is not unique, and we will consider this further in the example below. Using this matrix A, the quadratic form can be written as $q = \vec{x}^T A\vec{x}$.

$$\begin{aligned} q &= \vec{x}^T A\vec{x} \\ &= \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \\ &= \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} \begin{bmatrix} a_{11}x_1 + a_{21}x_2 + \cdots + a_{n1}x_n \\ a_{12}x_1 + a_{22}x_2 + \cdots + a_{n2}x_n \\ \vdots \\ a_{1n}x_1 + a_{2n}x_2 + \cdots + a_{nn}x_n \end{bmatrix} \\ &= a_{11}x_1^2 + a_{22}x_2^2 + \cdots + a_{nn}x_n^2 + a_{12}x_1x_2 + \cdots \end{aligned} \tag{8.4.10}$$

Let's explore how to find this matrix A. Consider the following example.

Example 8.4.13: Matrix of a Quadratic Form

Let a quadratic form q be given by

$$q = 6x_1^2 + 4x_1x_2 + 3x_2^2$$

Write q in the form $\vec{x}^T A\vec{x}$.

Solution

First, let $\vec{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ and $A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$.

Then, writing $q = \vec{x}^T A\vec{x}$ gives

$$\begin{aligned} q &= \begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \\ &= a_{11}x_1^2 + a_{21}x_1x_2 + a_{12}x_1x_2 + a_{22}x_2^2 \end{aligned} \tag{8.4.11}$$

Notice that we have an x_1x_2 term as well as an x_2x_1 term. Since multiplication is commutative, these terms can be combined. This means that q can be written

$$q = a_{11}x_1^2 + (a_{21} + a_{12})\, x_1x_2 + a_{22}x_2^2$$

Equating this to q as given in the example, we have

$$a_{11}x_1^2 + (a_{21} + a_{12})\, x_1x_2 + a_{22}x_2^2 = 6x_1^2 + 4x_1x_2 + 3x_2^2$$

Therefore,

$$\begin{aligned} a_{11} &= 6 \\ a_{22} &= 3 \\ a_{21} + a_{12} &= 4 \end{aligned} \tag{8.4.12}$$

This demonstrates that the matrix A is not unique, as there are several correct solutions to $a_{21} + a_{12} = 4$. However, we will *always* choose the coefficients such that $a_{21} = a_{12} = \frac{1}{2}(a_{21} + a_{12})$. This results in $a_{21} = a_{12} = 2$. This choice is key, as it will ensure that A turns out to be a symmetric matrix.

Hence,

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} 6 & 2 \\ 2 & 3 \end{bmatrix}$$

You can verify that $q = \vec{x}^T A\vec{x}$ holds for this choice of A.

The above procedure for choosing A to be symmetric applies for any quadratic form q. We will *always* choose coefficients such that $a_{ij} = a_{ji}$.

We now turn our attention to the focus of this section. Our goal is to start with a quadratic form q as given above and find a way to rewrite it to eliminate the x_ix_j terms. This is done through a change of variables. In other words, we wish to find y_i such that

$$q = d_{11}y_1^2 + d_{22}y_2^2 + \cdots + d_{nn}y_n^2$$

Letting $\vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$ and $D = [d_{ij}]$, we can write $q = \vec{y}^T D\vec{y}$ where D is the matrix of coefficients from q. There is something special about this matrix D that is crucial. Since no y_iy_j terms exist in q, it follows that $d_{ij} = 0$ for all $i \neq j$. Therefore, D is a diagonal matrix. Through this change of variables, we find the **principal axes** $y_1, y_2, \cdots, y_n$ of the quadratic form.

This discussion sets the stage for the following essential theorem.

Theorem 8.4.11: Diagonalizing a Quadratic Form

Let q be a quadratic form in the variables $x_1, \cdots, x_n$. It follows that q can be written in the form $q = \vec{x}^T A\vec{x}$ where

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

and $A = [a_{ij}]$ is the symmetric matrix of coefficients of q.

New variables $y_1, y_2, \cdots, y_n$ can be found such that $q = \vec{y}^T D\vec{y}$ where

$$\vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

and $D = [d_{ij}]$ is a diagonal matrix. The matrix D contains the eigenvalues of A and is found by orthogonally diagonalizing A.

While not a formal proof, the following discussion should convince you that the above theorem holds. Let q be a quadratic form in the variables $x_1, \cdots, x_n$. Then, q can be written in the form $q = \vec{x}^T A\vec{x}$ for a symmetric matrix A. By Theorem 8.4.3 we can orthogonally diagonalize the matrix A such that $U^T AU = D$ for an orthogonal matrix U and diagonal matrix D.

Then, the vector $\vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$ is found by $\vec{y} = U^T\vec{x}$. To see that this works, rewrite $\vec{y} = U^T\vec{x}$ as $\vec{x} = U\vec{y}$. Letting $q = \vec{x}^T A\vec{x}$, proceed as follows:

$$\begin{aligned} q &= \vec{x}^T A\vec{x} \\ &= (U\vec{y})^T A(U\vec{y}) \\ &= \vec{y}^T (U^T AU)\vec{y} \\ &= \vec{y}^T D\vec{y} \end{aligned} \tag{8.4.13}$$

The following procedure details the steps for the change of variables given in the above theorem.

Procedure 8.4.5: Diagonalizing a Quadratic Form

Let q be a quadratic form in the variables $x_1, \cdots, x_n$ given by

$$q = a_{11}x_1^2 + a_{22}x_2^2 + \cdots + a_{nn}x_n^2 + a_{12}x_1x_2 + \cdots$$

Then, q can be written as $q = d_{11}y_1^2 + \cdots + d_{nn}y_n^2$ as follows:

1. Write $q = \vec{x}^T A\vec{x}$ for a symmetric matrix A.
2. Orthogonally diagonalize A to be written as $U^T AU = D$ for an orthogonal matrix U and diagonal matrix D.
3. Write $\vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$. Then, $\vec{x} = U\vec{y}$.
4. The quadratic form q will now be given by

   $$q = d_{11}y_1^2 + \cdots + d_{nn}y_n^2 = \vec{y}^T D\vec{y}$$

   where $D = [d_{ij}]$ is the diagonal matrix found by orthogonally diagonalizing A.

Consider the following example.

Example 8.4.14: Choosing New Axes to Simplify a Quadratic Form

Consider the following level curve

$$6x_1^2 + 4x_1x_2 + 3x_2^2 = 7$$

shown in the following graph.

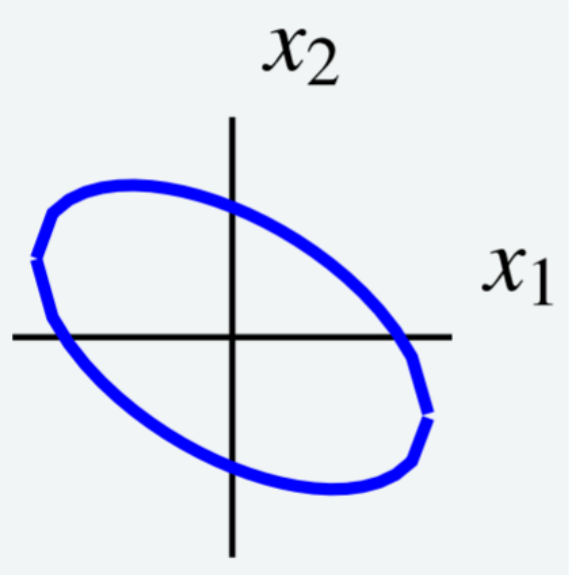


Figure 8.4.1

Use a change of variables to choose new axes such that the ellipse is oriented parallel to the new coordinate axes. In other words, use a change of variables to rewrite q to eliminate the x_1x_2 term.

Solution

Notice that the level curve is given by $q = 7$ for $q = 6x_1^2 + 4x_1x_2 + 3x_2^2$. This is the same quadratic form that we examined earlier in Example 8.4.13. Therefore we know that we can write $q = \vec{x}^T A\vec{x}$ for the matrix

$$A = \begin{bmatrix} 6 & 2 \\ 2 & 3 \end{bmatrix}$$

Now we want to orthogonally diagonalize A to write $U^T AU = D$ for an orthogonal matrix U and diagonal matrix D. The details are left to the reader, and you can verify that the resulting matrices are

$$\begin{aligned} U &= \begin{bmatrix} \frac{2}{\sqrt{5}} & -\frac{1}{\sqrt{5}} \\ \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \end{bmatrix} \\ D &= \begin{bmatrix} 7 & 0 \\ 0 & 2 \end{bmatrix} \end{aligned} \tag{8.4.14}$$

Next we write $\vec{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$. It follows that $\vec{x} = U\vec{y}$.

We can now express the quadratic form q in terms of y, using the entries from D as coefficients as follows:

$$\begin{aligned} q &= d_{11}y_1^2 + d_{22}y_2^2 \\ &= 7y_1^2 + 2y_2^2 \end{aligned} \tag{8.4.15}$$

Hence the level curve can be written $7y_1^2 + 2y_2^2 = 7$. The graph of this equation is given by:

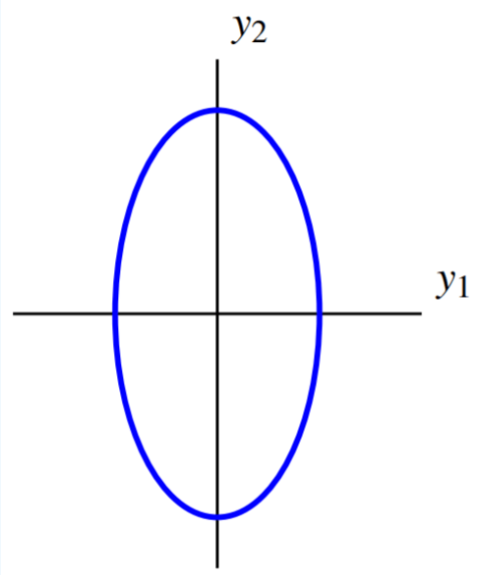


Figure 8.4.2

The change of variables results in new axes such that with respect to the new axes, the ellipse is oriented parallel to the coordinate axes. These are called the **principal axes** of the quadratic form.

The following is another example of diagonalizing a quadratic form.

Example 8.4.15: Choosing New Axes to Simplify a Quadratic Form

Consider the level curve

$$5x_1^2 - 6x_1x_2 + 5x_2^2 = 8$$

shown in the following graph.

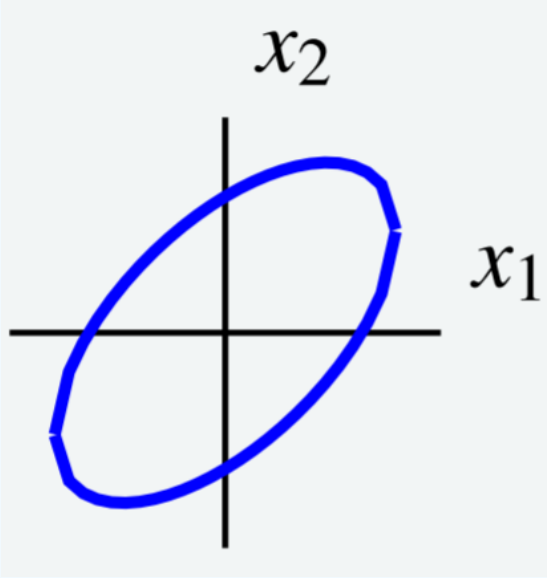


Figure 8.4.3

Use a change of variables to choose new axes such that the ellipse is oriented parallel to the new coordinate axes. In other words, use a change of variables to rewrite q to eliminate the x_1x_2 term.

Solution

First, express the level curve as $\vec{x}^T A\vec{x}$ where $\vec{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ and A is symmetric. Let $A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$. Then $q = \vec{x}^T A\vec{x}$ is given by

$$\begin{aligned} q &= \begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \\ &= a_{11}x_1^2 + (a_{12} + a_{21})x_1x_2 + a_{22}x_2^2 \end{aligned} \tag{8.4.16}$$

Equating this to the given description for q, we have

$$5x_1^2 - 6x_1x_2 + 5x_2^2 = a_{11}x_1^2 + (a_{12} + a_{21})x_1x_2 + a_{22}x_2^2$$

This implies that $a_{11} = 5, a_{22} = 5$ and in order for A to be symmetric, $a_{12} = a_{22} = \frac{1}{2}(a_{12} + a_{21}) = -3$. The result is $A = \begin{bmatrix} 5 & -3 \\ -3 & 5 \end{bmatrix}$. We can write $q = \vec{x}^T A\vec{x}$ as

$$\begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} 5 & -3 \\ -3 & 5 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = 8$$

Next, orthogonally diagonalize the matrix A to write $U^T AU = D$. The details are left to the reader and the necessary matrices are given by

$$\begin{aligned} U &= \begin{bmatrix} \frac{1}{2}\sqrt{2} & \frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} & -\frac{1}{2}\sqrt{2} \end{bmatrix} \\ D &= \begin{bmatrix} 2 & 0 \\ 0 & 8 \end{bmatrix} \end{aligned} \tag{8.4.17}$$

Write $\vec{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$, such that $\vec{x} = U\vec{y}$. Then it follows that q is given by

$$\begin{aligned} q &= d_{11}y_1^2 + d_{22}y_2^2 \\ &= 2y_1^2 + 8y_2^2 \end{aligned} \tag{8.4.18}$$

Therefore the level curve can be written as $2y_1^2 + 8y_2^2 = 8$.

This is an ellipse which is parallel to the coordinate axes. Its graph is of the form

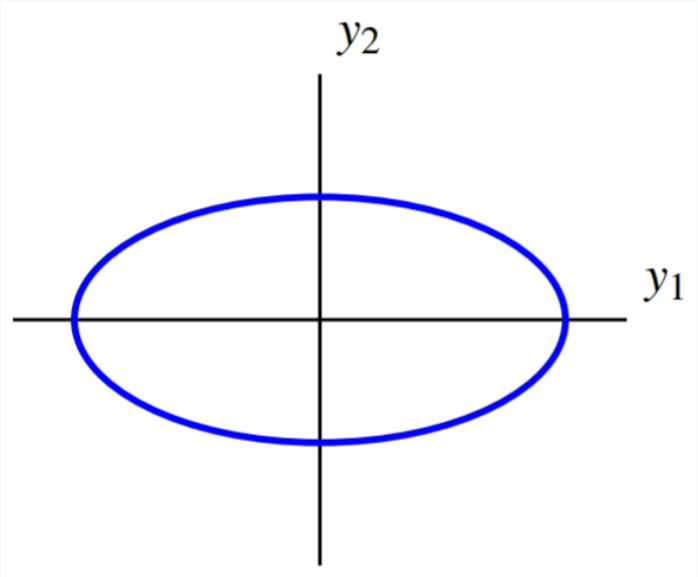


Figure 8.4.4

Thus this change of variables chooses new axes such that with respect to these new axes, the ellipse is oriented parallel to the coordinate axes.

Answers

Lemma 8.4.1: The Dot Product

This result follows from the definition of the dot product together with properties of matrix multiplication, as follows:

$$\begin{aligned} A\vec{x}\cdot\vec{y} &= \sum_{k,l} a_{kl}x_l y_k \\ &= \sum_{k,l} (a_{lk})^T x_l y_k \\ &= \vec{x}\cdot A^T\vec{y} \\ &= \vec{x}\cdot A\vec{y} \end{aligned} \tag{8.4.19}$$

The last step follows from $A^T = A$, since A is symmetric.

Theorem 8.4.1: Orthogonal Eigenvectors

Recall that for a complex number $a+ib$, the complex conjugate, denoted by $\overline{a+ib}$ is given by $\overline{a+ib} = a-ib$. The notation, $\overline{\vec{x}}$ will denote the vector which has every entry replaced by its complex conjugate.

Suppose A is a real symmetric matrix and $A\vec{x} = \lambda\vec{x}$. Then

$$\overline{\lambda\vec{x}}^T\vec{x} = \left(\overline{A\vec{x}}\right)^T\vec{x} = \overline{\vec{x}}^T A^T\vec{x} = \overline{\vec{x}}^T A\vec{x} = \lambda\overline{\vec{x}}^T\vec{x}$$

Dividing by $\overline{\vec{x}}^T\vec{x}$ on both sides yields $\overline{\lambda} = \lambda$ which says λ is real. To do this, we need to ensure that $\overline{\vec{x}}^T\vec{x} \neq 0$. Notice that $\overline{\vec{x}}^T\vec{x} = 0$ if and only if $\vec{x} = \vec{0}$. Since we chose $\vec{x}$ such that $A\vec{x} = \lambda\vec{x}$, $\vec{x}$ is an eigenvector and therefore must be nonzero.

Now suppose A is real symmetric and $A\vec{x} = \lambda\vec{x}$, $A\vec{y} = \mu\vec{y}$ where $\mu \neq \lambda$. Then since A is symmetric, it follows from Lemma 8.4.1 about the dot product that

$$\lambda\vec{x}\cdot\vec{y} = A\vec{x}\cdot\vec{y} = \vec{x}\cdot A\vec{y} = \vec{x}\cdot\mu\vec{y} = \mu\vec{x}\cdot\vec{y}$$

Hence $(\lambda-\mu)\,\vec{x}\cdot\vec{y} = 0$. It follows that, since $\lambda-\mu \neq 0$, it must be that $\vec{x}\cdot\vec{y} = 0$. Therefore the eigenvectors form an orthogonal set.

Theorem 8.4.2: Eigenvalues of Skew Symmetric Matrix

First, note that if $A = 0$ is the zero matrix, then A is skew symmetric and has eigenvalues equal to 0.

Suppose $A = -A^T$ so A is skew symmetric and $A\vec{x} = \lambda\vec{x}$. Then

$$\overline{\lambda\vec{x}}^T\vec{x} = \left(\overline{A\vec{x}}\right)^T\vec{x} = \overline{\vec{x}}^T A^T\vec{x} = -\overline{\vec{x}}^T A\vec{x} = -\lambda\overline{\vec{x}}^T\vec{x}$$

and so, dividing by $\overline{\vec{x}}^T\vec{x}$ as before, $\overline{\lambda} = -\lambda$. Letting $\lambda = a+ib$, this means $a-ib = -a-ib$ and so $a = 0$. Thus λ is pure imaginary.

Corollary 8.4.1: Orthonormal Set of Eigenvectors

Since A is symmetric, then by Theorem 8.4.3, there exists an orthogonal matrix U such that $U^TAU = D$, a diagonal matrix whose diagonal entries are the eigenvalues of A. Therefore, since A is symmetric and all the matrices are real,

$$\overline{D} = \overline{D^T} = \overline{U^TA^TU} = U^TA^TU = U^TAU = D$$

showing D is real because each entry of D equals its complex conjugate.

Now let

$$U = \begin{bmatrix} \vec{u}_1 & \vec{u}_2 & \cdots & \vec{u}_n \end{bmatrix}$$

where the $\vec{u}_i$ denote the columns of U and

$$D = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix}$$

The equation, $U^TAU = D$ implies $AU = UD$ and

$$\begin{aligned} AU &= \begin{bmatrix} A\vec{u}_1 & A\vec{u}_2 & \cdots & A\vec{u}_n \end{bmatrix} \\ &= \begin{bmatrix} \lambda_1\vec{u}_1 & \lambda_2\vec{u}_2 & \cdots & \lambda_n\vec{u}_n \end{bmatrix} \\ &= UD \end{aligned} \tag{8.4.20}$$

where the entries denote the columns of AU and UD respectively. Therefore, $A\vec{u}_i = \lambda_i\vec{u}_i$. Since the matrix U is orthogonal, the ij^{th} entry of U^TU equals δ_{ij} and so

$$\delta_{ij} = \vec{u}_i^T\vec{u}_j = \vec{u}_i\cdot\vec{u}_j$$

This proves the corollary because it shows the vectors $\{\vec{u}_i\}$ form an orthonormal set.

Corollary 8.4.2: Determinant and Trace

By Theorem 8.4.5, there exists an orthogonal matrix U such that $U^TAU = P$, where P is an upper triangular matrix. Since P is similar to A, the eigenvalues of P are $\lambda_1, \lambda_2, \ldots, \lambda_n$. Furthermore, since P is (upper) triangular, the entries on the main diagonal of P are its eigenvalues, so $\det(P) = \lambda_1\lambda_2\cdots\lambda_n$ and $trace(P) = \lambda_1 + \lambda_2 + \cdots + \lambda_n$. Since P and A are similar, $\det(A) = \det(P)$ and $trace(A) = trace(P)$, and therefore the results follow.

Proposition 8.4.1: Same Nonzero Eigenvalues

Suppose A is an $m\times n$ matrix, and suppose that λ is a nonzero eigenvalue of A^TA. Then there exists a nonzero vector $X \in \mathbb{R}^n$ such that

$$(A^TA)X = \lambda X. \tag{8.4.21}$$

Multiplying both sides of this equation by A yields:

$$\begin{aligned} A(A^TA)X &= A\lambda X \\ (AA^T)(AX) &= \lambda(AX). \end{aligned} \tag{8.4.22}$$

Since $\lambda \neq 0$ and $X \neq 0_n$, $\lambda X \neq 0_n$, and thus by equation (8.4.21), $(A^TA)X \neq 0_m$; thus $A^T(AX) \neq 0_m$, implying that $AX \neq 0_m$.

Therefore AX is an eigenvector of AA^T corresponding to eigenvalue λ. An analogous argument can be used to show that every nonzero eigenvalue of AA^T is an

eigenvalue of A^TA, thus completing the proof.

Theorem 8.4.6**: Singular Value Decomposition**

There exists an orthonormal basis, $\{\vec{v}_i\}_{i=1}^n$ such that $A^TA\vec{v}_i = \sigma_i^2\vec{v}_i$ where $\sigma_i^2 > 0$ for $i = 1, \cdots, k, (\sigma_i > 0)$ and equals zero if $i > k$. Thus for $i > k$, $A\vec{v}_i = \vec{0}$ because

$$A\vec{v}_i \cdot A\vec{v}_i = A^TA\vec{v}_i \cdot \vec{v}_i = \vec{0} \cdot \vec{v}_i = 0.$$

For $i = 1, \cdots, k$, define $\vec{u}_i \in \mathbb{R}^m$ by

$$\vec{u}_i = \sigma_i^{-1}A\vec{v}_i.$$

Thus $A\vec{v}_i = \sigma_i\vec{u}_i$. Now

$$\begin{aligned}\vec{u}_i \cdot \vec{u}_j &= \sigma_i^{-1}A\vec{v}_i \cdot \sigma_j^{-1}A\vec{v}_j = \sigma_i^{-1}\vec{v}_i \cdot \sigma_j^{-1}A^TA\vec{v}_j \\ &= \sigma_i^{-1}\vec{v}_i \cdot \sigma_j^{-1}\sigma_j^2\vec{v}_j = \frac{\sigma_j}{\sigma_i}(\vec{v}_i \cdot \vec{v}_j) = \delta_{ij}.\end{aligned} \tag{8.4.23}$$

Thus $\{\vec{u}_i\}_{i=1}^k$ is an orthonormal set of vectors in $\mathbb{R}^m$. Also,

$$AA^T\vec{u}_i = AA^T\sigma_i^{-1}A\vec{v}_i = \sigma_i^{-1}AA^TA\vec{v}_i = \sigma_i^{-1}A\sigma_i^2\vec{v}_i = \sigma_i^2\vec{u}_i.$$

Now extend $\{\vec{u}_i\}_{i=1}^k$ to an orthonormal basis for all of $\mathbb{R}^m$, $\{\vec{u}_i\}_{i=1}^m$ and let

$$U = \begin{bmatrix} \vec{u}_1 & \cdots & \vec{u}_m \end{bmatrix}$$

while $V = (\vec{v}_1 \cdots \vec{v}_n)$. Thus U is the matrix which has the $\vec{u}_i$ as columns and V is defined as the matrix which has the $\vec{v}_i$ as columns. Then

$$U^TAV = \begin{bmatrix} \vec{u}_1^T \\ \vdots \\ \vec{u}_k^T \\ \vdots \\ \vec{u}_m^T \end{bmatrix} A \begin{bmatrix} \vec{v}_1 \cdots \vec{v}_n \end{bmatrix}$$

$$= \begin{bmatrix} \vec{u}_1^T \\ \vdots \\ \vec{u}_k^T \\ \vdots \\ \vec{u}_m^T \end{bmatrix} \begin{bmatrix} \sigma_1\vec{u}_1 & \cdots & \sigma_k\vec{u}_k & \vec{0} & \cdots & \vec{0} \end{bmatrix} = \begin{bmatrix} \sigma & 0 \\ 0 & 0 \end{bmatrix}$$

where σ is given in the statement of the theorem.

Lemma 8.4.3**: Positive Definite Matrix and Invertibility**

If $A\vec{v} = \vec{0}$, then 0 is an eigenvalue if $\vec{v}$ is nonzero, which does not happen for a positive definite matrix. Hence $\vec{v} = \vec{0}$ and so A is one to one. This is sufficient to conclude that it is invertible.

Theorem 8.4.7**: Positive Definite Matrix**

Since A is symmetric, there exists an orthogonal matrix U so that

$$U^TAU = diag(\lambda_1, \lambda_2, \ldots, \lambda_n) = D,$$

where $\lambda_1, \lambda_2, \ldots, \lambda_n$ are the (not necessarily distinct) eigenvalues of A. Let $\vec{x} \in \mathbb{R}^n$, $\vec{x} \neq \vec{0}$, and define $\vec{y} = U^T\vec{x}$. Then

$$\vec{x}^TA\vec{x} = \vec{x}^T(UDU^T)\vec{x} = (\vec{x}^TU)D(U^T\vec{x}) = \vec{y}^TD\vec{y}.$$

Writing $\vec{y}^T = \begin{bmatrix} y_1 & y_2 & \cdots & y_n \end{bmatrix}$,

$$\begin{aligned}\vec{x}^TA\vec{x} &= \begin{bmatrix} y_1 & y_2 & \cdots & y_n \end{bmatrix} diag(\lambda_1, \lambda_2, \ldots, \lambda_n) \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \\ &= \lambda_1y_1^2 + \lambda_2y_2^2 + \cdots \lambda_ny_n^2.\end{aligned} \tag{8.4.24}$$

($\Rightarrow$) First we will assume that A is positive definite and prove that $\vec{x}^TA\vec{x}$ is positive.

Suppose A is positive definite, and $\vec{x} \in \mathbb{R}^n$, $\vec{x} \neq \vec{0}$. Since U^T is invertible, $\vec{y} = U^T\vec{x} \neq \vec{0}$, and thus $y_j \neq 0$ for some j, implying $y_j^2 > 0$ for some j. Furthermore, since all eigenvalues of A are positive, $\lambda_iy_i^2 \geq 0$ for all i and $\lambda_jy_j^2 > 0$. Therefore, $\vec{x}^TA\vec{x} > 0$.

($\Leftarrow$) Now we will assume $\vec{x}^TA\vec{x}$ is positive and show that A is positive definite.

If $\vec{x}^TA\vec{x} > 0$ whenever $\vec{x} \neq \vec{0}$, choose $\vec{x} = U\vec{e}_j$, where $\vec{e}_j$ is the j^{th} column of I_n. Since U is invertible, $\vec{x} \neq \vec{0}$, and thus

$$\vec{y} = U^T\vec{x} = U^T(U\vec{e}_j) = \vec{e}_j.$$

Thus $y_j = 1$ and $y_i = 0$ when $i \neq j$, so

$$\lambda_1y_1^2 + \lambda_2y_2^2 + \cdots \lambda_ny_n^2 = \lambda_j,$$

i.e., $\lambda_j = \vec{x}^TA\vec{x} > 0$. Therefore, A is positive definite.

Lemma 8.4.4**: Positive Definite and Submatrices**

This follows right away from the above definition. Let $\vec{x} \in \mathbb{R}^k$ be nonzero. Then

$$\vec{x}^TA_k\vec{x} = \begin{bmatrix} \vec{x}^T & 0 \end{bmatrix} A \begin{bmatrix} \vec{x} \\ 0 \end{bmatrix} > 0$$

by the assumption that A is positive definite.

Theorem 8.4.8**: Positive Matrix and Determinant of** A_k

We prove this theorem by induction on n. It is clearly true if $n = 1$. Suppose then that it is true for $n - 1$ where $n \geq 2$. Since $\det(A) = \det(A_n) > 0$, it follows that all the eigenvalues are nonzero. We need to show that they are all positive. Suppose not. Then there is some even number of them which are negative, even because

the product of all the eigenvalues is known to be positive, equaling $\det(A)$. Pick two, λ_1 and λ_2 and let $A\vec{u}_i = \lambda_i \vec{u}_i$ where $\vec{u}_i \neq \vec{0}$ for $i = 1, 2$ and $\vec{u}_1 \cdot \vec{u}_2 = 0$. Now if $\vec{y} \equiv \alpha_1 \vec{u}_1 + \alpha_2 \vec{u}_2$ is an element of $span\{\vec{u}_1, \vec{u}_2\}$, then since these are eigenvalues and $\vec{u}_1 \cdot \vec{u}_2 = 0$, a short computation shows

$$\begin{aligned} &\left(\alpha_1 \vec{u}_1 + \alpha_2 \vec{u}_2\right)^T A \left(\alpha_1 \vec{u}_1 + \alpha_2 \vec{u}_2\right) \\ &= |\alpha_1|^2 \lambda_1 \vec{u}_1^2 + |\alpha_2|^2 \lambda_2 \vec{u}_2^2 < 0. \end{aligned}$$

Now letting $\vec{x} \in \mathbb{R}^{n-1}$, we can use the induction hypothesis to write

$$\begin{bmatrix} x^T & 0 \end{bmatrix} A \begin{bmatrix} \vec{x} \\ 0 \end{bmatrix} = \vec{x}^T A_{n-1} \vec{x} > 0.$$

Now the dimension of $\{\vec{z} \in \mathbb{R}^n : z_n = 0\}$ is $n-1$ and the dimension of $span\{\vec{u}_1, \vec{u}_2\} = 2$ and so there must be some nonzero $\vec{x} \in \mathbb{R}^n$ which is in both of these subspaces of $\mathbb{R}^n$. However, the first computation would require that $\vec{x}^T A \vec{x} < 0$ while the second would require that $\vec{x}^T A \vec{x} > 0$. This contradiction shows that all the eigenvalues must be positive. This proves the if part of the theorem. The converse can also be shown to be correct, but it is the direction which was just shown which is of most interest.

Corollary 8.4.4: Symmetric and Negative Definite Matrix

This is immediate from the above theorem when we notice, that A is negative definite if and only if $-A$ is positive definite. Therefore, if $\det(-A_k) > 0$ for all $k = 1, \cdots, n$, it follows that A is negative definite. However, $\det(-A_k) = (-1)^k \det(A_k)$.

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8.5: SUPPLEMENTAL NOTES - MORE ON EIGENVALUES AND INTRO TO EIGENSPACES

There is never enough that can be said about Eigenvalues and Eigenspaces so here is a bit more information. See if you can define Eigenspaces after you read these notes. There are a number of applications in the sciences. What are Markov Chains? They are mentioned elsewhere in this book.

8.5.1: The Eigenvalue-Eigenvector Equation

8.5.2: Eigenspaces

8.5.3: Eigenvalues and Eigenvectors - Visualizations

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8.5.1: The Eigenvalue-Eigenvector Equation

In Section 12, we developed the idea of eigenvalues and eigenvectors in the case of linear transformations $\Re^2 \to \Re^2$. In this section, we will develop the idea more generally.

Definition: the Eigenvalue-Eigenvector Equation

For a linear transformation $L: V \to V$, then λ is an *eigenvalue* of L with $eigenvector\ v \neq 0_V$ if

$$Lv = \lambda v. \tag{8.5.1.1}$$

This equation says that the direction of v is invariant (unchanged) under L.

Let's try to understand this equation better in terms of matrices. Let V be a finite-dimensional vector space and let $L: V \to V$. If we have a basis for V we can represent L by a square matrix M and find eigenvalues λ and associated eigenvectors v by solving the homogeneous system

$$(M - \lambda I)v = 0. \tag{8.5.1.2}$$

This system has non-zero solutions if and only if the matrix

$$M - \lambda I \tag{8.5.1.3}$$

is singular, and so we require that

$$\det(\lambda I - M) = 0. \tag{8.5.1.4}$$

The left hand side of this equation is a polynomial in the variable λ called the $characteristic\ polynomial\ P_M(\lambda)$ of M. For an $n \times n$ matrix, the characteristic polynomial has degree n. Then

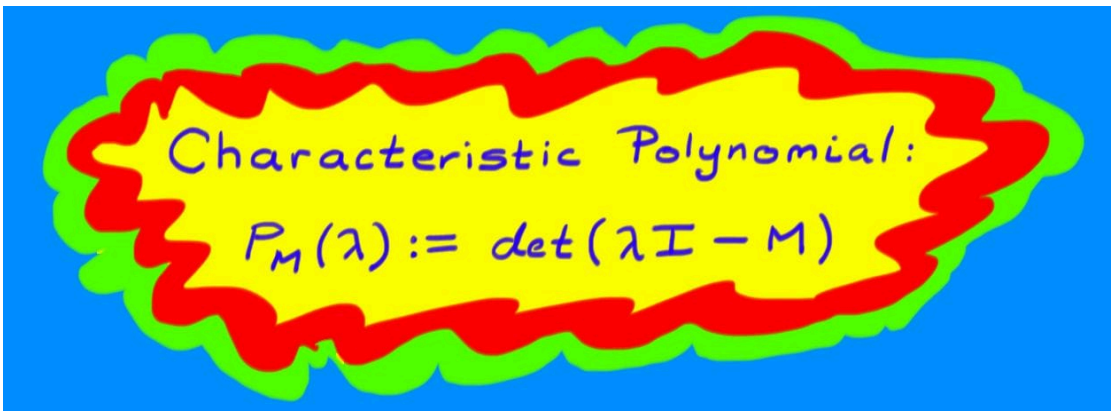
$$P_M(\lambda) = \lambda^n + c_1\lambda^{n-1} + \cdots + c_n. \tag{8.5.1.5}$$

Notice that $P_M(0) = \det(-M) = (-1)^n \det M$.

The Fundamental Theorem of Algebra states that any polynomial can be factored into a product of first order polynomials over C. Then there exists a collection of n complex numbers λ_i (possibly with repetition) such that

$$P_M(\lambda) = (\lambda - \lambda_1)(\lambda - \lambda_2)\cdots(\lambda - \lambda_n) \implies P_M(\lambda_i) = 0 \tag{8.5.1.6}$$

The eigenvalues λ_i of M are exactly the roots of $P_M(\lambda)$. These eigenvalues could be real or complex or zero, and they need not all be different. The number of times that any given root λ_i appears in the collection of eigenvalues is called its $multiplicity$.



Example 8.5.1.1:

Let L be the linear transformation $L:\Re^3 \to \Re^3$ given by

$$L\begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} 2x+y-z \\ x+2y-z \\ -x-y+2z \end{pmatrix}. \tag{8.5.1.7}$$

In the standard basis the matrix M representing L has columns Le_i for each i, so:

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} \overset{L}{\mapsto} \begin{pmatrix} 2 & 1 & -1 \\ 1 & 2 & -1 \\ -1 & -1 & 2 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix}. \tag{8.5.1.8}$$

Then the characteristic polynomial of L is

$$\begin{aligned} P_M(\lambda) &= \det \begin{pmatrix} \lambda-2 & -1 & 1 \\ -1 & \lambda-2 & 1 \\ 1 & 1 & \lambda-2 \end{pmatrix} \\ &= (\lambda-2)[(\lambda-2)^2-1] + [-(\lambda-2)-1] + [-(\lambda-2)-1] \\ &= (\lambda-1)^2(\lambda-4)\,. \end{aligned}$$

So L has eigenvalues $\lambda_1 = 1$ (with multiplicity 2), and $\lambda_2 = 4$ (with multiplicity 1).

To find the eigenvectors associated to each eigenvalue, we solve the homogeneous system $(M-\lambda_i I)X = 0$ for each i.

1. $\boxed{\lambda = 4:}$ We set up the augmented matrix for the linear system:

$$\begin{pmatrix} -2 & 1 & -1 & 0 \\ 1 & -2 & -1 & 0 \\ -1 & -1 & -2 & 0 \end{pmatrix} \sim \begin{pmatrix} 1 & -2 & -1 & 0 \\ 0 & -3 & -3 & 0 \\ 0 & -3 & -3 & 0 \end{pmatrix} \sim \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \tag{8.5.1.9}$$

So we see that $z = z =: t$, $y = -t$, and $x = -t$ gives a formula for eigenvectors in terms of the free parameter t. Any such eigenvector is of the form $t\begin{pmatrix} -1 \\ -1 \\ 1 \end{pmatrix}$; thus L leaves a line through the origin invariant.

2. $\boxed{\lambda = 1:}$ Again we set up an augmented matrix and find the solution set:

$$\begin{pmatrix} 1 & 1 & -1 & 0 \\ 1 & 1 & -1 & 0 \\ -1 & -1 & 1 & 0 \end{pmatrix} \sim \begin{pmatrix} 1 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \tag{8.5.1.10}$$

Then the solution set has two free parameters, s and t, such that $z = z =: t$, $y = y =: s$, and $x = -s + t$. Thus L leaves invariant the set:

$$\left\{ s\begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix} + t\begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \middle| s,t \in \Re \right\}. \tag{8.5.1.11}$$

This set is a plane through the origin. So the multiplicity two eigenvalue has two independent eigenvectors, $\begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix}$ and $\begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$ that determine an invariant plane.

Example 8.5.1.1:

Let V be the vector space of smooth $(i.e. infinitely\ differentiable)$ functions $f: \mathfrak{R} \to \mathfrak{R}$. Then the derivative is a linear operator $\frac{d}{dx}: V \to V$. What are the eigenvectors of the derivative? In this case, we don't have a matrix to work with, so we have to make do. A function f is an eigenvector of $\frac{d}{dx}$ if there exists some number λ such that $\frac{d}{dx} f = \lambda f$. An obvious candidate is the exponential function, $e^{\lambda x}$; indeed, $\frac{d}{dx} e^{\lambda x} = \lambda e^{\lambda x}$.

The operator $\frac{d}{dx}$ has an eigenvector $e^{\lambda x}$ for every $\lambda \in \mathfrak{R}$.

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8.5.2: Eigenspaces

fIn the previous example, we found two eigenvectors

$$\begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix} \text{ and } \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \tag{8.5.2.1}$$

for L, both with eigenvalue 1. Notice that

$$\begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} \tag{8.5.2.2}$$

is also an eigenvector of L with eigenvalue 1. In fact, any linear combination

$$r \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix} + s \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \tag{8.5.2.3}$$

of these two eigenvectors will be another eigenvector with the same eigenvalue.

More generally, let $\{v_1, v_2, ...\}$ be eigenvectors of some linear transformation L with the same eigenvalue λ. A $linear\ combination$ of the v_i can be written $c^1v_1 + c^2v_2 + \cdots$ for some constants $\{c^1, c^2, ...\}$. Then:

$$\begin{aligned} L(c^1v_1 + c^2v_2 + \cdots) &= c^1Lv_1 + c^2Lv_2 + \cdots \ \ by\ linearity\ of\ L \\ &= c^1\lambda v_1 + c^2\lambda v_2 + \cdots \ \ since\ Lv_i = \lambda v_i \\ &= \lambda(c^1v_1 + c^2v_2 + \cdots). \end{aligned}$$

So every linear combination of the v_i is an eigenvector of L with the same eigenvalue λ. In simple terms, any sum of eigenvectors is again an eigenvector $if\ they\ share\ the\ same\ eigenvalue$.

The space of all vectors with eigenvalue λ is called an $eigenspace$. It is, in fact, a vector space contained within the larger vector space V: It contains 0_V, since $L0_V = 0_V = \lambda 0_V$, and is closed under addition and scalar multiplication by the above calculation. All other vector space properties are inherited from the fact that V itself is a vector space. In other words, the subspace theorem, 9.1.1 chapter 9, ensures that $V_\lambda := \{v \in V | Lv = 0\}$ is a subspace of V.

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8.5.3: Eigenvalues and Eigenvectors - Visualizations

Learning Objectives

1. Learn the definition of eigenvector and eigenvalue.
2. Learn to find eigenvectors and eigenvalues geometrically.
3. Learn to decide if a number is an eigenvalue of a matrix, and if so, how to find an associated eigenvector.
4. *Recipe:* find a basis for the λ-eigenspace.
5. *Pictures:* whether or not a vector is an eigenvector, eigenvectors of standard matrix transformations.
6. *Theorem:* the expanded invertible matrix theorem.
7. *Vocabulary word:* ***eigenspace***.
8. *Essential vocabulary words:* ***eigenvector***, ***eigenvalue***.

In this section, we define eigenvalues and eigenvectors. These form the most important facet of the structure theory of square matrices. As such, eigenvalues and eigenvectors tend to play a key role in the real-life applications of linear algebra.

Eigenvalues and Eigenvectors

Here is the most important definition in this text.

Definition 8.5.3.1: Eigenvector and Eigenvalue

Let A be an $n \times n$ matrix.

1. An ***eigenvector*** of A is a *nonzero* vector v in $\mathbb{R}^n$ such that $Av = \lambda v$, for some scalar λ.
2. An ***eigenvalue*** of A is a scalar λ such that the equation $Av = \lambda v$ has a *nontrivial* solution.

If $Av = \lambda v$ for $v \neq 0$, we say that λ is the ***eigenvalue for*** v, and that v is an ***eigenvector for*** λ.

The German prefix "eigen" roughly translates to "self" or "own". An eigenvector of A is a vector that is taken to a multiple of itself by the matrix transformation $T(x) = Ax$, which perhaps explains the terminology. On the other hand, "eigen" is often translated as "characteristic"; we may think of an eigenvector as describing an intrinsic, or characteristic, property of A.

Note 8.5.3.1

Eigenvalues and eigenvectors are only for square matrices.

Note 8.5.3.2

Eigenvectors are *by definition nonzero*. Eigenvalues may be equal to zero.

We do not consider the zero vector to be an eigenvector: since $A0 = 0 = \lambda 0$ for *every* scalar λ, the associated eigenvalue would be undefined.

If someone hands you a matrix A and a vector v, it is easy to check if v is an eigenvector of A: simply multiply v by A and see if Av is a scalar multiple of v. On the other hand, given just the matrix A, it is not obvious at all how to find the eigenvectors. We will

learn how to do this in Section 5.2.

Example 8.5.3.1: Verifying eigenvectors

Consider the matrix

$$A = \begin{pmatrix} 2 & 2 \\ -4 & 8 \end{pmatrix} \quad \text{and vectors} \quad v = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \quad w = \begin{pmatrix} 2 \\ 1 \end{pmatrix}.$$

Which are eigenvectors? What are their eigenvalues?

Solution

We have

$$Av = \begin{pmatrix} 2 & 2 \\ -4 & 8 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} = 4v.$$

Hence, v is an eigenvector of A, with eigenvalue $\lambda = 4$. On the other hand,

$$Aw = \begin{pmatrix} 2 & 2 \\ -4 & 8 \end{pmatrix} \begin{pmatrix} 2 \\ 1 \end{pmatrix} = \begin{pmatrix} 6 \\ 0 \end{pmatrix}.$$

which is not a scalar multiple of w. Hence, w is not an eigenvector of A.

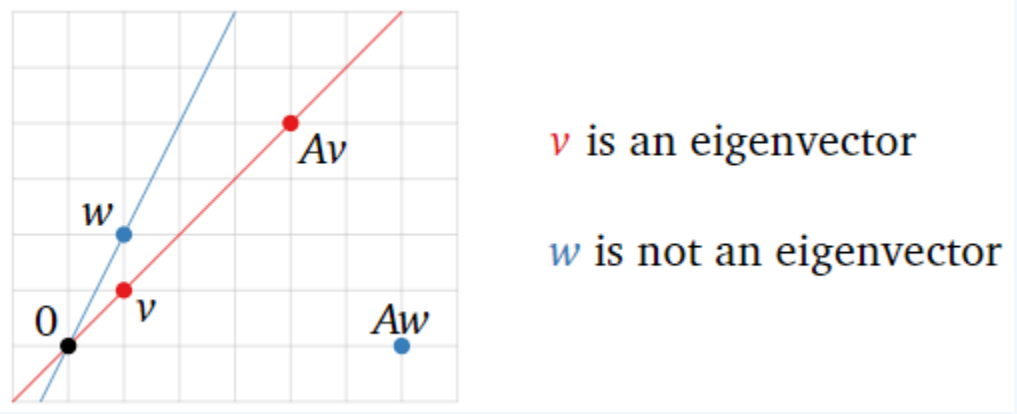


Figure 8.5.3.1

Example 8.5.3.2: Verifying eigenvectors

Consider the matrix

$$A = \begin{pmatrix} 0 & 6 & 8 \\ \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{2} & 0 \end{pmatrix} \quad \text{and vectors} \quad v = \begin{pmatrix} 16 \\ 4 \\ 1 \end{pmatrix} \quad w = \begin{pmatrix} 2 \\ 2 \\ 2 \end{pmatrix}.$$

Which are eigenvectors? What are their eigenvalues?

Solution

We have

$$Av = \begin{pmatrix} 0 & 6 & 8 \\ \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{2} & 0 \end{pmatrix} \begin{pmatrix} 16 \\ 4 \\ 1 \end{pmatrix} = \begin{pmatrix} 32 \\ 8 \\ 2 \end{pmatrix} = 2v.$$

Hence, v is an eigenvector of A, with eigenvalue $\lambda = 2$. On the other hand,

$$Aw = \begin{pmatrix} 0 & 6 & 8 \\ \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{2} & 0 \end{pmatrix} \begin{pmatrix} 2 \\ 2 \\ 2 \end{pmatrix} = \begin{pmatrix} 28 \\ 1 \\ 1 \end{pmatrix},$$

which is not a scalar multiple of w. Hence, w is not an eigenvector of A.

Example 8.5.3.3: An eigenvector with eigenvalue 0

Let

$$A = \begin{pmatrix} 1 & 3 \\ 2 & 6 \end{pmatrix} \qquad v = \begin{pmatrix} -3 \\ 1 \end{pmatrix}.$$

Is v an eigenvector of A? If so, what is its eigenvalue?

Solution

The product is

$$Av = \begin{pmatrix} 1 & 3 \\ 2 & 6 \end{pmatrix} \begin{pmatrix} -3 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} = 0v.$$

Hence, v is an eigenvector with eigenvalue *zero*.

As noted above, an eigen*value* is allowed to be zero, but an eigen*vector* is not.

To say that $Av = \lambda v$ means that Av and λv are *collinear with the origin*. So, an eigenvector of A is a nonzero vector v such that Av and v lie on the same line through the origin. In this case, Av is a scalar multiple of v; the eigenvalue is the scaling factor.

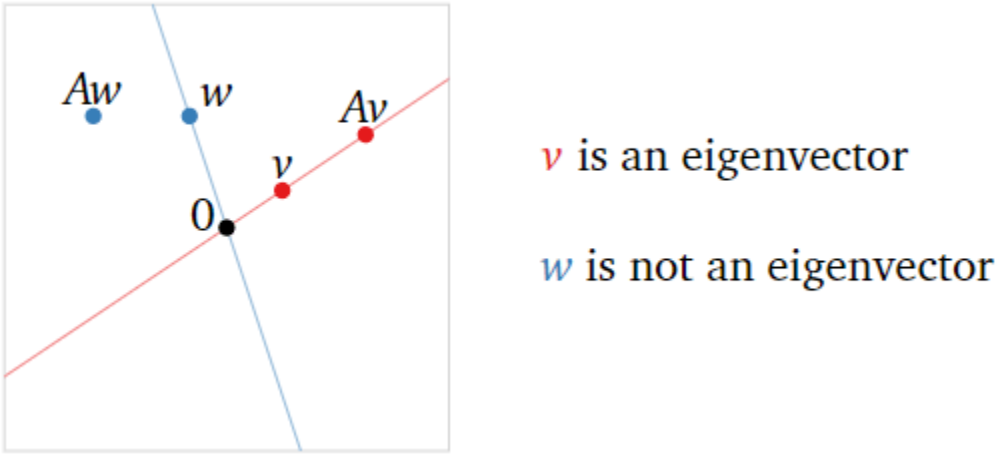


Figure 8.5.3.2

For matrices that arise as the standard matrix of a linear transformation, it is often best to draw a picture, then find the eigenvectors and eigenvalues geometrically by studying which vectors are not moved off of their line. For a transformation that is

defined geometrically, it is not necessary even to compute its matrix to find the eigenvectors and eigenvalues.

Example 8.5.3.4: Reflection

Here is an example of this. Let $T\colon \mathbb{R}^2 \to \mathbb{R}^2$ be the linear transformation that reflects over the line L defined by $y = -x$, and let A be the matrix for T. We will find the eigenvalues and eigenvectors of A without doing any computations.

This transformation is defined geometrically, so we draw a picture.

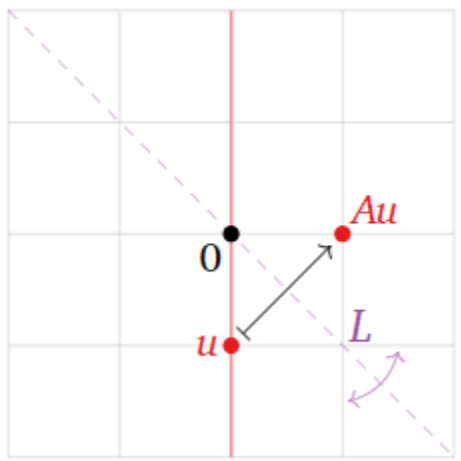


Figure 8.5.3.3

The vector u is not an eigenvector, because Au is not collinear with u and the origin.

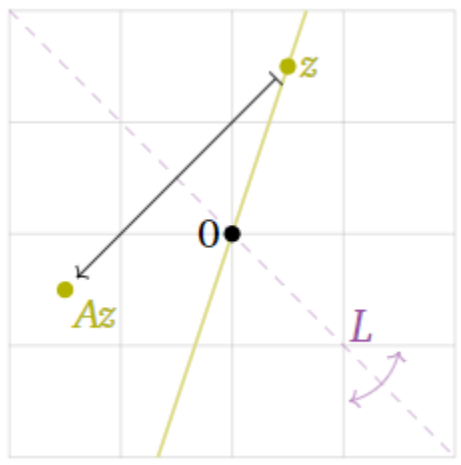


Figure 8.5.3.4

The vector z is not an eigenvector either.

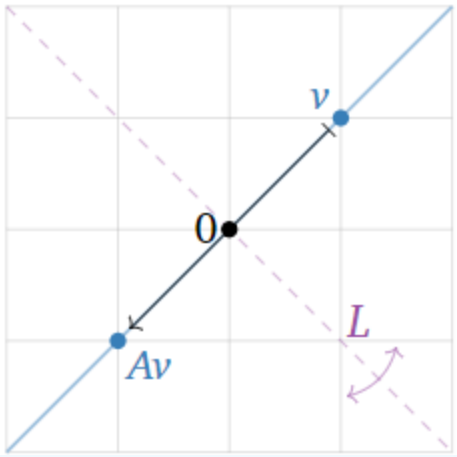


Figure 8.5.3.5

The vector v is an eigenvector because Av is collinear with v and the origin. The vector Av has the same length as v, but the opposite direction, so the associated eigenvalue is -1.

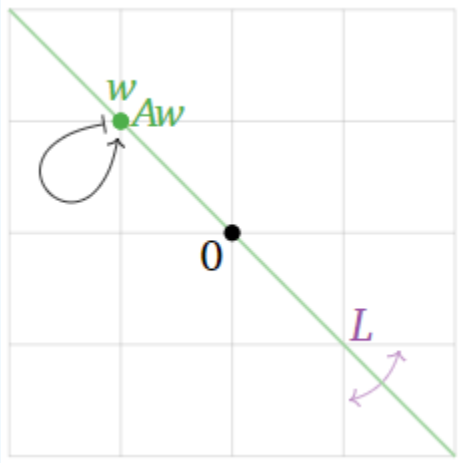


Figure 8.5.3.6

The vector w is an eigenvector because Aw is collinear with w and the origin: indeed, Aw is equal to w! This means that w is an eigenvector with eigenvalue 1.

It appears that all eigenvectors lie either on L, or on the line perpendicular to L. The vectors on L have eigenvalue 1, and the vectors perpendicular to L have eigenvalue -1.

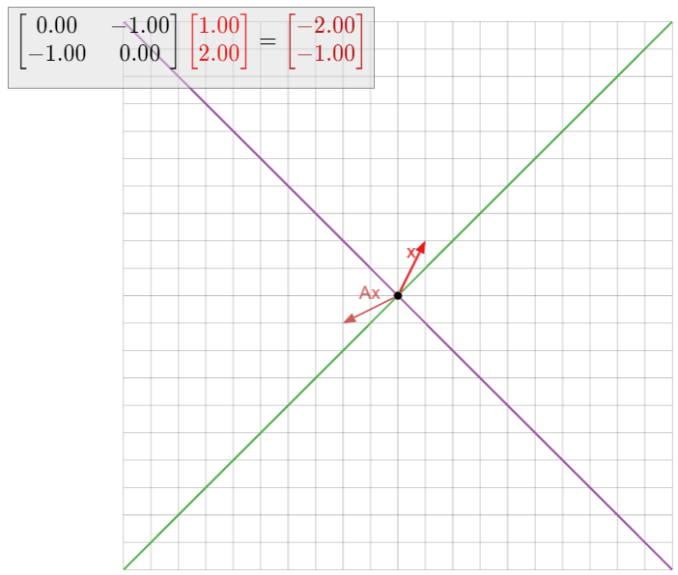


Figure 8.5.3.7: An eigenvector of A is a vector x such that Ax is collinear with x and the origin. Click and drag the head of x to convince yourself that all such vectors lie either on L, or on the line perpendicular to L.

We will now give five more examples of this nature

Example 8.5.3.5: Projection

Let $T: \mathbb{R}^2 \to \mathbb{R}^2$ be the linear transformation that projects a vector vertically onto the x-axis, and let A be the matrix for T. Find the eigenvalues and eigenvectors of A without doing any computations.

Solution

This transformation is defined geometrically, so we draw a picture.

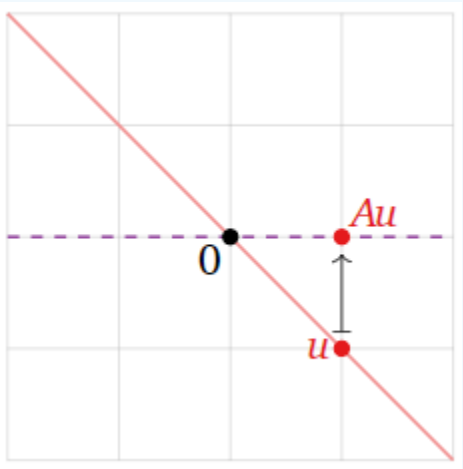


Figure 8.5.3.8

The vector u is not an eigenvector, because Au is not collinear with u and the origin.

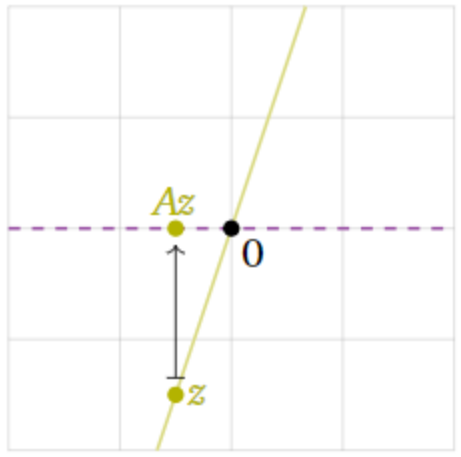


Figure 8.5.3.9

The vector z is not an eigenvector either.

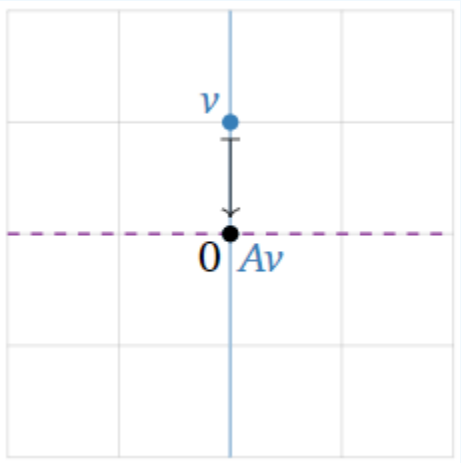


Figure 8.5.3.10

The vector v is an eigenvector. Indeed, Av is the zero vector, which is collinear with v and the origin; since $Av = 0v$, the associated eigenvalue is 0.

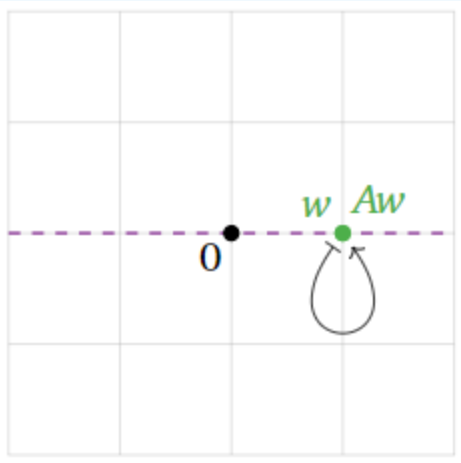


Figure 8.5.3.11

The vector w is an eigenvector because Aw is collinear with w and the origin: indeed, Aw is equal to w! This means that w is an eigenvector with eigenvalue 1.

It appears that all eigenvectors lie on the x-axis or the y-axis. The vectors on the x-axis have eigenvalue 1, and the vectors on the y-axis have eigenvalue 0.

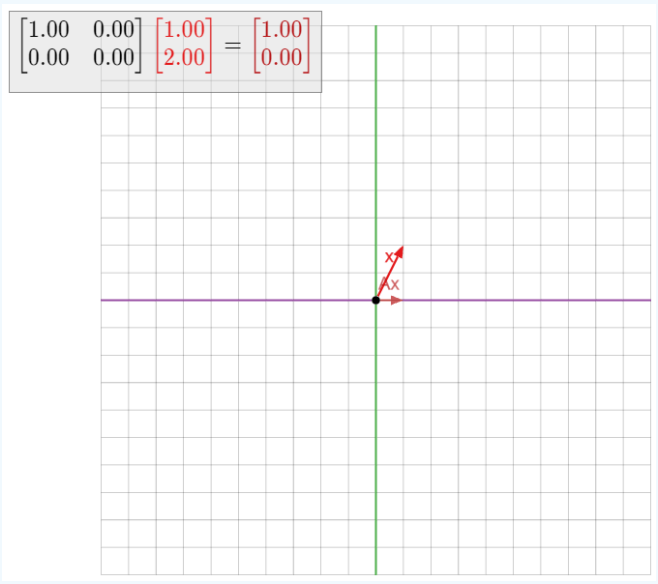


Figure 8.5.3.12: An eigenvector of A is a vector x such that Ax is collinear with x and the origin. Click and drag the head of x to convince yourself that all such vectors lie on the coordinate axes.

Example 8.5.3.6: Identity

Find all eigenvalues and eigenvectors of the identity matrix I_n.

Solution

The identity matrix has the property that $I_n v = v$ for all vectors v in $\mathbb{R}^n$. We can write this as $I_n v = 1 \cdot v$, so *every* nonzero vector is an eigenvector with eigenvalue 1.

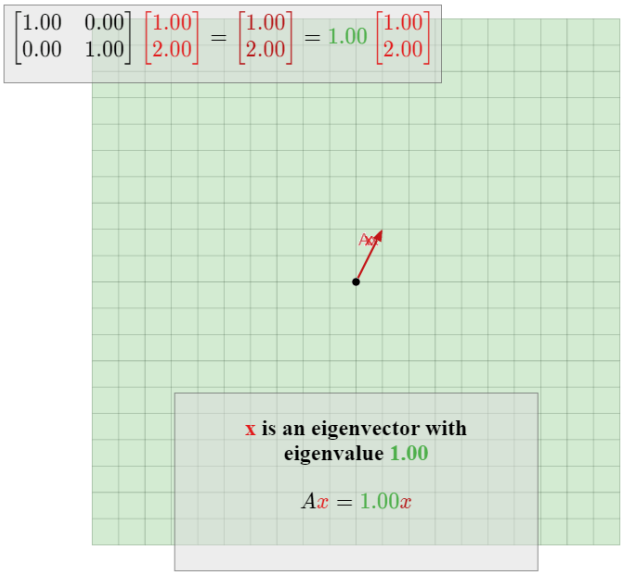


Figure 8.5.3.13: Every nonzero vector is an eigenvector of the identity matrix.

Example 8.5.3.7: Dilation

Let $T: \mathbb{R}^2 \to \mathbb{R}^2$ be the linear transformation that dilates by a factor of 1.5, and let A be the matrix for T. Find the eigenvalues and eigenvectors of A without doing any computations.

Solution

We have

$$Av = T(v) = 1.5v$$

for every vector v in $\mathbb{R}^2$. Therefore, by definition every nonzero vector is an eigenvector with eigenvalue 1.5.

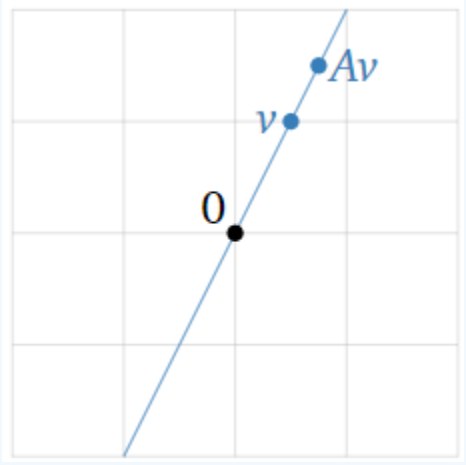


Figure 8.5.3.14

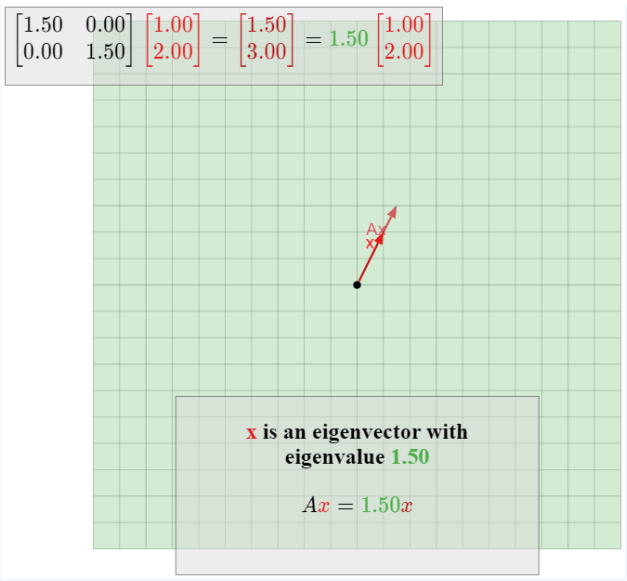


Figure 8.5.3.15: Every nonzero vector is an eigenvector of a dilation matrix.

Example 8.5.3.8: Shear

Let

$$A = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}$$

and let $T(x) = Ax$, so T is a shear in the x-direction. Find the eigenvalues and eigenvectors of A without doing any computations.

Solution

In equations, we have

$$A\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x+y \\ y \end{pmatrix}.$$

This tells us that a shear takes a vector and adds its y-coordinate to its x-coordinate. Since the x-coordinate changes but not the y-coordinate, this tells us that any vector v with nonzero y-coordinate cannot be collinear with Av and the origin.

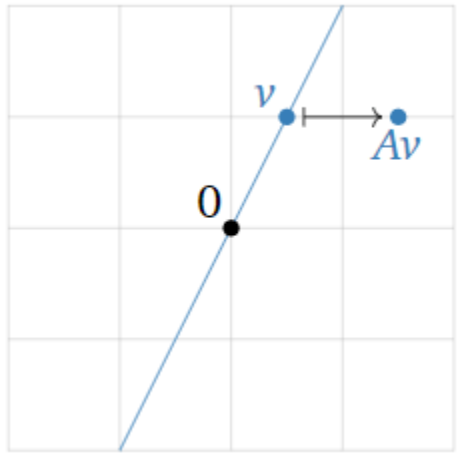


Figure 8.5.3.16

On the other hand, any vector v on the x-axis has zero y-coordinate, so it is not moved by A. Hence v is an eigenvector with eigenvalue 1.

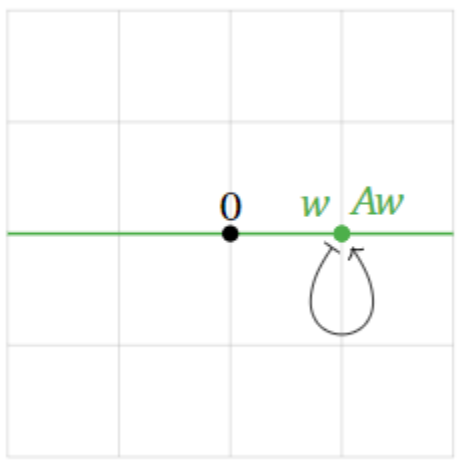


Figure 8.5.3.17

Accordingly, all eigenvectors of A lie on the x-axis, and have eigenvalue 1.



Figure 8.5.3.18: All eigenvectors of a shear lie on the x-axis. Click and drag the head of x to find the eigenvectors.

Example 8.5.3.9: Rotation

Let $T: \mathbb{R}^2 \to \mathbb{R}^2$ be the linear transformation that rotates counterclockwise by 90°, and let A be the matrix for T. Find the eigenvalues and eigenvectors of A without doing any computations.

Solution

If v is any nonzero vector, then Av is rotated by an angle of 90° from v. Therefore, Av is not on the same line as v, so v is not an eigenvector. And of course, the zero vector is never an eigenvector.

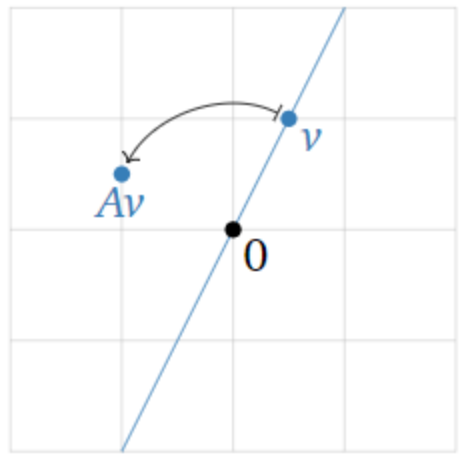


Figure 8.5.3.19

Therefore, this matrix *has no eigenvectors and eigenvalues.*

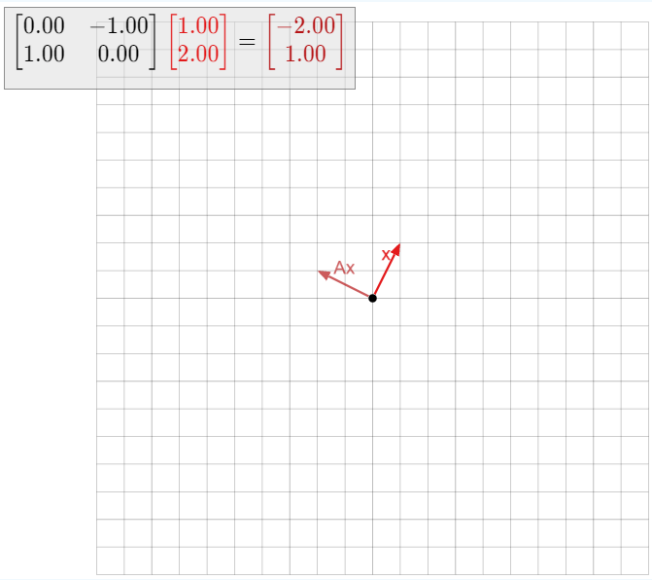


Figure 8.5.3.20: This rotation matrix has no eigenvectors. Click and drag the head of x to find one.

Here we mention one basic fact about eigenvectors.

Fact 8.5.3.1: Eigenvectors with Distinct Eigenvalues are Linearly Independent

Let $v_1, v_2, \ldots, v_k$ be eigenvectors of a matrix A, and suppose that the corresponding eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_k$ are *distinct* (all different from each other). Then $\{v_1, v_2, \ldots, v_k\}$ is linearly independent.

Proof available at the end of this section.

When $k = 2$, this says that if v_1, v_2 are eigenvectors with eigenvalues $\lambda_1 \neq \lambda_2$, then v_2 is not a multiple of v_1. In fact, any nonzero multiple cv_1 of v_1 is also an eigenvector with eigenvalue λ_1:

$$A(cv_1) = cAv_1 = c(\lambda_1 v_1) = \lambda_1(cv_1).$$

As a consequence of the above Fact 8.5.3.1, we have the following.

Note 8.5.3.3

An $n \times n$ matrix A has at most n eigenvalues.

Eigenspaces

Suppose that A is a square matrix. We already know how to check if a given vector is an eigenvector of A and in that case to find the eigenvalue. Our next goal is to check if a given real number is an eigenvalue of A and in that case to find all of the corresponding eigenvectors. Again this will be straightforward, but more involved. The only missing piece, then, will be to find the eigenvalues of A; this is the main content of Section 5.2.

Let A be an $n \times n$ matrix, and let λ be a scalar. The eigenvectors with eigenvalue λ, if any, are the nonzero solutions of the equation $Av = \lambda v$. We can rewrite this equation as follows:

$$\begin{aligned} & Av = \lambda v \\ \iff \quad & Av - \lambda v = 0 \\ \iff \quad & Av - \lambda I_n v = 0 \\ \iff \quad & (A - \lambda I_n)v = 0. \end{aligned}$$

Therefore, the eigenvectors of A with eigenvalue λ, if any, are the nontrivial solutions of the matrix equation $(A - \lambda I_n)v = 0$, i.e., the nonzero vectors in $\mathrm{Nul}(A - \lambda I_n)$. If this equation has no nontrivial solutions, then λ is not an eigenvector of A.

The above observation is important because it says that *finding the eigenvectors for a given eigenvalue means solving a homogeneous system of equations*. For instance, if

$$A = \begin{pmatrix} 7 & 1 & 3 \\ -3 & 2 & -3 \\ -3 & -2 & -1 \end{pmatrix},$$

then an eigenvector with eigenvalue λ is a nontrivial solution of the matrix equation

$$\begin{pmatrix} 7 & 1 & 3 \\ -3 & 2 & -3 \\ -3 & -2 & -1 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \lambda \begin{pmatrix} x \\ y \\ z \end{pmatrix}.$$

This translates to the system of equations

$$\begin{cases} 7x + y + 3z = \lambda x \\ -3x + 2y - 3z = \lambda y \\ -3x - 2y - z = \lambda z \end{cases} \longrightarrow \begin{cases} (7-\lambda)x + y + 3z = 0 \\ -3x + (2-\lambda)y - 3z = 0 \\ -3x - 2y + (-1-\lambda)z = 0. \end{cases}$$

This is the same as the homogeneous matrix equation

$$\begin{pmatrix} 7-\lambda & 1 & 3 \\ -3 & 2-\lambda & -3 \\ -3 & -2 & -1-\lambda \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} = 0,$$

i.e., $(A - \lambda I_3)v = 0$.

Definition 8.5.3.2: λ-eigenspace

Let A be an $n \times n$ matrix, and let λ be an eigenvalue of A. The ***λ-eigenspace*** of A is the solution set of $(A - \lambda I_n)v = 0$, i.e., the subspace $\mathrm{Nul}(A - \lambda I_n)$.

The λ-eigenspace is a subspace because it is the null space of a matrix, namely, the matrix $A - \lambda I_n$. This subspace consists of the zero vector and all eigenvectors of A with eigenvalue λ.

Note 8.5.3.4

Since a nonzero subspace is infinite, *every eigenvalue has infinitely many eigenvectors*. (For example, multiplying an eigenvector by a nonzero scalar gives another eigenvector.) On the other hand, there can be at most n linearly independent eigenvectors of an $n \times n$ matrix, since $\mathbb{R}^n$ has dimension n.

Example 8.5.3.10: Computing eigenspaces

For each of the numbers $\lambda = -2, 1, 3$, decide if λ is an eigenvalue of the matrix

$$A = \begin{pmatrix} 2 & -4 \\ -1 & -1 \end{pmatrix},$$

and if so, compute a basis for the λ-eigenspace.

Solution

The number 3 is an eigenvalue of A if and only if $\text{Nul}(A - 3I_2)$ is nonzero. Hence, we have to solve the matrix equation $(A - 3I_2)v = 0$. We have

$$A - 3I_2 = \begin{pmatrix} 2 & -4 \\ -1 & -1 \end{pmatrix} - 3\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} -1 & -4 \\ -1 & -4 \end{pmatrix}.$$

The reduced row echelon form of this matrix is

$$\begin{pmatrix} 1 & 4 \\ 0 & 0 \end{pmatrix} \xrightarrow{\text{parametric form}} \begin{cases} x &= -4y \\ y &= y \end{cases} \xrightarrow{\text{parametric vector form}} \begin{pmatrix} x \\ y \end{pmatrix} = y\begin{pmatrix} -4 \\ 1 \end{pmatrix}.$$

Since y is a free variable, the null space of $A - 3I_2$ is nonzero, so 3 is an eigenvector. A basis for the 3-eigenspace is $\left\{\begin{pmatrix} -4 \\ 1 \end{pmatrix}\right\}$.

Concretely, we have shown that the eigenvectors of A with eigenvalue 3 are exactly the nonzero multiples of $\begin{pmatrix} -4 \\ 1 \end{pmatrix}$. In particular, $\begin{pmatrix} -4 \\ 1 \end{pmatrix}$ is an eigenvector, which we can verify:

$$\begin{pmatrix} 2 & -4 \\ -1 & 1 \end{pmatrix}\begin{pmatrix} -4 \\ 1 \end{pmatrix} = \begin{pmatrix} -12 \\ 3 \end{pmatrix} = 3\begin{pmatrix} -4 \\ 1 \end{pmatrix}.$$

The number 1 is an eigenvalue of A if and only if $\text{Nul}(A - I_2)$ is nonzero. Hence, we have to solve the matrix equation $(A - I_2)v = 0$. We have

$$A - I_2 = \begin{pmatrix} 2 & -4 \\ -1 & -1 \end{pmatrix} - \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} 1 & -4 \\ -1 & -2 \end{pmatrix}.$$

This matrix has determinant -6, so it is invertible. By Theorem 3.6.1 in Section 3.6, we have $\text{Nul}(A - I_2) = \{0\}$, so 1 is not an eigenvalue.

The eigenvectors of A with eigenvalue -2, if any, are the nonzero solutions of the matrix equation $(A + 2I_2)v = 0$. We have

$$A + 2I_2 = \begin{pmatrix} 2 & -4 \\ -1 & -1 \end{pmatrix} + 2\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} 4 & -4 \\ -1 & 1 \end{pmatrix}.$$

The reduced row echelon form of this matrix is

$$\begin{pmatrix} 1 & -1 \\ 0 & 0 \end{pmatrix} \xrightarrow{\text{parametric form}} \begin{cases} x = y \\ y = y \end{cases} \xrightarrow{\text{parametric vector form}} \begin{pmatrix} x \\ y \end{pmatrix} = y \begin{pmatrix} 1 \\ 1 \end{pmatrix}.$$

Hence there exist eigenvectors with eigenvalue -2, namely, any nonzero multiple of $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$. A basis for the -2-eigenspace is $\left\{\begin{pmatrix} 1 \\ 1 \end{pmatrix}\right\}$.

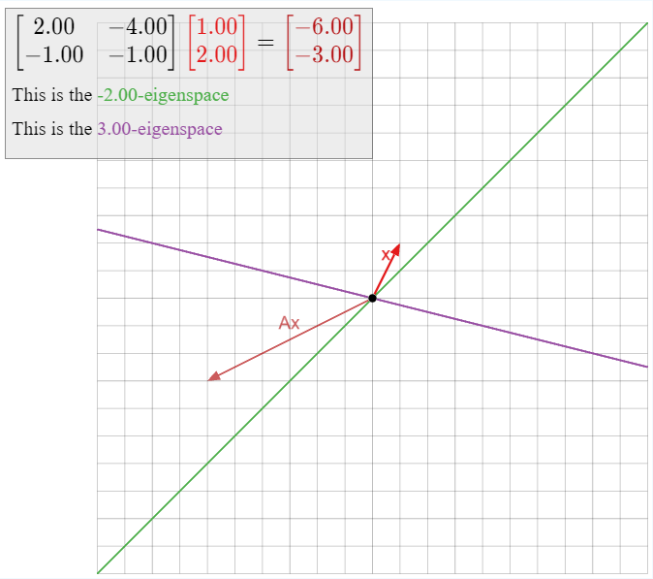


Figure 8.5.3.21: The 3-eigenspace is the line spanned by $\begin{pmatrix} -4 \\ 1 \end{pmatrix}$. This means that A scales every vector in that line by a factor of 3. Likewise, the -2-eigenspace is the line spanned by $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$. Click and drag the vector x around to see how A acts on that vector.

Example 8.5.3.11: Computing eigenspaces

For each of the numbers $\lambda = 0, \frac{1}{2}, 2$, decide if λ is an eigenvector of the matrix

$$A = \begin{pmatrix} 7/2 & 0 & 3 \\ -3/2 & 2 & -3 \\ -3/2 & 0 & -1 \end{pmatrix},$$

and if so, compute a basis for the λ-eigenspace.

Solution

The number 2 is an eigenvalue of A if and only if $\text{Nul}(A - 2I_3)$ is nonzero. Hence, we have to solve the matrix equation $(A - 2I_3)v = 0$. We have

$$A - 2I_3 = \begin{pmatrix} 7/2 & 0 & 3 \\ -3/2 & 2 & -3 \\ -3/2 & 0 & 1 \end{pmatrix} - 2\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 3/2 & 0 & 3 \\ -3/2 & 0 & -3 \\ -3/2 & 0 & -3 \end{pmatrix}.$$

The reduced row echelon form of this matrix is

$$\begin{pmatrix} 1 & 0 & 2 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \xrightarrow{\text{parametric form}} \begin{cases} x = -2z \\ y = y \\ z = z \end{cases} \xrightarrow{\text{parametric vector form}} \begin{pmatrix} x \\ y \\ z \end{pmatrix} = y \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} + z \begin{pmatrix} -2 \\ 0 \\ 1 \end{pmatrix}.$$

The matrix $A - 2I_3$ has two free variables, so the null space of $A - 2I_3$ is nonzero, and thus 2 is an eigenvector. A basis for the 2-eigenspace is

$$\left\{ \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} -2 \\ 0 \\ 1 \end{pmatrix} \right\}.$$

This is a *plane* in $\mathbb{R}^3$.

The eigenvectors of A with eigenvalue $\frac{1}{2}$, if any, are the nonzero solutions of the matrix equation $(A - \frac{1}{2}I_3)v = 0$. We have

$$A - \frac{1}{2}I_3 = \begin{pmatrix} 7/2 & 0 & 3 \\ -3/2 & 2 & -3 \\ -3/2 & 0 & 1 \end{pmatrix} - \frac{1}{2}\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 3 & 0 & 3 \\ -3/2 & 3/2 & -3 \\ -3/2 & 0 & -3/2 \end{pmatrix}.$$

The reduced row echelon form of this matrix is

$$\begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \end{pmatrix} \xrightarrow{\text{parametric form}} \begin{cases} x = -z \\ y = z \\ z = z \end{cases} \xrightarrow{\text{parametric vector form}} \begin{pmatrix} x \\ y \\ z \end{pmatrix} = z\begin{pmatrix} -1 \\ 1 \\ 1 \end{pmatrix}.$$

Hence there exist eigenvectors with eigenvalue $\frac{1}{2}$, so $\frac{1}{2}$ is an eigenvalue. A basis for the $\frac{1}{2}$-eigenspace is

$$\left\{ \begin{pmatrix} -1 \\ 1 \\ 1 \end{pmatrix} \right\}.$$

This is a *line* in $\mathbb{R}^3$.

The number 0 is an eigenvalue of A if and only if $\text{Nul}(A - 0I_3) = \text{Nul}(A)$ is nonzero. This is the same as asking whether A is noninvertible, by Theorem 3.6.1 in Section 3.6. The determinant of A is $\det(A) = 2 \neq 0$, so A is invertible by the invertibility property, Proposition 4.1.2 in Section 4.1. It follows that 0 is not an eigenvalue of A.

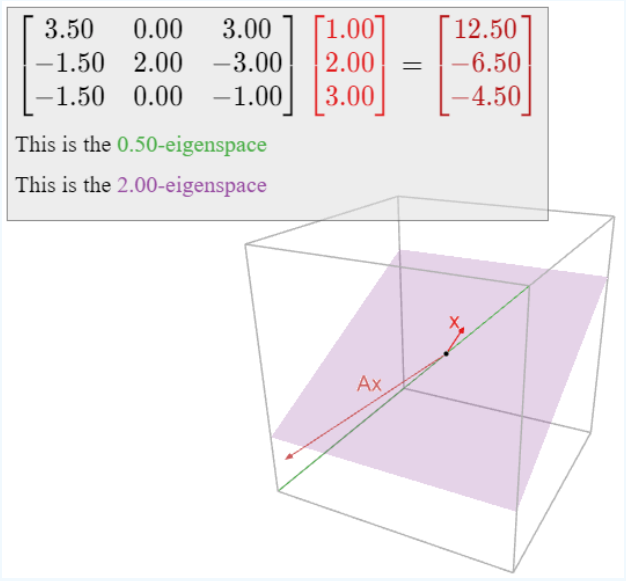


Figure 8.5.3.22: The 2-eigenspace is the violet plane. This means that A scales every vector in that plane by a factor of 2. The $\frac{1}{2}$-eigenspace is the green line. Click and drag the vector x around to see how A acts on that vector.

Example 8.5.3.12: Reflection

Let $T\colon \mathbb{R}^2 \to \mathbb{R}^2$ be the linear transformation that reflects over the line L defined by $y = -x$, and let A be the matrix for T. Find all eigenspaces of A.

Solution

We showed in Example 8.5.3.4 that all eigenvectors with eigenvalue 1 lie on L, and all eigenvectors with eigenvalue -1 lie on the line $L^\perp$ that is perpendicular to L. Hence, L is the 1-eigenspace, and $L^\perp$ is the -1-eigenspace.

None of this required any computations, but we can verify our conclusions using algebra. First we compute the matrix A:

$$T\begin{pmatrix}1\\0\end{pmatrix} = \begin{pmatrix}0\\-1\end{pmatrix} \quad T\begin{pmatrix}0\\1\end{pmatrix} = \begin{pmatrix}-1\\0\end{pmatrix} \quad \Longrightarrow \quad A = \begin{pmatrix}0 & -1\\-1 & 0\end{pmatrix}.$$

Computing the 1-eigenspace means solving the matrix equation $(A - I_2)v = 0$. We have

$$A - I_2 = \begin{pmatrix}0 & -1\\-1 & 0\end{pmatrix} - \begin{pmatrix}1 & 0\\0 & 1\end{pmatrix} = \begin{pmatrix}-1 & -1\\-1 & -1\end{pmatrix} \xrightarrow{\text{RREF}} \begin{pmatrix}1 & 1\\0 & 0\end{pmatrix}.$$

The parametric form of the solution set is $x = -y$, or equivalently, $y = -x$, which is exactly the equation for L. Computing the -1-eigenspace means solving the matrix equation $(A + I_2)v = 0$; we have

$$A + I_2 = \begin{pmatrix}0 & -1\\-1 & 0\end{pmatrix} + \begin{pmatrix}1 & 0\\0 & 1\end{pmatrix} = \begin{pmatrix}1 & -1\\-1 & 1\end{pmatrix} \xrightarrow{\text{RREF}} \begin{pmatrix}1 & -1\\0 & 0\end{pmatrix}.$$

The parametric form of the solution set is $x = y$, or equivalently, $y = x$, which is exactly the equation for $L^\perp$.

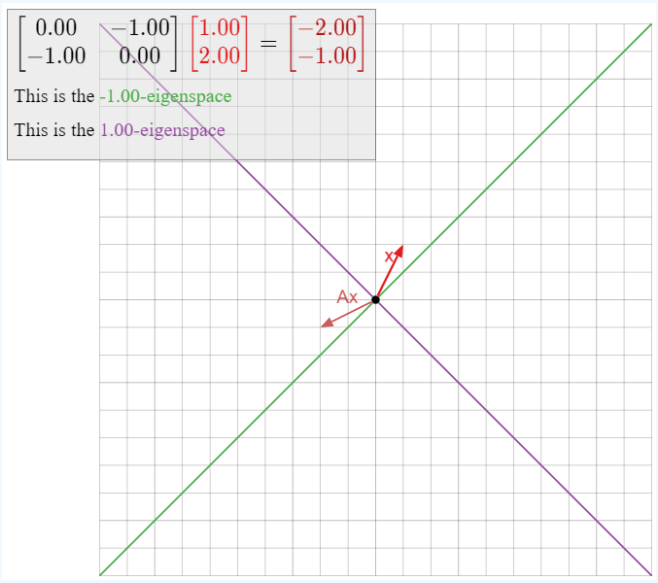


Figure 8.5.3.23: The violet line L is the 1-eigenspace, and the green line $L^\perp$ is the -1-eigenspace.

Recipe: Eigenspaces

Let A be an $n \times n$ matrix and let λ be a number.

1. λ is an eigenvalue of A if and only if $(A-\lambda I_n)v=0$ has a nontrivial solution, if and only if $\mathrm{Nul}(A-\lambda I_n)\neq\{0\}$.
2. In this case, finding a basis for the λ-eigenspace of A means finding a basis for $\mathrm{Nul}(A-\lambda I_n)$, which can be done by finding the parametric vector form of the solutions of the homogeneous system of equations $(A-\lambda I_n)v=0$.
3. The dimension of the λ-eigenspace of A is equal to the number of free variables in the system of equations $(A-\lambda I_n)v=0$, which is the number of columns of $A-\lambda I_n$ without pivots.
4. The eigenvectors with eigenvalue λ are the nonzero vectors in $\mathrm{Nul}(A-\lambda I_n)$, or equivalently, the nontrivial solutions of $(A-\lambda I_n)v=0$.

We conclude with an observation about the 0-eigenspace of a matrix.

Fact 8.5.3.2

Let A be an $n\times n$ matrix.

1. The number 0 is an eigenvalue of A if and only if A is not invertible.
2. In this case, the 0-eigenspace of A is $\mathrm{Nul}(A)$.

Proof available at the end of this section.

Concretely, an eigenvector with eigenvalue 0 is a nonzero vector v such that $Av=0v$, i.e., such that $Av=0$. These are exactly the nonzero vectors in the null space of A.

The Invertible Matrix Theorem: Addenda

We now have two new ways of saying that a matrix is invertible, so we add them to the invertible matrix theorem, Theorem 3.6.1 in Section 3.6.

Theorem 8.5.3.1: Invertible Matrix Theorem

Let A be an $n\times n$ matrix, and let $T\colon\mathbb{R}^n\to\mathbb{R}^n$ be the matrix transformation $T(x)=Ax$. The following statements are equivalent:

1. A is invertible.
2. A has n pivots.
3. $\mathrm{Nul}(A)=\{0\}$.
4. The columns of A are linearly independent.
5. The columns of A span $\mathbb{R}^n$.
6. $Ax=b$ has a unique solution for each b in $\mathbb{R}^n$.
7. T is invertible.
8. T is one-to-one.
9. T is onto.
10. $\det(A)\neq 0$.
11. 0 is not an eigenvalue of A.

Answers

Fact 8.5.3.1: Eigenvectors with Distinct Eigenvalues are Linearly Independent

Suppose that $\{v_1,v_2,\ldots,v_k\}$ were linearly *de*pendent. According to the increasing span criterion, Theorem 2.5.2 in Section 2.5, this means that for some j, the vector v_j is in $\mathrm{Span}\{v_1,v_2,\ldots,v_{j-1}\}$. If we choose the *first* such j, then $\{v_1,v_2,\ldots,v_{j-1}\}$ is linearly independent. Note that $j>1$ since $v_1\neq 0$.

Since v_j is in $\mathrm{Span}\{v_1,v_2,\ldots,v_{j-1}\},$, we can write

$$v_j=c_1v_1+c_2v_2+\cdots+c_{j-1}v_{j-1}$$

for some scalars $c_1,c_2,\ldots,c_{j-1}$. Multiplying both sides of the above equation by A gives

$$\begin{aligned}\lambda_jv_j=Av_j&=A\big(c_1v_1+c_2v_2+\cdots+c_{j-1}v_{j-1}\big)\\&=c_1Av_1+c_2Av_2+\cdots+c_{j-1}Av_{j-1}\\&=c_1\lambda_1v_1+c_2\lambda_2v_2+\cdots+c_{j-1}\lambda_{j-1}v_{j-1}.\end{aligned}$$

Subtracting λ_j times the first equation from the second gives

$$0 = \lambda_j v_j - \lambda_j v_j = c_1(\lambda_1 - \lambda_j)v_1 + c_2(\lambda_2 - \lambda_j)v_2 + \cdots + c_{j-1}(\lambda_{j-1} - \lambda_j)v_{j-1}.$$

Since $\lambda_i \neq \lambda_j$ for $i < j$, this is an equation of linear dependence among $v_1, v_2, \ldots, v_{j-1}$, which is impossible because those vectors are linearly independent. Therefore, $\{v_1, v_2, \ldots, v_k\}$ must have been linearly independent after all.

Fact 8.5.3.2

We know that 0 is an eigenvalue of A if and only if $\mathrm{Nul}(A - 0I_n) = \mathrm{Nul}(A)$ is nonzero, which is equivalent to the noninvertibility of A by Theorem 3.6.1 in Section 3.6. In this case, the 0-eigenspace is by definition $\mathrm{Nul}(A - 0I_n) = \mathrm{Nul}(A)$.

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8.E: Exercises

Exercise $8.E.1$

If A is an invertible $n \times n$ matrix, compare the eigenvalues of A and A^{-1}. More generally, for m an arbitrary integer, compare the eigenvalues of A and A^m.

Answer available at the end of this section.

Exercise $8.E.2$

If A is an $n \times n$ matrix and c is a nonzero constant, compare the eigenvalues of A and cA.

Answer available at the end of this section.

Exercise $8.E.3$

Let $A,\ B$ be invertible $n \times n$ matrices which commute. That is, $AB = BA$. Suppose X is an eigenvector of B. Show that then AX must also be an eigenvector for B.

Answer available at the end of this section.

Exercise $8.E.4$

Suppose A is an $n \times n$ matrix and it satisfies $A^m = A$ for some m a positive integer larger than 1. Show that if λ is an eigenvalue of A then $|\lambda|$ equals either 0 or 1.

Answer available at the end of this section.

Exercise $8.E.5$

Show that if $AX = \lambda X$ and $AY = \lambda Y$, then whenever $k,\ p$ are scalars,

$$A(kX + pY) = \lambda(kX + pY)$$

Does this imply that $kX + pY$ is an eigenvector? Explain.

Answer available at the end of this section.

Exercise $8.E.6$

Suppose A is a 3×3 matrix and the following information is available.

$$A\begin{bmatrix}0\\-1\\-1\end{bmatrix}=0\begin{bmatrix}0\\-1\\-1\end{bmatrix}$$
$$A\begin{bmatrix}1\\1\\1\end{bmatrix}=-2\begin{bmatrix}1\\1\\1\end{bmatrix} \quad (8.E.1)$$
$$A\begin{bmatrix}-2\\-3\\-2\end{bmatrix}=-2\begin{bmatrix}-2\\-3\\-2\end{bmatrix}$$

Find $A\begin{bmatrix}1\\-4\\3\end{bmatrix}$.

Exercise $8.E.7$

Suppose A is a 3×3 matrix and the following information is available.

$$A\begin{bmatrix}-1\\-2\\-2\end{bmatrix}=1\begin{bmatrix}-1\\-2\\-2\end{bmatrix}$$
$$A\begin{bmatrix}1\\1\\1\end{bmatrix}=0\begin{bmatrix}1\\1\\1\end{bmatrix} \quad (8.E.2)$$
$$A\begin{bmatrix}-1\\-4\\-3\end{bmatrix}=2\begin{bmatrix}-1\\-4\\-3\end{bmatrix}$$

Find $A\begin{bmatrix}3\\-4\\3\end{bmatrix}$.

Exercise $8.E.8$

Suppose A is a 3×3 matrix and the following information is available.

$$A\begin{bmatrix}0\\-1\\-1\end{bmatrix}=2\begin{bmatrix}0\\-1\\-1\end{bmatrix}$$
$$A\begin{bmatrix}1\\1\\1\end{bmatrix}=1\begin{bmatrix}1\\1\\1\end{bmatrix} \quad (8.E.3)$$
$$A\begin{bmatrix}-3\\-5\\-4\end{bmatrix}=-3\begin{bmatrix}-3\\-5\\-4\end{bmatrix}$$

Find $A\begin{bmatrix}2\\-3\\3\end{bmatrix}$.

Exercise $8.E.9$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} -6 & -92 & 12 \\ 0 & 0 & 0 \\ -2 & -31 & 4 \end{bmatrix}$$

One eigenvalue is -2.

Exercise $8.E.10$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} -2 & -17 & -6 \\ 0 & 0 & 0 \\ 1 & 9 & 3 \end{bmatrix}$$

One eigenvalue is 1.

Exercise $8.E.11$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} 9 & 2 & 8 \\ 2 & -6 & -2 \\ -8 & 2 & -5 \end{bmatrix}$$

One eigenvalue is -3.

Exercise $8.E.12$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} 6 & 76 & 16 \\ -2 & -21 & -4 \\ 2 & 64 & 17 \end{bmatrix}$$

One eigenvalue is -2.

Exercise $8.E.13$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} 3 & 5 & 2 \\ -8 & -11 & -4 \\ 10 & 11 & 3 \end{bmatrix}$$

One eigenvalue is -3.

Exercise $8.E.14$

Is it possible for a nonzero matrix to have only 0 as an eigenvalue?

Answer available at the end of this section.

Exercise $8.E.15$

If A is the matrix of a linear transformation which rotates all vectors in $\mathbb{R}^2$ through 60°, explain why A cannot have any real eigenvalues. Is there an angle such that rotation through this angle would have a real eigenvalue? What eigenvalues would be obtainable in this way?

Exercise $8.E.16$

Let A be the 2×2 matrix of the linear transformation which rotates all vectors in $\mathbb{R}^2$ through an angle of θ. For which values of θ does A have a real eigenvalue?

Answer available at the end of this section.

Exercise $8.E.17$

Let T be the linear transformation which reflects vectors about the x axis. Find a matrix for T and then find its eigenvalues and eigenvectors.

Answer available at the end of this section.

Exercise $8.E.18$

Let T be the linear transformation which rotates all vectors in $\mathbb{R}^2$ counterclockwise through an angle of $\pi/2$. Find a matrix of T and then find eigenvalues and eigenvectors.

Answer available at the end of this section.

Exercise $8.E.19$

Let T be the linear transformation which reflects all vectors in $\mathbb{R}^3$ through the xy plane. Find a matrix for T and then obtain its eigenvalues and eigenvectors.

Answer available at the end of this section.

Exercise $8.E.20$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} 5 & -18 & -32 \\ 0 & 5 & 4 \\ 2 & -5 & -11 \end{bmatrix}$$

One eigenvalue is 1. Diagonalize if possible.

Answer available at the end of this section.

Exercise $8.E.21$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} -12 & -28 & 28 \\ 4 & 9 & -8 \\ -4 & -8 & 9 \end{bmatrix}$$

One eigenvalue is 3. Diagonalize if possible.

Answer available at the end of this section.

Exercise $8.E.22$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} 89 & 38 & 268 \\ 14 & 2 & 40 \\ -30 & -12 & -90 \end{bmatrix}$$

One eigenvalue is -3. Diagonalize if possible.

Answer available at the end of this section.

Exercise $8.E.23$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} 1 & 90 & 0 \\ 0 & -2 & 0 \\ 3 & 89 & -2 \end{bmatrix}$$

One eigenvalue is 1. Diagonalize if possible.

Exercise $8.E.24$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} 11 & 45 & 30 \\ 10 & 26 & 20 \\ -20 & -60 & -44 \end{bmatrix}$$

One eigenvalue is 1. Diagonalize if possible.

Exercise $8.E.25$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} 95 & 25 & 24 \\ -196 & -53 & -48 \\ -164 & -42 & -43 \end{bmatrix}$$

One eigenvalue is 5. Diagonalize if possible.

Exercise $8.E.26$

Suppose A is an $n \times n$ matrix and let V be an eigenvector such that $AV = \lambda V$. Also suppose the characteristic polynomial of A is

$$\det(xI - A) = x^n + a_{n-1}x^{n-1} + \cdots + a_1 x + a_0$$

Explain why

$$(A^n + a_{n-1}A^{n-1} + \cdots + a_1 A + a_0 I)V = 0$$

If A is diagonalizable, give a proof of the Cayley Hamilton theorem based on this. This theorem says A satisfies its characteristic equation

$$A^n + a_{n-1}A^{n-1} + \cdots + a_1 A + a_0 I = 0$$

Exercise $8.E.27$

Suppose the characteristic polynomial of an $n \times n$ matrix A is $1 - X^n$. Find A^{mn} where m is an integer.

Answer available at the end of this section.

Exercise $8.E.28$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} 15 & -24 & 7 \\ -6 & 5 & -1 \\ -58 & 76 & -20 \end{bmatrix}$$

One eigenvalue is -2. Diagonalize if possible. Hint: This one has some complex eigenvalues.

Exercise $8.E.29$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} 15 & -25 & 6 \\ -13 & 23 & -4 \\ -91 & 155 & -30 \end{bmatrix}$$

One eigenvalue is 2. Diagonalize if possible. Hint: This one has some complex eigenvalues.

Exercise $8.E.30$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} -11 & -12 & 4 \\ 8 & 17 & -4 \\ -4 & 28 & -3 \end{bmatrix}$$

One eigenvalue is 1. Diagonalize if possible. Hint: This one has some complex eigenvalues.

Exercise $8.E.31$

Find the eigenvalues and eigenvectors of the matrix

$$\begin{bmatrix} 14 & -12 & 5 \\ -6 & 2 & -1 \\ -69 & 51 & -21 \end{bmatrix}$$

One eigenvalue is -3. Diagonalize if possible. Hint: This one has some complex eigenvalues.

Exercise $8.E.32$

Suppose A is an $n \times n$ matrix consisting entirely of real entries but $a+ib$ is a complex eigenvalue having the eigenvector, $X+iY$ Here X and Y are real vectors. Show that then $a-ib$ is also an eigenvalue with the eigenvector, $X-iY$. Hint: You should remember that the conjugate of a product of complex numbers equals the product of the conjugates. Here $a+ib$ is a complex number whose conjugate equals $a-ib$.

Answer available at the end of this section.

Exercise $8.E.33$

Let $A = \begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix}$. Diagonalize A to find A^{10}.

Answer available at the end of this section.

Exercise $8.E.34$

Let $A = \begin{bmatrix} 1 & 4 & 1 \\ 0 & 2 & 5 \\ 0 & 0 & 5 \end{bmatrix}$. Diagonalize A to find A^{50}.

Exercise $8.E.35$

Let $A = \begin{bmatrix} 1 & -2 & -1 \\ 2 & -1 & 1 \\ -2 & 3 & 1 \end{bmatrix}$. Diagonalize A to find A^{100}.

Exercise $8.E.36$

The following is a Markov (migration) matrix for three locations

$$\begin{bmatrix} \frac{7}{10} & \frac{1}{9} & \frac{1}{5} \\ \frac{1}{10} & \frac{7}{9} & \frac{2}{5} \\ \frac{1}{5} & \frac{1}{9} & \frac{2}{5} \end{bmatrix}$$

a. Initially, there are 90 people in location $1,\ 81$ in location 2, and 85 in location 3. How many are in each location after one time period?
b. The total number of individuals in the migration process is 256. After a long time, how many are in each location?

Answer available at the end of this section.

Exercise $8.E.37$

The following is a Markov (migration) matrix for three locations

$$\begin{bmatrix} \frac{1}{5} & \frac{1}{5} & \frac{2}{5} \\ \frac{2}{5} & \frac{2}{5} & \frac{1}{5} \\ \frac{2}{5} & \frac{2}{5} & \frac{2}{5} \end{bmatrix}$$

a. Initially, there are 130 individuals in location 1, 300 in location 2, and 70 in location 3. How many are in each location after two time periods?
b. The total number of individuals in the migration process is 500. After a long time, how many are in each location?

Answer available at the end of this section.

Exercise $8.E.38$

The following is a Markov (migration) matrix for three locations

$$\begin{bmatrix} \frac{3}{10} & \frac{3}{8} & \frac{1}{3} \\ \frac{1}{10} & \frac{3}{8} & \frac{1}{3} \\ \frac{3}{5} & \frac{1}{4} & \frac{1}{3} \end{bmatrix}$$

The total number of individuals in the migration process is 480. After a long time, how many are in each location?

Answer available at the end of this section.

Exercise $8.E.39$

The following is a Markov (migration) matrix for three locations

$$\begin{bmatrix} \frac{3}{10} & \frac{1}{3} & \frac{1}{5} \\ \frac{3}{10} & \frac{1}{3} & \frac{7}{10} \\ \frac{2}{5} & \frac{1}{3} & \frac{1}{10} \end{bmatrix}$$

The total number of individuals in the migration process is 1155. After a long time, how many are in each location?

Exercise $8.E.40$

The following is a Markov (migration) matrix for three locations

$$\begin{bmatrix} \frac{2}{5} & \frac{1}{10} & \frac{1}{8} \\ \frac{3}{10} & \frac{2}{5} & \frac{5}{8} \\ \frac{3}{10} & \frac{1}{2} & \frac{1}{4} \end{bmatrix}$$

The total number of individuals in the migration process is 704. After a long time, how many are in each location?

Exercise $8.E.41$

A person sets off on a random walk with three possible locations. The Markov matrix of probabilities $A = [a_{ij}]$ is given by

$$\begin{bmatrix} 0.1 & 0.3 & 0.7 \\ 0.1 & 0.3 & 0.2 \\ 0.8 & 0.4 & 0.1 \end{bmatrix}$$

If the walker starts in location 2, what is the probability of ending back in location 2 at time $n = 3$?

Answer available at the end of this section.

Exercise $8.E.42$

A person sets off on a random walk with three possible locations. The Markov matrix of probabilities $A = [a_{ij}]$ is given by

$$\begin{bmatrix} 0.5 & 0.1 & 0.6 \\ 0.2 & 0.9 & 0.2 \\ 0.3 & 0 & 0.2 \end{bmatrix}$$

It is unknown where the walker starts, but the probability of starting in each location is given by

$$X_0 = \begin{bmatrix} 0.2 \\ 0.25 \\ 0.55 \end{bmatrix}$$

What is the probability of the walker being in location 1 at time $n = 2$?

Answer available at the end of this section.

Exercise $8.E.43$

You own a trailer rental company in a large city and you have four locations, one in the South East, one in the North East, one in the North West, and one in the South West. Denote these locations by SE, NE, NW, and SW respectively. Suppose that the following table is observed to take place.

Table $8.E.1$

	SE	NE	NW	SW
SE	$\frac{1}{3}$	$\frac{1}{10}$	$\frac{1}{10}$	$\frac{1}{5}$
NE	$\frac{1}{3}$	$\frac{7}{10}$	$\frac{1}{5}$	$\frac{1}{10}$
NW	$\frac{2}{9}$	$\frac{1}{10}$	$\frac{3}{5}$	$\frac{1}{5}$
SW	$\frac{1}{9}$	$\frac{1}{10}$	$\frac{1}{10}$	$\frac{1}{2}$

In this table, the probability that a trailer starting at NE ends in NW is $1/10$, the probability that a trailer starting at SW ends in NW is $1/5$, and so forth. Approximately how many will you have in each location after a long time if the total number of trailers is 413?

Answer available at the end of this section.

Exercise $8.E.44$

You own a trailer rental company in a large city and you have four locations, one in the South East, one in the North East, one in the North West, and one in the South West. Denote these locations by SE, NE, NW, and SW respectively. Suppose that the following table is observed to take place.

Table $8.E.2$

	SE	NE	NW	SW
SE	$\frac{1}{7}$	$\frac{1}{4}$	$\frac{1}{10}$	$\frac{1}{5}$
NE	$\frac{2}{7}$	$\frac{1}{4}$	$\frac{1}{5}$	$\frac{1}{10}$
NW	$\frac{1}{7}$	$\frac{1}{4}$	$\frac{3}{5}$	$\frac{1}{5}$
SW	$\frac{3}{7}$	$\frac{1}{4}$	$\frac{1}{10}$	$\frac{1}{2}$

In this table, the probability that a trailer starting at NE ends in NW is 1/10, the probability that a trailer starting at SW ends in NW is 1/5, and so forth. Approximately how many will you have in each location after a long time if the total number of trailers is 1469.

Exercise 8.E.45

The following table describes the transition probabilities between the states rainy, partly cloudy and sunny. The symbol p.c. indicates partly cloudy. Thus if it starts off p.c. it ends up sunny the next day with probability $\frac{1}{5}$. If it starts off sunny, it ends up sunny the next day with probability $\frac{2}{5}$ and so forth.

Table 8.E.3

	rains	sunny	p.c.
rains	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{3}$
sunny	$\frac{1}{5}$	$\frac{2}{5}$	$\frac{1}{3}$
p.c.	$\frac{3}{5}$	$\frac{2}{5}$	$\frac{1}{3}$

Given this information, what are the probabilities that a given day is rainy, sunny, or partly cloudy?

Exercise 8.E.46

The following table describes the transition probabilities between the states rainy, partly cloudy and sunny. The symbol p.c. indicates partly cloudy. Thus if it starts off p.c. it ends up sunny the next day with probability $\frac{1}{10}$. If it starts off sunny, it ends up sunny the next day with probability $\frac{2}{5}$ and so forth.

Table 8.E.4

	rains	sunny	p.c.
rains	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{3}$
sunny	$\frac{1}{10}$	$\frac{2}{5}$	$\frac{4}{9}$
p.c.	$\frac{7}{10}$	$\frac{2}{5}$	$\frac{2}{9}$

Given this information, what are the probabilities that a given day is rainy, sunny, or partly cloudy?

Exercise 8.E.47

You own a trailer rental company in a large city and you have four locations, one in the South East, one in the North East, one in the North West, and one in the South West. Denote these locations by SE, NE, NW, and SW respectively. Suppose that the following table is observed to take place.

Table 8.E.5

	SE	NE	NW	SW
SE	$\frac{5}{11}$	$\frac{1}{10}$	$\frac{1}{10}$	$\frac{1}{5}$
NE	$\frac{1}{11}$	$\frac{7}{10}$	$\frac{1}{5}$	$\frac{1}{10}$
NW	$\frac{2}{11}$	$\frac{1}{10}$	$\frac{3}{5}$	$\frac{1}{5}$
SW	$\frac{3}{11}$	$\frac{1}{10}$	$\frac{1}{10}$	$\frac{1}{2}$

In this table, the probability that a trailer starting at NE ends in NW is 1/10, the probability that a trailer starting at SW ends in NW is 1/5, and so forth. Approximately how many will you have in each location after a long time if the total number of trailers is 407?

Exercise 8.E.48

The University of Poohbah offers three degree programs, scouting education (SE), dance appreciation (DA), and engineering (E). It has been determined that the probabilities of transferring from one program to another are as in the following table.

Table 8.E.6

	SE	DA	E
SE	.8	.1	.3
DA	.1	.7	.5
E	.1	.2	.2

where the number indicates the probability of transferring from the top program to the program on the left. Thus the probability of going from DA to E is .2. Find the probability that a student is enrolled in the various programs.

Exercise 8.E.49

In the city of Nabal, there are three political persuasions, republicans (R), democrats (D), and neither one (N). The following table shows the transition probabilities between the political parties, the top row being the initial political party and the side row being the political affiliation the following year.

Table 8.E.7

	R	D	N
R	$\frac{1}{5}$	$\frac{1}{6}$	$\frac{2}{7}$
D	$\frac{1}{5}$	$\frac{1}{3}$	$\frac{4}{7}$
N	$\frac{3}{5}$	$\frac{1}{2}$	$\frac{1}{7}$

Find the probabilities that a person will be identified with the various political persuasions. Which party will end up being most important?

Exercise 8.E.50

The following table describes the transition probabilities between the states rainy, partly cloudy and sunny. The symbol p.c. indicates partly cloudy. Thus if it starts off p.c. it ends up sunny the next day with probability $\frac{1}{5}$. If it starts off sunny, it ends up sunny the next day with probability $\frac{2}{7}$ and so forth.

Table 8.E.8

	rains	sunny	p.c.
rains	$\frac{1}{5}$	$\frac{2}{7}$	$\frac{5}{9}$
sunny	$\frac{1}{5}$	$\frac{2}{7}$	$\frac{1}{3}$
p.c.	$\frac{3}{5}$	$\frac{3}{7}$	$\frac{1}{9}$

Given this information, what are the probabilities that a given day is rainy, sunny, or partly cloudy?

Exercise 8.E.51

Find the solution to the initial value problem

$$\begin{bmatrix} x \\ y \end{bmatrix}' = \begin{bmatrix} 0 & -1 \\ 6 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$
$$\begin{bmatrix} x(0) \\ y(0) \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \end{bmatrix} \tag{8.E.4}$$

Hint: form the matrix exponential e^{At} and then the solution is $e^{At}C$ where C is the initial vector,

Answer available at the end of this section.

Exercise $8.E.52$

Find the solution to the initial value problem

$$\begin{bmatrix} x \\ y \end{bmatrix}' = \begin{bmatrix} -4 & -3 \\ 6 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$
$$\begin{bmatrix} x(0) \\ y(0) \end{bmatrix} = \begin{bmatrix} 3 \\ 4 \end{bmatrix} \tag{8.E.5}$$

Hint: form the matrix exponential e^{At} and then the solution is $e^{At}C$ where C is the initial vector.

Exercise $8.E.53$

Find the solution to the initial value problem

$$\begin{bmatrix} x \\ y \end{bmatrix}' = \begin{bmatrix} -1 & 2 \\ -4 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$
$$\begin{bmatrix} x(0) \\ y(0) \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \end{bmatrix} \tag{8.E.6}$$

Hint: form the matrix exponential e^{At} and then the solution is $e^{At}C$ where C is the initial vector.

Exercise $8.E.54$

Find the eigenvalues and an orthonormal basis of eigenvectors for A.

$$A = \begin{bmatrix} 11 & -1 & -4 \\ -1 & 11 & -4 \\ -4 & -4 & 14 \end{bmatrix}$$

Hint: Two eigenvalues are 12 and 18.

Answer available at the end of this section.

Exercise $8.E.55$

Find the eigenvalues and an orthonormal basis of eigenvectors for A.

$$A = \begin{bmatrix} 4 & 1 & -2 \\ 1 & 4 & -2 \\ -2 & -2 & 7 \end{bmatrix}$$

Hint: One eigenvalue is 3.

Answer available at the end of this section.

Exercise $8.E.56$

Find the eigenvalues and an orthonormal basis of eigenvectors for A. Diagonalize A by finding an orthogonal matrix U and a diagonal matrix D such that $U^TAU = D$.

$$A = \begin{bmatrix} -1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & -1 \end{bmatrix}$$

Hint: One eigenvalue is -2.

Answer available at the end of this section.

Exercise $8.E.57$

Find the eigenvalues and an orthonormal basis of eigenvectors for A. Diagonalize A by finding an orthogonal matrix U and a diagonal matrix D such that $U^TAU = D$.

$$A = \begin{bmatrix} 17 & -7 & -4 \\ -7 & 17 & -4 \\ -4 & -4 & 14 \end{bmatrix}$$

Hint: Two eigenvalues are 18 and 24.

Answer available at the end of this section.

Exercise $8.E.58$

Find the eigenvalues and an orthonormal basis of eigenvectors for A. Diagonalize A by finding an orthogonal matrix U and a diagonal matrix D such that $U^TAU = D$.

$$A = \begin{bmatrix} 13 & 1 & 4 \\ 1 & 13 & 4 \\ 4 & 4 & 10 \end{bmatrix}$$

Hint: Two eigenvalues are 12 and 18.

Answer available at the end of this section.

Exercise $8.E.59$

Find the eigenvalues and an orthonormal basis of eigenvectors for A. Diagonalize A by finding an orthogonal matrix U and a diagonal matrix D such that $U^TAU = D$.

$$A = \begin{bmatrix} -\frac{5}{3} & \frac{1}{15}\sqrt{6}\sqrt{5} & \frac{8}{15}\sqrt{5} \\ \frac{1}{15}\sqrt{6}\sqrt{5} & -\frac{14}{5} & -\frac{1}{15}\sqrt{6} \\ \frac{8}{15}\sqrt{5} & -\frac{1}{15}\sqrt{6} & \frac{7}{15} \end{bmatrix}$$

Hint: The eigenvalues are $-3, -2, 1$.

Answer available at the end of this section.

Exercise $8.E.60$

Find the eigenvalues and an orthonormal basis of eigenvectors for A. Diagonalize A by finding an orthogonal matrix U and a diagonal matrix D such that $U^TAU = D$.

$$A = \begin{bmatrix} 3 & 0 & 0 \\ 0 & \frac{3}{2} & \frac{1}{2} \\ 0 & \frac{1}{2} & \frac{3}{2} \end{bmatrix}$$

Answer available at the end of this section.

Exercise $8.E.61$

Find the eigenvalues and an orthonormal basis of eigenvectors for A. Diagonalize A by finding an orthogonal matrix U and a diagonal matrix D such that $U^TAU = D$.

$$A = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 5 & 1 \\ 0 & 1 & 5 \end{bmatrix}$$

Answer available at the end of this section.

Exercise $8.E.62$

Find the eigenvalues and an orthonormal basis of eigenvectors for A. Diagonalize A by finding an orthogonal matrix U and a diagonal matrix D such that $U^TAU = D$.

$$A = \begin{bmatrix} \frac{4}{3} & \frac{1}{3}\sqrt{3}\sqrt{2} & \frac{1}{3}\sqrt{2} \\ \frac{1}{3}\sqrt{3}\sqrt{2} & 1 & -\frac{1}{3}\sqrt{3} \\ \frac{1}{3}\sqrt{2} & -\frac{1}{3}\sqrt{3} & \frac{5}{3} \end{bmatrix}$$

Hint: The eigenvalues are $0, 2, 2$ where 2 is listed twice because it is a root of multiplicity 2.

Answer available at the end of this section.

Exercise $8.E.63$

Find the eigenvalues and an orthonormal basis of eigenvectors for A. Diagonalize A by finding an orthogonal matrix U and a diagonal matrix D such that $U^TAU = D$.

$$A = \begin{bmatrix} 1 & \frac{1}{6}\sqrt{3}\sqrt{2} & \frac{1}{6}\sqrt{3}\sqrt{6} \\ \frac{1}{6}\sqrt{3}\sqrt{2} & \frac{3}{2} & \frac{1}{12}\sqrt{2}\sqrt{6} \\ \frac{1}{6}\sqrt{3}\sqrt{6} & \frac{1}{12}\sqrt{2}\sqrt{6} & \frac{1}{2} \end{bmatrix}$$

Hint: The eigenvalues are $2, 1, 0$.

Answer available at the end of this section.

Exercise $8.E.64$

Find the eigenvalues and an orthonormal basis of eigenvectors for the matrix

$$A = \begin{bmatrix} \frac{1}{3} & \frac{1}{6}\sqrt{3}\sqrt{2} & -\frac{7}{18}\sqrt{3}\sqrt{6} \\ \frac{1}{6}\sqrt{3}\sqrt{2} & \frac{3}{2} & -\frac{1}{12}\sqrt{2}\sqrt{6} \\ -\frac{7}{18}\sqrt{3}\sqrt{6} & -\frac{1}{12}\sqrt{2}\sqrt{6} & -\frac{5}{6} \end{bmatrix}$$

Hint: The eigenvalues are $1, 2, -2$.

Answer available at the end of this section.

Exercise $8.E.65$

Find the eigenvalues and an orthonormal basis of eigenvectors for the matrix

$$A = \begin{bmatrix} -\frac{1}{2} & -\frac{1}{5}\sqrt{6}\sqrt{5} & \frac{1}{10}\sqrt{5} & \\ -\frac{1}{5}\sqrt{6}\sqrt{5} & \frac{7}{5} & -\frac{1}{5}\sqrt{6} & \\ \frac{1}{10} & \sqrt{5} & -\frac{1}{5}\sqrt{6} & -\frac{9}{10} \end{bmatrix}$$

Hint: The eigenvalues are $-1, 2, -1$ where -1 is listed twice because it has multiplicity 2 as a zero of the characteristic equation.

Answer available at the end of this section.

Exercise $8.E.66$

Explain why a matrix A is symmetric if and only if there exists an orthogonal matrix U such that $A = U^T D U$ for D a diagonal matrix.

Answer available at the end of this section.

Exercise $8.E.67$

Show that if A is a real symmetric matrix and λ and μ are two different eigenvalues, then if X is an eigenvector for λ and Y is an eigenvector for μ, then $X \bullet Y = 0$. Also all eigenvalues are real. Supply reasons for each step in the following argument. First

$$\lambda X^T \overline{X} = (AX)^T \overline{X} = X^T A \overline{X} = X^T \overline{AX} = X^T \overline{\lambda X} = \overline{\lambda} X^T \overline{X}$$

and so $\lambda = \overline{\lambda}$. This shows that all eigenvalues are real. It follows all the eigenvectors are real. Why? Now let X, Y, μ and λ be given as above.

$$\lambda(X \bullet Y) = \lambda X \bullet Y = AX \bullet Y = X \bullet AY = X \bullet \mu Y = \mu(X \bullet Y) = \mu(X \bullet Y)$$

and so

$$(\lambda - \mu) X \bullet Y = 0$$

Why does it follow that $X \bullet Y = 0$?

Answer available at the end of this section.

Exercise $8.E.68$

Find the Cholesky factorization for the matrix

$$\begin{bmatrix} 1 & 2 & 0 \\ 2 & 6 & 4 \\ 0 & 4 & 10 \end{bmatrix}$$

Exercise $8.E.69$

Find the Cholesky factorization for the matrix

$$\begin{bmatrix} 4 & 8 & 0 \\ 8 & 17 & 2 \\ 0 & 2 & 13 \end{bmatrix}$$

Exercise $8.E.70$

Find the Cholesky factorization for the matrix

$$\begin{bmatrix} 4 & 8 & 0 \\ 8 & 20 & 8 \\ 0 & 8 & 20 \end{bmatrix}$$

Exercise $8.E.71$

Find the Cholesky factorization for the matrix

$$\begin{bmatrix} 1 & 2 & 1 \\ 2 & 8 & 10 \\ 1 & 10 & 18 \end{bmatrix}$$

Exercise $8.E.72$

Find the Cholesky factorization for the matrix

$$\begin{bmatrix} 1 & 2 & 1 \\ 2 & 8 & 10 \\ 1 & 10 & 26 \end{bmatrix}$$

Exercise $8.E.73$

Suppose you have a lower triangular matrix L and it is invertible. Show that LL^T must be positive definite.

Exercise $8.E.74$

Using the Gram Schmidt process or the QR factorization, find an orthonormal basis for the following span:

$$span\left\{\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \\ 3 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}\right\}$$

Answer available at the end of this section.

Exercise $8.E.75$

Using the Gram Schmidt process or the QR factorization, find an orthonormal basis for the following span:

$$span\left\{\begin{bmatrix}1\\2\\1\\0\end{bmatrix},\begin{bmatrix}2\\-1\\3\\1\end{bmatrix},\begin{bmatrix}1\\0\\0\\1\end{bmatrix}\right\}$$

Answer available at the end of this section.

Exercise $8.E.76$

a. $\begin{bmatrix}1&2&3\\0&3&4\\0&0&1\end{bmatrix}$

b. $\begin{bmatrix}2&1\\2&1\end{bmatrix}$

c. $\begin{bmatrix}1&2\\-1&2\end{bmatrix}$

d. $\begin{bmatrix}1&1\\2&3\end{bmatrix}$

e. $\begin{bmatrix}\sqrt{11}&1&3\sqrt{6}\\\sqrt{11}&7&-\sqrt{6}\\2\sqrt{11}&-4&-\sqrt{6}\end{bmatrix}$ Hint: Notice that the columns are orthogonal.

Answer available at the end of this section.

Exercise $8.E.77$

Using a computer algebra system, find a QR factorization for the following matrices.

a. $\begin{bmatrix}1&1&2\\3&-2&3\\2&1&1\end{bmatrix}$

b. $\begin{bmatrix}1&2&1&3\\4&5&-4&3\\2&1&2&1\end{bmatrix}$

c. $\begin{bmatrix}1&2\\3&2\\1&-4\end{bmatrix}$ Find the thin QR factorization of this one.

Answer available at the end of this section.

Exercise $8.E.78$

A quadratic form in three variables is an expression of the form $a_1x^2+a_2y^2+a_3z^2+a_4xy+a_5xz+a_6yz$. Show that every such quadratic form may be written as

$$\begin{bmatrix}x&y&z\end{bmatrix}A\begin{bmatrix}x\\y\\z\end{bmatrix}$$

where A is a symmetric matrix.

Answer available at the end of this section.

Exercise $8.E.79$

Given a quadratic form in three variables, x, y, and z, show there exists an orthogonal matrix U and variables x', y', z' such that

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = U \begin{bmatrix} x' \\ y' \\ z' \end{bmatrix}$$

with the property that in terms of the new varaibles, the quadratic form is

$$\lambda_1 (x')^2 + \lambda_2 (y')^2 + \lambda_3 (z')^2$$

where the numbers, λ_1, λ_2, and λ_3 are the eigenvalues of the matrix A in Exercise $8.E.78$.

Answer available at the end of this section.

Exercise $8.E.80$

Consider the quadratic form q given by $q = 3x_1^2 - 12x_1x_2 - 2x_2^2$.

a. Write q in the form $\vec{x}^T A \vec{x}$ for an appropriate symmetric matrix A.
b. Use a change of variables to rewrite q to eliminate the x_1x_2 term.

Answer available at the end of this section.

Exercise $8.E.81$

Consider the quadratic form q given by $q = -2x_1^2 + 2x_1x_2 - 2x_2^2$.

a. Write q in the form $\vec{x}^T A \vec{x}$ for an appropriate symmetric matrix A.
b. Use a change of variables to rewrite q to eliminate the x_1x_2 term.

Answer available at the end of this section.

Exercise $8.E.82$

Consider the quadratic form q given by $q = 7x_1^2 + 6x_1x_2 - x_2^2$.

a. Write q in the form $\vec{x}^T A \vec{x}$ for an appropriate symmetric matrix A.
b. Use a change of variables to rewrite q to eliminate the x_1x_2 term.

Answer available at the end of this section.

Answers

Exercise $8.E.1$

$A^m X = \lambda^m X$ for any integer. In the case of -1, $A^{-1}\lambda X = AA^{-1}X = X$ so $A^{-1}X = \lambda^{-1}X$. Thus the eigenvalues of A^{-1} are just λ^{-1} where λ is an eigenvalue of A.

Exercise $8.E.2$

Say $AX = \lambda X$. Then $cAX = c\lambda X$ and so the eigenvalues of cA are just $c\lambda$ where λ is an eigenvalue of A.

Exercise $8.E.3$

$BAX = ABX = A\lambda X = \lambda AX$. Here it is assumed that $BX = \lambda X$.

Exercise $8.E.4$

Let X be the eigenvector. Then $A^m X = \lambda^m X$, $A^m X = AX = \lambda X$ and so

$$\lambda^m = \lambda$$

Hence if $\lambda \neq 0$, then

$$\lambda^{m-1} = 1$$

and so $|\lambda| = 1$.

Exercise $8.E.5$

The formula follows from properties of matrix multiplications. However, this vector might not be an eigenvector because it might equal 0 and eigenvectors cannot equal 0.

Exercise $8.E.14$

Yes. $\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$ works.

Exercise $8.E.16$

When you think of this geometrically, it is clear that the only two values of θ are 0 and π or these added to integer multiples of 2π.

Exercise $8.E.17$

The matrix of T is $\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$. The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} 0 \\ 1 \end{bmatrix}\right\} \leftrightarrow -1, \left\{\begin{bmatrix} 1 \\ 0 \end{bmatrix}\right\} \leftrightarrow 1$$

Exercise $8.E.18$

The matrix of T is $\begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$. The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} -i \\ 1 \end{bmatrix}\right\} \leftrightarrow -i, \left\{\begin{bmatrix} i \\ 1 \end{bmatrix}\right\} \leftrightarrow i$$

Exercise $8.E.19$

The matrix of T is $\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{bmatrix}$. The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}\right\} \leftrightarrow -1, \left\{\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}\right\} \leftrightarrow 1$$

Exercise $8.E.20$

The eigenvalues are $-1, -1, 1$. The eigenvectors corresponding to the eigenvalues are:

$$\left\{\begin{bmatrix} 10 & -2 & 3 \end{bmatrix}\right\} \leftrightarrow -1, \left\{\begin{bmatrix} 7 \\ -2 \\ 2 \end{bmatrix}\right\} \leftrightarrow 1$$

Therefore this matrix is not diagonalizable.

Exercise $8.E.21$

The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} 2 \\ 0 \\ 1 \end{bmatrix}\right\} \leftrightarrow 1, \left\{\begin{bmatrix} -2 \\ 1 \\ 0 \end{bmatrix}\right\} \leftrightarrow 1, \left\{\begin{bmatrix} 7 \\ -2 \\ 2 \end{bmatrix}\right\} \leftrightarrow 3$$

The matrix P needed to diagonalize the above matrix is

$$\begin{bmatrix} 2 & -2 & 7 \\ 0 & 1 & -2 \\ 1 & 0 & 2 \end{bmatrix}$$

and the diagonal matrix D is

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 3 \end{bmatrix}$$

Exercise $8.E.22$

The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} -6 \\ -1 \\ -2 \end{bmatrix}\right\} \leftrightarrow 6, \left\{\begin{bmatrix} -5 \\ -2 \\ 2 \end{bmatrix}\right\} \leftrightarrow -3, \left\{\begin{bmatrix} -8 \\ -2 \\ 3 \end{bmatrix}\right\} \leftrightarrow 2$$

The matrix P needed to diagonalize the above matrix is

$$\begin{bmatrix} -6 & -5 & -8 \\ -1 & -2 & -2 \\ 2 & 2 & 3 \end{bmatrix}$$

and the diagonal matrix D is

$$\begin{bmatrix} 6 & 0 & 0 \\ 0 & -3 & 0 \\ 0 & 0 & -2 \end{bmatrix}$$

Exercise $8.E.27$

The eigenvalues are distinct because they are the nth roots of 1. Hence if X is a given vector with

$$X = \sum_{j=1}^{n} a_j V_j$$

then

$$A^{nm}X = A^{nm}\sum_{j=1}^{n} a_j V_j = \sum_{j=1}^{n} a_j A^{nm} V_j = \sum_{j=1}^{n} a_j V_j = X$$

so $A^{nm} = I$.

Exercise $8.E.32$

$AX = (a+ib)X$. Now take conjugates of both sides. Since A is real,

$$A\overline{X} = (a-ib)\overline{X}$$

Exercise $8.E.33$

First we write $A = PDP^{-1}$.

$$\begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix} = \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix}\begin{bmatrix} -1 & 0 \\ 0 & 3 \end{bmatrix} = \begin{bmatrix} -\frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{bmatrix}$$

Therefore $A^{10} = PD^{10}P^{-1}$.

$$\begin{aligned} \begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix}^{10} &= \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix}\begin{bmatrix} -1 & 0 \\ 0 & 3 \end{bmatrix}^{10}\begin{bmatrix} -\frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{bmatrix} \\ &= \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix}\begin{bmatrix} (-1)^{10} & 0 \\ 0 & 3^{10} \end{bmatrix}\begin{bmatrix} -\frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{bmatrix} \\ &= \begin{bmatrix} 29525 & 29524 \\ 29524 & 29525 \end{bmatrix} \end{aligned} \tag{8.E.7}$$

Exercise $8.E.36$

a. Multiply the given matrix by the initial state vector given by $\begin{bmatrix} 90 \\ 81 \\ 85 \end{bmatrix}$. After one time period there are 89 people in location 1, 106 in location 2, and 61 in location 3.

b. Solve the system given by $(I-A)X_s = 0$ where A is the migration matrix and $X_s = \begin{bmatrix} x_{1s} \\ x_{2s} \\ x_{3s} \end{bmatrix}$ is the steady state vector. The solution to this system is given by

$$\begin{aligned} x_{1s} &= \frac{8}{5}x_{3s} \\ x_{2s} &= \frac{63}{25}x_{3s} \end{aligned} \tag{8.E.8}$$

Letting $x_{3s} = t$ and using the fact that there are a total of 256 individuals, we must solve

$$\frac{8}{5}t + \frac{63}{25}t + t = 256$$

We find that $t = 50$. Therefore after a long time, there are 80 people in location 1, 126 in location 2, and 50 in location 3.

Exercise $8.E.37$

Exercise $8.E.38$

We solve $(I-A)X_s = 0$ to find the steady state vector $X_s = \begin{bmatrix} x_{1s} \\ x_{2s} \\ x_{3s} \end{bmatrix}$. The solution to the system is given by

$$\begin{aligned} x_{1s} &= \frac{5}{6}x_{3s} \\ x_{2s} &= \frac{2}{3}x_{3s} \end{aligned} \tag{8.E.9}$$

Letting $x_{3s} = t$ and using the fact that there are a total of 480 individuals, we must solve

$$\frac{5}{6}t + \frac{2}{3}t + t = 480$$

We find that $t = 192$. Therefore after a long time, there are 160 people in location 1, 128 in location 2, and 192 in location 3.

Exercise $8.E.41$

$$X_3 = \begin{bmatrix} 0.38 \\ 0.18 \\ 0.44 \end{bmatrix}$$

Therefore the probability of ending up back in location 2 is 0.18.

Exercise $8.E.42$

$$X_2 = \begin{bmatrix} 0.367 \\ 0.4625 \\ 0.1705 \end{bmatrix}$$

Therefore the probability of ending up in location 1 is 0.367.

Exercise $8.E.43$

The migration matrix is

$$A = \begin{bmatrix} \frac{1}{3} & \frac{1}{10} & \frac{1}{10} & \frac{1}{5} \\ \frac{1}{3} & \frac{7}{10} & \frac{1}{5} & \frac{1}{10} \\ \frac{2}{9} & \frac{1}{10} & \frac{3}{5} & \frac{1}{5} \\ \frac{1}{9} & \frac{1}{10} & \frac{1}{10} & \frac{1}{2} \end{bmatrix}$$

To find the number of trailers in each location after a long time we solve system $(I - A)X_s = 0$ for the steady state vector $X_s = \begin{bmatrix} x_{1s} \\ x_{2s} \\ x_{3s} \\ x_{4s} \end{bmatrix}$. The solution to the system is

$$\begin{aligned} x_{1s} &= \frac{9}{10}x_{4s} \\ x_{2s} &= \frac{12}{5}x_{4s} \\ x_{3s} &= \frac{8}{5}x_{4s} \end{aligned} \tag{8.E.10}$$

Letting $x_{4s} = t$ and using the fact that there are a total of 413 trailers we must solve

$$\frac{9}{10}t + \frac{12}{5}t + \frac{8}{5}t + t = 413$$

We find that $t = 70$. Therefore after a long time, there are 63 trailers in the SE, 168 in the NE, 112 in the NW and 70 in the SW.

Exercise $8.E.51$

The solution is

$$e^{At}C = \begin{bmatrix} 8e^{2t} - 6e^{3t} \\ 18e^{3t} - 16e^{2t} \end{bmatrix}$$

Exercise $8.E.54$

The eigenvectors and eigenvalues are:

$$\left\{ \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \right\} \leftrightarrow 6, \left\{ \frac{1}{\sqrt{2}} \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix} \right\} \leftrightarrow 12, \left\{ \frac{1}{\sqrt{6}} \begin{bmatrix} -1 \\ -1 \\ 2 \end{bmatrix} \right\} \leftrightarrow 18$$

Exercise $8.E.55$

The eigenvectors and eigenvalues are:

$$\left\{ \frac{1}{\sqrt{2}} \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix}, \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \right\} \leftrightarrow 3, \left\{ \frac{1}{\sqrt{6}} \begin{bmatrix} -1 \\ -1 \\ 2 \end{bmatrix} \right\} \leftrightarrow 9$$

Exercise $8.E.56$

The eigenvectors and eigenvalues are:

$$\left\{ \begin{bmatrix} \frac{1}{3}\sqrt{3} \\ \frac{1}{3}\sqrt{3} \\ \frac{1}{3}\sqrt{3} \end{bmatrix} \right\} \leftrightarrow 1, \left\{ \begin{bmatrix} -\frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} \\ 0 \end{bmatrix}, \begin{bmatrix} -\frac{1}{6}\sqrt{6} \\ -\frac{1}{6}\sqrt{6} \\ \frac{1}{3}\sqrt{2}\sqrt{3} \end{bmatrix} \right\} \leftrightarrow -2$$

$$\begin{bmatrix} \sqrt{3}/3 & -\sqrt{2}/2 & -\sqrt{6}/6 \\ \sqrt{3}/3 & \sqrt{2}/2 & -\sqrt{6}/6 \\ \sqrt{3}/3 & 0 & \frac{1}{3}\sqrt{2}\sqrt{3} \end{bmatrix}^T \begin{bmatrix} -1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & -1 \end{bmatrix}$$

$$\begin{bmatrix} \sqrt{3}/3 & -\sqrt{2}/2 & -\sqrt{6}/6 \\ \sqrt{3}/3 & \sqrt{2}/2 & -\sqrt{6}/6 \\ \sqrt{3}/3 & 0 & \frac{1}{3}\sqrt{2}\sqrt{3} \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ 0 & -2 & 0 \\ 0 & 0 & -2 \end{bmatrix}$$

Exercise $8.E.57$

The eigenvectors and eigenvalues are:

$$\left\{ \begin{bmatrix} \frac{1}{3}\sqrt{3} \\ \frac{1}{3}\sqrt{3} \\ \frac{1}{3}\sqrt{3} \end{bmatrix} \right\} \leftrightarrow 6, \left\{ \begin{bmatrix} -\frac{1}{6}\sqrt{6} \\ -\frac{1}{6}\sqrt{6} \\ \frac{1}{3}\sqrt{2}\sqrt{3} \end{bmatrix} \right\} \leftrightarrow 18, \left\{ \begin{bmatrix} -\frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} \\ 0 \end{bmatrix} \right\} \leftrightarrow 24$$

The matrix U has these as its columns.

Exercise $8.E.58$

The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} -\frac{1}{6}\sqrt{6} \\ -\frac{1}{6}\sqrt{6} \\ \frac{1}{3}\sqrt{2}\sqrt{3} \end{bmatrix}\right\} \leftrightarrow 6, \left\{\begin{bmatrix} -\frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} \\ 0 \end{bmatrix}\right\} \leftrightarrow 12, \left\{\begin{bmatrix} \frac{1}{3}\sqrt{3} \\ \frac{1}{3}\sqrt{3} \\ \frac{1}{3}\sqrt{3} \end{bmatrix}\right\} \leftrightarrow 18.$$

The matrix U has these as its columns.

Exercise $8.E.59$

The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} \frac{1}{6}\sqrt{6} \\ 0 \\ \frac{1}{6}\sqrt{5}\sqrt{6} \end{bmatrix}\right\} \leftrightarrow 1, \left\{\begin{bmatrix} -\frac{1}{3}\sqrt{2}\sqrt{3} \\ -\frac{1}{5}\sqrt{5} \\ \frac{1}{15}\sqrt{2}\sqrt{15} \end{bmatrix}\right\} - 2, \left\{\begin{bmatrix} -\frac{1}{6}\sqrt{6} \\ \frac{2}{5}\sqrt{5} \\ \frac{1}{30}\sqrt{30} \end{bmatrix}\right\} \leftrightarrow -3$$

These vectors are the columns of U.

Exercise $8.E.60$

The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} 0 \\ -\frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} \end{bmatrix}\right\} \leftrightarrow 1, \left\{\begin{bmatrix} 0 \\ \frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} \end{bmatrix}\right\} \leftrightarrow 2, \left\{\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}\right\} \leftrightarrow 3.$$

These vectors are the columns of the matrix U.

Exercise $8.E.61$

The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}\right\} \leftrightarrow 2, \left\{\begin{bmatrix} 0 \\ -\frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} \end{bmatrix}\right\} \leftrightarrow 4, \left\{\begin{bmatrix} 0 \\ \frac{1}{2}\sqrt{2} \\ \frac{1}{2}\sqrt{2} \end{bmatrix}\right\} \leftrightarrow 6.$$

These vectors are the columns of U.

Exercise $8.E.62$

The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} -\frac{1}{5}\sqrt{2}\sqrt{5} \\ \frac{1}{5}\sqrt{3}\sqrt{5} \\ \frac{1}{5}\sqrt{5} \end{bmatrix}\right\} \leftrightarrow 0, \left\{\begin{bmatrix} \frac{1}{3}\sqrt{3} \\ 0 \\ \frac{1}{3}\sqrt{2}\sqrt{3} \end{bmatrix}, \begin{bmatrix} \frac{1}{5}\sqrt{2}\sqrt{5} \\ \frac{1}{5}\sqrt{3}\sqrt{5} \\ -\frac{1}{5}\sqrt{5} \end{bmatrix}\right\} \leftrightarrow 2.$$

The columns are these vectors.

Exercise $8.E.63$

The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} -\frac{1}{3}\sqrt{3} \\ 0 \\ \frac{1}{3}\sqrt{2}\sqrt{3} \end{bmatrix}\right\} \leftrightarrow 0, \left\{\begin{bmatrix} \frac{1}{3}\sqrt{3} \\ -\frac{1}{2}\sqrt{2} \\ \frac{1}{6}\sqrt{6} \end{bmatrix}\right\} \leftrightarrow 1, \left\{\begin{bmatrix} \frac{1}{3}\sqrt{3} \\ \frac{1}{2}\sqrt{2} \\ \frac{1}{6}\sqrt{6} \end{bmatrix}\right\} \leftrightarrow 2.$$

The columns are these vectors.

Exercise $8.E.64$

The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} -\frac{1}{3}\sqrt{3} \\ \frac{1}{2}\sqrt{2} \\ \frac{1}{6}\sqrt{6} \end{bmatrix}\right\} \leftrightarrow 1, \left\{\begin{bmatrix} \frac{1}{3}\sqrt{3} \\ 0 \\ \frac{1}{3}\sqrt{2}\sqrt{3} \end{bmatrix}\right\} \leftrightarrow -2, \left\{\begin{bmatrix} \frac{1}{3}\sqrt{3} \\ \frac{1}{2}\sqrt{2} \\ -\frac{1}{6}\sqrt{6} \end{bmatrix}\right\} \leftrightarrow 2.$$

Then the columns of U are these vectors.

Exercise $8.E.65$

The eigenvectors and eigenvalues are:

$$\left\{\begin{bmatrix} -\frac{1}{6}\sqrt{6} \\ 0 \\ \frac{1}{6}\sqrt{5}\sqrt{6} \end{bmatrix}, \begin{bmatrix} \frac{1}{3}\sqrt{2}\sqrt{3} \\ \frac{1}{5}\sqrt{5} \\ \frac{1}{15}\sqrt{2}\sqrt{15} \end{bmatrix}\right\} \leftrightarrow -1, \left\{\begin{bmatrix} \frac{1}{6}\sqrt{6} \\ -\frac{2}{5}\sqrt{5} \\ \frac{1}{30}\sqrt{30} \end{bmatrix}\right\} \leftrightarrow 2.$$

The columns of U are these vectors.

$$\begin{bmatrix} -\frac{1}{6}\sqrt{6} & \frac{1}{3}\sqrt{2}\sqrt{3} & \frac{1}{6}\sqrt{6} \\ 0 & \frac{1}{5}\sqrt{5} & -\frac{2}{5}\sqrt{5} \\ \frac{1}{6}\sqrt{5}\sqrt{6} & \frac{1}{15}\sqrt{2}\sqrt{15} & \frac{1}{30}\sqrt{30} \end{bmatrix}^T \begin{bmatrix} -\frac{1}{2} & -\frac{1}{5}\sqrt{6}\sqrt{5} & \frac{1}{10}\sqrt{5} \\ -\frac{1}{5}\sqrt{6}\sqrt{5} & \frac{7}{5} & -\frac{1}{5}\sqrt{6} \\ \frac{1}{10}\sqrt{5} & -\frac{1}{5}\sqrt{6} & -\frac{9}{10} \end{bmatrix}.$$

$$\begin{bmatrix} -\frac{1}{6}\sqrt{6} & \frac{1}{3}\sqrt{2}\sqrt{3} & \frac{1}{6}\sqrt{6} \\ 0 & \frac{1}{5}\sqrt{5} & -\frac{2}{5}\sqrt{5} \\ \frac{1}{6}\sqrt{5}\sqrt{6} & \frac{1}{15}\sqrt{2}\sqrt{15} & \frac{1}{30}\sqrt{30} \end{bmatrix} = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

Exercise $8.E.66$

If A is given by the formula, then

$$A^T = U^T D^T U = U^T D U = A$$

Next suppose $A = A^T$. Then by the theorems on symmetric matrices, there exists an orthogonal matrix U such that

$$UAU^T = D$$

for D diagonal. Hence

$$A = U^T D U$$

Exercise $8.E.67$

Since $\lambda \neq \mu$, it follows $X \bullet Y = 0$.

Exercise $8.E.74$

Using the QR factorization, we have:

$$\begin{bmatrix} 1 & 2 & 1 \\ 2 & -1 & 0 \\ 1 & 3 & 0 \end{bmatrix} = \begin{bmatrix} \frac{1}{6}\sqrt{6} & \frac{3}{10}\sqrt{2} & \frac{7}{15}\sqrt{3} \\ \frac{1}{3}\sqrt{6} & -\frac{2}{5}\sqrt{2} & -\frac{1}{15}\sqrt{3} \\ \frac{1}{6}\sqrt{6} & \frac{1}{2}\sqrt{2} & -\frac{1}{3}\sqrt{3} \end{bmatrix} \begin{bmatrix} \sqrt{6} & \frac{1}{2}\sqrt{6} & \frac{1}{6}\sqrt{6} \\ 0 & \frac{5}{2}\sqrt{2} & \frac{3}{10}\sqrt{2} \\ 0 & 0 & \frac{7}{15}\sqrt{3} \end{bmatrix}$$

A solution is then

$$\begin{bmatrix} \frac{1}{6}\sqrt{6} \\ \frac{1}{3}\sqrt{6} \\ \frac{1}{6}\sqrt{6} \end{bmatrix}, \begin{bmatrix} \frac{3}{10}\sqrt{2} \\ -\frac{2}{5}\sqrt{2} \\ \frac{1}{2}\sqrt{2} \end{bmatrix}, \begin{bmatrix} \frac{7}{15}\sqrt{3} \\ -\frac{1}{15}\sqrt{3} \\ -\frac{1}{3}\sqrt{3} \end{bmatrix}$$

Exercise $8.E.75$

$$\begin{bmatrix} 1 & 2 & 1 \\ 2 & -1 & 0 \\ 1 & 3 & 0 \\ 0 & 1 & 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{6}\sqrt{6} & \frac{1}{6}\sqrt{2}\sqrt{3} & \frac{5}{111}\sqrt{3}\sqrt{37} & \frac{7}{111}\sqrt{111} \\ \frac{1}{3}\sqrt{6} & -\frac{2}{9}\sqrt{2}\sqrt{3} & \frac{1}{333}\sqrt{3}\sqrt{37} & -\frac{2}{111}\sqrt{111} \\ \frac{1}{6}\sqrt{6} & \frac{5}{18}\sqrt{2}\sqrt{3} & -\frac{17}{333}\sqrt{3}\sqrt{37} & -\frac{1}{37}\sqrt{111} \\ 0 & \frac{1}{9}\sqrt{2}\sqrt{3} & \frac{22}{333}\sqrt{3}\sqrt{37} & -\frac{7}{111}\sqrt{111} \end{bmatrix} \begin{bmatrix} \sqrt{6} & \frac{1}{2}\sqrt{6} & \frac{1}{6}\sqrt{6} \\ 0 & \frac{3}{2}\sqrt{2}\sqrt{3} & \frac{5}{18}\sqrt{2}\sqrt{3} \\ 0 & 0 & \frac{1}{9}\sqrt{3}\sqrt{37} \\ 0 & 0 & 0 \end{bmatrix}$$

Then a solution is

$$\begin{bmatrix} \frac{1}{6}\sqrt{6} & \\ \frac{1}{3}\sqrt{6} & \\ \frac{1}{6}\sqrt{6} & 0 \end{bmatrix}, \begin{bmatrix} \frac{1}{6}\sqrt{2}\sqrt{3} \\ -\frac{2}{9}\sqrt{2}\sqrt{3} \\ \frac{5}{18}\sqrt{2}\sqrt{3} \\ \frac{1}{9}\sqrt{2}\sqrt{3} \end{bmatrix}, \begin{bmatrix} \frac{5}{111}\sqrt{3}\sqrt{37} \\ \frac{1}{333}\sqrt{3}\sqrt{37} \\ -\frac{17}{333}\sqrt{3}\sqrt{37} \\ \frac{22}{333}\sqrt{3}\sqrt{37} \end{bmatrix}$$

Exercise $8.E.76$

Exercise $8.E.77$

Exercise $8.E.78$

$$\begin{bmatrix} x & y & z \end{bmatrix} \begin{bmatrix} a_1 & a_4/2 & a_5/2 \\ a_4/2 & a_2 & a_6/2 \\ a_5/2 & a_6/2 & a_3 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Exercise $8.E.79$

The quadratic form may be written as

$$\vec{x}^T A \vec{x}$$

where $A = A^T$. By the theorem about diagonalizing a symmetric matrix, there exists an orthogonal matrix U such that

$$U^T A U = D,\ A = U D U^T$$

Then the quadratic form is

$$\vec{x}^T U D U^T \vec{x} = (U^T \vec{x})^T D (U^T \vec{x})$$

where D is a diagonal matrix having the real eigenvalues of A down the main diagonal. Now simply let

$$\vec{x}' = U^T \vec{x}$$

Exercise $8.E.80$

Exercise $8.E.81$

Exercise $8.E.82$

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9: APPENDICES

9.1: Sets and Set Notation
9.2: Complex Numbers
9.3: Proofs
9.4: Well Ordering and Induction

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9.1: Sets and Set Notation

A set is a collection of things called **elements**. For example $\{1,2,3,8\}$ would be a set consisting of the elements 1,2,3, and 8. To indicate that 3 is an element of $\{1,2,3,8\}$, it is customary to write $3 \in \{1,2,3,8\}$. We can also indicate when an element is not in a set, by writing $9 \notin \{1,2,3,8\}$ which says that 9 is not an element of $\{1,2,3,8\}$. Sometimes a rule specifies a set. For example you could specify a set as all integers larger than 2. This would be written as

$$S = \{x \in \mathbb{Z} : x > 2\}.$$

This notation says: S is the set of all integers, x, such that $x > 2$.

Suppose A and B are sets with the property that every element of A is an element of B. Then we say that A is a subset of B. For example, $\{1,2,3,8\}$ is a subset of $\{1,2,3,4,5,8\}$. In symbols, we write

$$\{1,2,3,8\} \subseteq \{1,2,3,4,5,8\}.$$

It is sometimes said that "A is contained in B" or even "B contains A". The same statement about the two sets may also be written as

$$\{1,2,3,4,5,8\} \supseteq \{1,2,3,8\}.$$

We can also talk about the **union** of two sets, which we write as $A \cup B$. This is the set consisting of everything which is an element of at least one of the sets, A or B. As an example of the union of two sets, consider

$$\{1,2,3,8\} \cup \{3,4,7,8\} = \{1,2,3,4,7,8\}.$$

This set is made up of the numbers which are in at least one of the two sets.

In general

$$A \cup B = \{x : x \in A \text{ or } x \in B\}$$

Notice that an element which is in *both* A and B is also in the union, as well as elements which are in only one of A or B.

Another important set is the intersection of two sets A and B, written $A \cap B$. This set consists of everything which is in *both* of the sets. Thus $\{1,2,3,8\} \cap \{3,4,7,8\} = \{3,8\}$ because 3 and 8 are those elements the two sets have in common. In general,

$$A \cap B = \{x : x \in A \text{ and } x \in B\}$$

If A and B are two sets, $A \setminus B$ denotes the set of things which are in A but not in B. Thus

$$A \setminus B = \{x \in A : x \notin B\}$$

For example, if $A = \{1,2,3,8\}$ and $B = \{3,4,7,8\}$, then $A \setminus B = \{1,2,3,8\} \setminus \{3,4,7,8\} = \{1,2\}$.

A special set which is very important in mathematics is the empty set denoted by $\emptyset$, which is defined as the set which has no elements in it. It follows that the empty set is a subset of every set. This is true because if it were not so, there would have to exist a set A, such that $\emptyset$ has something in it which is not in A. However, $\emptyset$ has nothing in it and so it must be that $\emptyset \subseteq A$.

We can also use brackets to denote sets which are intervals of numbers. Let a and b be real numbers. Then

- $[a,b] = \{x \in \mathbb{R} : a \leq x \leq b\}$
- $[a,b) = \{x \in \mathbb{R} : a \leq x < b\}$
- $(a,b) = \{x \in \mathbb{R} : a < x < b\}$
- $(a,b] = \{x \in \mathbb{R} : a < x \leq b\}$
- $[a,\infty) = \{x \in \mathbb{R} : x \geq a\}$
- $(-\infty,a] = \{x \in \mathbb{R} : x \leq a\}$

These sorts of sets of real numbers are called intervals. The two points a and b are called endpoints, or bounds, of the interval. In particular, a is the *lower bound* while b is the *upper bound* of the above intervals, where applicable. Other intervals such as

$(-\infty, b)$ are defined by analogy to what was just explained. In general, the curved parenthesis, $($, indicates the end point is not included in the interval, while the square parenthesis, $[$, indicates this end point is included. The reason that there will always be a curved parenthesis next to ∞ or $-\infty$ is that these are not real numbers and cannot be included in the interval in the way a real number can.

To illustrate the use of this notation relative to intervals consider three examples of inequalities. Their solutions will be written in the interval notation just described.

Example 9.1.1: Solving an Inequality

Solve the inequality $2x + 4 \leq x - 8$.

Solution

We need to find x such that $2x + 4 \leq x - 8$. Solving for x, we see that $x \leq -12$ is the answer. This is written in terms of an interval as $(-\infty, -12]$.

Consider the following example.

Example 9.1.2: Solving an Inequality

Solve the inequality $(x + 1)(2x - 3) \geq 0$.

Solution

We need to find x such that $(x + 1)(2x - 3) \geq 0$. The solution is given by $x \leq -1$ or $x \geq \frac{3}{2}$. Therefore, x which fit into either of these intervals gives a solution. In terms of set notation this is denoted by $(-\infty, -1] \cup [\frac{3}{2}, \infty)$.

Consider one last example.

Example 9.1.3: Solving an Inequality

Solve the inequality $x(x + 2) \geq -4$.

Solution

This inequality is true for any value of x where x is a real number. We can write the solution as $\mathbb{R}$ or $(-\infty, \infty)$.

In the next section, we examine another important mathematical concept.

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9.2: Complex Numbers

The fact that the square of every real number is nonnegative shows that the equation $x^2 + 1 = 0$ has no real root; in other words, there is no real number u such that $u^2 = -1$. So the set of real numbers is inadequate for finding all roots of all polynomials. This kind of problem arises with other number systems as well. The set of integers contains no solution of the equation $3x + 2 = 0$, and the rational numbers had to be invented to solve such equations. But the set of rational numbers is also incomplete because, for example, it contains no root of the polynomial $x^2 - 2$. Hence the real numbers were invented. In the same way, the set of complex numbers was invented, which contains all real numbers together with a root of the equation $x^2 + 1 = 0$. However, the process ends here: the complex numbers have the property that *every* polynomial with complex coefficients has a (complex) root. This fact is known as the fundamental theorem of algebra.

One pleasant aspect of the complex numbers is that, whereas describing the real numbers in terms of the rationals is a rather complicated business, the complex numbers are quite easy to describe in terms of real numbers. Every **complex number** has the form

$$a + bi$$

where a and b are real numbers, and i is a root of the polynomial $x^2 + 1$. Here a and b are called the **real part** and the **imaginary part** of the complex number, respectively. The real numbers are now regarded as special complex numbers of the form $a + 0i = a$, with zero imaginary part. The complex numbers of the form $0 + bi = bi$ with zero real part are called **pure imaginary** numbers. The complex number i itself is called the **imaginary unit** and is distinguished by the fact that

$$i^2 = -1$$

As the terms *complex* and *imaginary* suggest, these numbers met with some resistance when they were first used. This has changed; now they are essential in science and engineering as well as mathematics, and they are used extensively. The names persist, however, and continue to be a bit misleading: These numbers are no more "*complex*" than the real numbers, and the number i is no more "*imaginary*" than -1.

Much as for polynomials, two complex numbers are declared to be **equal** if and only if they have the same real parts and the same imaginary parts. In symbols,

$$a + bi = a' + b'i \quad \text{if and only if } a = a' \text{ and } b = b'$$

The addition and subtraction of complex numbers is accomplished by adding and subtracting real and imaginary parts:

$$(a + bi) + (a' + b'i) = (a + a') + (b + b')i$$
$$(a + bi) - (a' + b'i) = (a - a') + (b - b')i$$

This is analogous to these operations for linear polynomials $a + bx$ and $a' + b'x$, and the multiplication of complex numbers is also analogous with one difference: $i^2 = -1$. The definition is

$$(a + bi)(a' + b'i) = (aa' - bb') + (ab' + ba')i$$

With these definitions of equality, addition, and multiplication, the complex numbers *satisfy all the basic arithmetical axioms adhered to by the real numbers* (the verifications are omitted). One consequence of this is that they can be manipulated in the obvious fashion, except that i^2 is replaced by -1 wherever it occurs, and the rule for equality must be observed.

Example 9.2.1

If $z = 2 - 3i$ and $w = -1 + i$, write each of the following in the form $a + bi$: $z + w$, $z - w$, zw, $\frac{1}{3}z$, and z^2.

Solution

$$z+w=(2-3i)+(-1+i)=(2-1)+(-3+1)i=1-2i$$
$$z-w=(2-3i)-(-1+i)=(2+1)+(-3-1)i=3-4i$$
$$zw=(2-3i)(-1+i)=(-2-3i^2)+(2+3)i=1+5i$$
$$\frac{1}{3}z=\frac{1}{3}(2-3i)=\frac{2}{3}-i$$
$$z^2=(2-3i)(2-3i)=(4+9i^2)+(-6-6)i=-5-12i$$

Example 9.2.2

Find all complex numbers z such as that $z^2=i$.

Solution

Write $z=a+bi$; we must determine a and b. Now $z^2=(a^2-b^2)+(2ab)i$, so the condition $z^2=i$ becomes

$$(a^2-b^2)+(2ab)i=0+i$$

Equating real and imaginary parts, we find that $a^2=b^2$ and $2ab=1$. The solution is $a=b=\pm\frac{1}{\sqrt{2}}$, so the complex numbers required are $z=\frac{1}{\sqrt{2}}+\frac{1}{\sqrt{2}}i$ and $z=-\frac{1}{\sqrt{2}}-\frac{1}{\sqrt{2}}i$.

As for real numbers, it is possible to divide by every nonzero complex number z. That is, there exists a complex number w such that $wz=1$. As in the real case, this number w is called the **inverse** of z and is denoted by z^{-1} or $\frac{1}{z}$. Moreover, if $z=a+bi$, the fact that $z\neq 0$ means that $a\neq 0$ or $b\neq 0$. Hence $a^2+b^2\neq 0$, and an explicit formula for the inverse is

$$\frac{1}{z}=\frac{a}{a^2+b^2}-\frac{b}{a^2+b^2}i$$

In actual calculations, the work is facilitated by two useful notions: the conjugate and the absolute value of a complex number. The next example illustrates the technique.

Example 9.2.3

Write $\frac{3+2i}{2+5i}$ in the form $a+bi$.

Solution

Multiply top and bottom by the complex number $2-5i$ (obtained from the denominator by negating the imaginary part). The result is

$$\frac{3+2i}{2+5i}=\frac{(2-5i)(3+2i)}{(2-5i)(2+5i)}=\frac{(6+10)+(4-15)i}{2^2-(5i)^2}=\frac{16}{29}-\frac{11}{29}i$$

Hence the simplified form is $\frac{16}{29}-\frac{11}{29}i$, as required.

The key to this technique is that the product $(2-5i)(2+5i)=29$ in the denominator turned out to be a *real* number. The situation in general leads to the following notation: If $z=a+bi$ is a complex number, the **conjugate** of z is the complex number, denoted $\overline{z}$, given by

$$\overline{z}=a-bi \quad \text{where } z=a+bi$$

Hence $\overline{z}$ is obtained from z by negating the imaginary part. Thus $\overline{(2+3i)}=2-3i$ and $\overline{(1-i)}=1+i$. If we multiply $z=a+bi$ by $\overline{z}$, we obtain

$$z\overline{z}=a^2+b^2 \quad \text{where } z=a+bi$$

The real number a^2+b^2 is always nonnegative, so we can state the following definition: The **absolute value** or **modulus** of a

complex number $z = a + bi$, denoted by $|z|$, is the positive square root $\sqrt{a^2 + b^2}$; that is,

$$|z| = \sqrt{a^2 + b^2} \quad \text{where } z = a + bi$$

For example, $|2 - 3i| = \sqrt{2^2 + (-3)^2} = \sqrt{13}$ and $|1 + i| = \sqrt{1^2 + 1^2} = \sqrt{2}$.

Note that if a real number a is viewed as the complex number $a + 0i$, its absolute value (as a complex number) is $|a| = \sqrt{a^2}$, which agrees with its absolute value as a *real* number.

With these notions in hand, we can describe the technique applied in Example A.3 as follows: When converting a quotient $\frac{z}{w}$ of complex numbers to the form $a + bi$, multiply top and bottom by the conjugate $\overline{w}$ of the denominator.

The following list contains the most important properties of conjugates and absolute values. Throughout, z and w denote complex numbers.

$C1.$	$\overline{z \pm w} = \overline{z} \pm \overline{w}$	$C7.$	$\frac{1}{z} = \frac{1}{\lvert z\rvert^2}\overline{z}$
$C2.$	$\overline{zw} = \overline{z}\,\overline{w}$	$C8.$	$\lvert z\rvert \geq 0$ for all complex numbers z
$C3.$	$\overline{(\frac{z}{w})} = \frac{\overline{z}}{\overline{w}}$	$C9.$	$\lvert z\rvert = 0$ if and only if $z = 0$
$C4.$	$\overline{(\overline{z})} = z$	$C10.$	$\lvert zw\rvert = \lvert z\rvert\lvert w\rvert$
$C5.$	z is real if and only if $\overline{z} = z$	$C11.$	$\lvert\frac{z}{w}\rvert = \frac{\lvert z\rvert}{\lvert w\rvert}$
$C6.$	$z\overline{z} = \lvert z\rvert^2$	$C12.$	$\lvert z + w\rvert \leq \lvert z\rvert + \lvert w\rvert$ **(triangle inequality)**\index*complexnumber!triangleinequality*\

All these properties (except property C12) can (and should) be verified by the reader for arbitrary complex numbers $z = a + bi$ and $w = c + di$. They are not independent; for example, property C10 follows from properties C2 and C6.

The triangle inequality, as its name suggests, comes from a geometric representation of the complex numbers analogous to identification of the real numbers with the points of a line. The representation is achieved as follows:

Introduce a rectangular coordinate system in the plane (Figure 9.2.1), and identify the complex number $a + bi$ with the point (a, b). When this is done, the plane is called the **complex plane**. Note that the point $(a, 0)$ on the x axis now represents the *real* number $a = a + 0i$, and for this reason, the x axis is called the **real axis**. Similarly, the y axis is called the **imaginary axis**. The identification $(a, b) = a + bi$ of the geometric point (a, b) and the complex number $a + bi$ will be used in what follows without comment. For example, the origin will be referred to as 0.

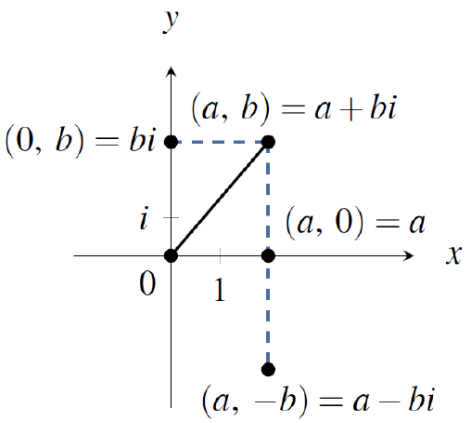


Figure 9.2.1

This representation of the complex numbers in the complex plane gives a useful way of describing the absolute value and conjugate of a complex number $z = a + bi$. The absolute value $|z| = \sqrt{a^2 + b^2}$ is just the distance from z to the origin. This makes properties C8 and C9 quite obvious. The conjugate $\overline{z} = a - bi$ of z is just the reflection of z in the real axis (x axis), a fact that makes properties C4 and C5 clear.

Given two complex numbers $z_1 = a_1 + b_1 i = (a_1, b_1)$ and $z_2 = a_2 + b_2 i = (a_2, b_2)$, the absolute value of their difference

$$|z_1 - z_2| = \sqrt{(a_1 - a_2)^2 + (b_1 - b_2)^2}$$

is just the distance between them. This gives the **complex distance formula**:

$$|z_1 - z_2| \text{ is the distance between } z_1 \text{ and } z_2$$

This useful fact yields a simple verification of the triangle inequality, property C12. Suppose z and w are given complex numbers. Consider the triangle in Figure $9.2.2$ whose vertices are 0, w, and $z + w$. The three sides have lengths $|z|$, $|w|$, and $|z + w|$ by the complex distance formula, so the inequality

$$|z + w| \leq |z| + |w|$$

expresses the obvious geometric fact that the sum of the lengths of two sides of a triangle is at least as great as the length of the third side.

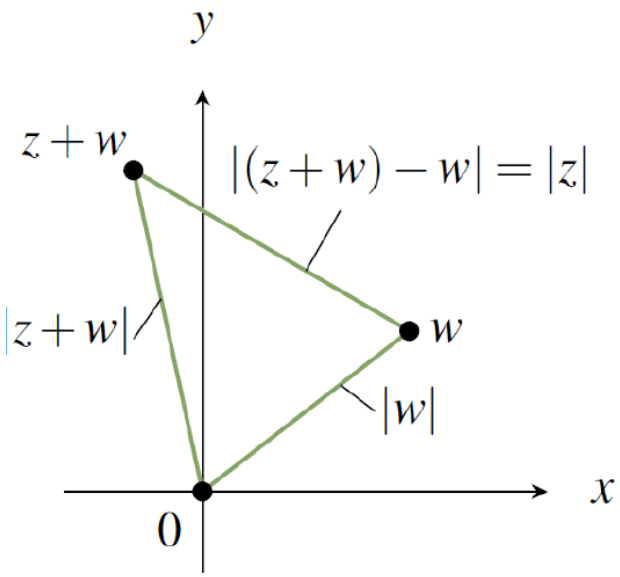


Figure $9.2.1$: Copy and Paste Caption here. (Copyright; author via source)

The representation of complex numbers as points in the complex plane has another very useful property: It enables us to give a geometric description of the sum and product of two complex numbers. To obtain the description for the sum, let

$$z = a + bi = (a, b)$$
$$w = c + di = (c, d)$$

denote two complex numbers. We claim that the four points 0, z, w, and $z + w$ form the vertices of a parallelogram. In fact, in Figure $9.2.3$ the lines from 0 to z and from w to $z + w$ have slopes

$$\frac{b - 0}{a - 0} = \frac{b}{a} \quad \text{and} \quad \frac{(b + d) - d}{(a + c) - c} = \frac{b}{a}$$

respectively, so these lines are parallel. (If it happens that $a = 0$, then both these lines are vertical.) Similarly, the lines from z to $z + w$ and from 0 to w are also parallel, so the figure with vertices 0, z, w, and $z + w$ is indeed a parallelogram. Hence, the complex number $z + w$ can be obtained geometrically from z and w by *completing* the parallelogram. This is sometimes called the **parallelogram law** of complex addition. Readers who have studied mechanics will recall that velocities and accelerations add in the same way; in fact, these are all special cases of *vector* addition.

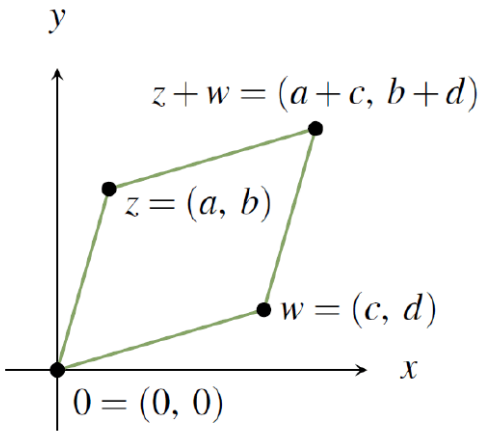


Figure 9.2.3

Polar Form

The geometric description of what happens when two complex numbers are multiplied is at least as elegant as the parallelogram law of addition, but it requires that the complex numbers be represented in polar form. Before discussing this, we pause to recall the general definition of the trigonometric functions sine and cosine. An angle θ in the complex plane is in **standard position** if it is measured counterclockwise from the positive real axis as indicated in Figure 9.2.4. Rather than using degrees to measure angles, it is more natural to use radian measure. This is defined as follows: The circle with its centre at the origin and radius 1 (called the **unit circle**) is drawn in Figure [fig:0033966]. It has circumference 2π, and the **radian measure** of θ is the length of the arc on the unit circle counterclockwise from 1 to the point P on the unit circle determined by θ. Hence $90^\circ = \frac{\pi}{2}$, $45^\circ = \frac{\pi}{4}$, $180^\circ = \pi$, and a full circle has the angle $360^\circ = 2\pi$. Angles measured clockwise from 1 are negative; for example, $-i$ corresponds to $-\frac{\pi}{2}$ (or to $\frac{3\pi}{2}$).

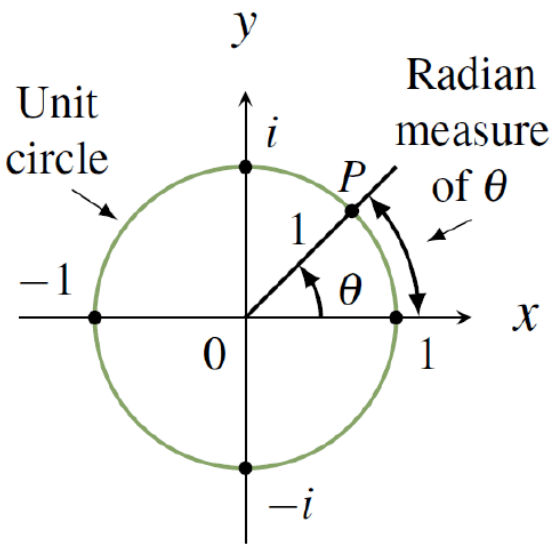


Figure 9.2.4

Consider an angle θ in the range $0 \leq \theta \leq \frac{\pi}{2}$. If θ is plotted in standard position as in Figure [fig:0033966], it determines a unique point P on the unit circle, and P has coordinates $(\cos\theta, \sin\theta)$ by elementary trigonometry. However, *any* angle θ (acute or not) determines a unique point on the unit circle, so we *define* the **cosine** and **sine** of θ (written $\cos\theta$ and $\sin\theta$) to be the x and y coordinates of this point. For example, the points

$$1 = (1,0) \quad i = (0,1) \quad -1 = (-1,0) \quad -i = (0,-1)$$

plotted in Figure [fig:0033966] are determined by the angles 0, $\frac{\pi}{2}$, π, $\frac{3\pi}{2}$, respectively. Hence

$$\cos 0 = 1 \qquad \cos \tfrac{\pi}{2} = 0 \qquad \cos \pi = -1 \qquad \cos \tfrac{3\pi}{2} = 0$$
$$\sin 0 = 0 \qquad \sin \tfrac{\pi}{2} = 1 \qquad \sin \pi = 0 \qquad \sin \tfrac{3\pi}{2} = -1$$

Now we can describe the polar form of a complex number. Let $z = a + bi$ be a complex number, and write the absolute value of z as

$$r = |z| = \sqrt{a^2 + b^2}$$

If $z \neq 0$, the angle θ shown in Figure $9.2.5$ is called an **argument** of z and is denoted

$$\theta = \arg z$$

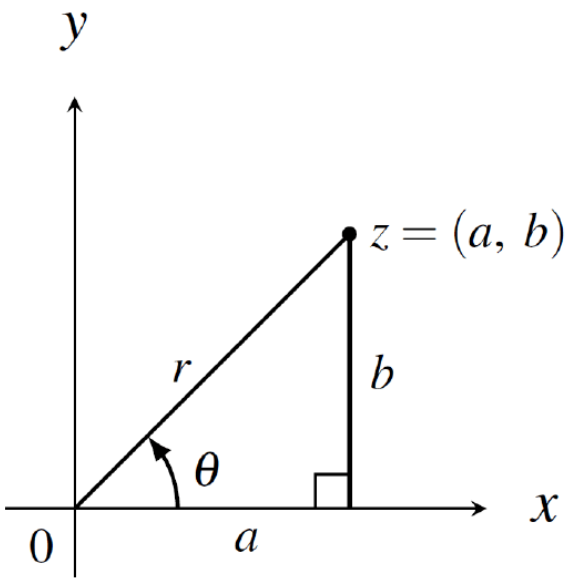


Figure $9.2.5$

This angle is not unique ($\theta + 2\pi k$ would do as well for any $k = 0, \pm 1, \pm 2, \ldots$). However, there is only one argument θ in the range $-\pi < \theta \leq \pi$, and this is sometimes called the **principal argument** of z.

Returning to Figure $9.2.5$, we find that the real and imaginary parts a and b of z are related to r and θ by

$$a = r \cos \theta$$
$$b = r \sin \theta$$

Hence the complex number $z = a + bi$ has the form

$$z = r(\cos \theta + i \sin \theta) \quad r = |z|, \theta = \arg(z)$$

The combination $\cos \theta + i \sin \theta$ is so important that a special notation is used:

$$e^{i\theta} = \cos \theta + i \sin \theta$$

is called **Euler's formula** after the great Swiss mathematician Leonhard Euler (1707–1783). With this notation, z is written

$$z = re^{i\theta} \quad r = |z|, \theta = \arg(z)$$

This is a **polar form** of the complex number z. Of course it is not unique, because the argument can be changed by adding a multiple of 2π.

Example 9.2.4

Write $z_1 = -2 + 2i$ and $z_2 = -i$ in polar form.

Solution

The two numbers are plotted in the complex plane in Figure 9.2.6.

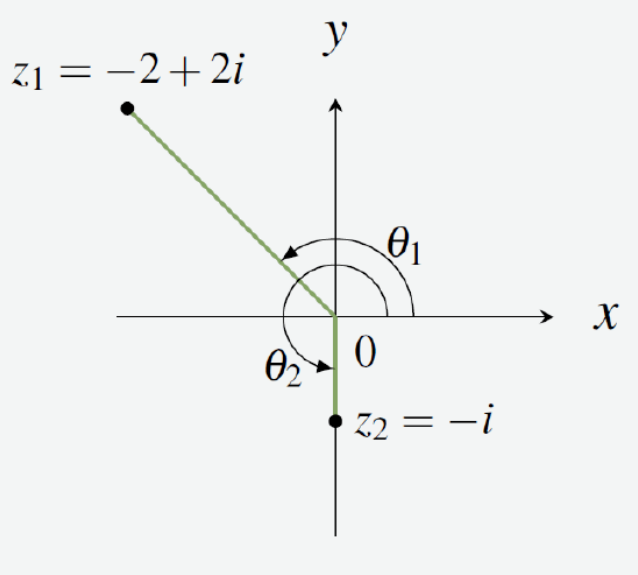


Figure 9.2.6

The absolute values are

$$r_1 = |-2 + 2i| = \sqrt{(-2)^2 + 2^2} = 2\sqrt{2}$$
$$r_2 = |-i| = \sqrt{0^2 + (-1)^2} = 1$$

By inspection of Figure [fig:0033996], arguments of z_1 and z_2 are

$$\theta_1 = \arg(-2 + 2i) = \frac{3\pi}{4}$$
$$\theta_2 = \arg(-i) = \frac{3\pi}{2}$$

The corresponding polar forms are $z_1 = -2 + 2i = 2\sqrt{2}e^{3\pi i/4}$ and $z_2 = -i = e^{3\pi i/2}$. Of course, we could have taken the argument $-\frac{\pi}{2}$ for z_2 and obtained the polar form $z_2 = e^{-\pi i/2}$.

In Euler's formula $e^{i\theta} = \cos\theta + i\sin\theta$, the number e is the familiar constant $e = 2.71828\ldots$ from calculus. The reason for using e will not be given here; the reason why $\cos\theta + i\sin\theta$ is written as an *exponential* function of θ is that the **law of exponents** holds:

$$e^{i\theta} \cdot e^{i\phi} = e^{i(\theta+\phi)}$$

where θ and ϕ are any two angles. In fact, this is an immediate consequence of the addition identities for $\sin(\theta + \phi)$ and $\cos(\theta + \phi)$:

$$\begin{aligned} e^{i\theta}e^{i\phi} &= (\cos\theta + i\sin\theta)(\cos\phi + i\sin\phi) \\ &= (\cos\theta\cos\phi - \sin\theta\sin\phi) + i(\cos\theta\sin\phi + \sin\theta\cos\phi) \\ &= \cos(\theta + \phi) + i\sin(\theta + \phi) \\ &= e^{i(\theta+\phi)} \end{aligned}$$

This is analogous to the rule $e^a e^b = e^{a+b}$, which holds for real numbers a and b, so it is not unnatural to use the exponential notation $e^{i\theta}$ for the expression $\cos\theta + i\sin\theta$. In fact, a whole theory exists wherein functions such as e^z, $\sin z$, and $\cos z$ are studied, where z is a *complex* variable. Many deep and beautiful theorems can be proved in this theory, one of which is the so-called fundamental theorem of algebra mentioned later (Theorem A.4). We shall not pursue this here.

The geometric description of the multiplication of two complex numbers follows from the law of exponents.

Theorem 9.2.1: Multiplication Rule

If $z_1 = r_1 e^{i\theta_1}$ and $z_2 = r_2 e^{i\theta_2}$ are complex numbers in polar form, then

$$z_1 z_2 = r_1 r_2 e^{i(\theta_1+\theta_2)}$$

In other words, to multiply two complex numbers, simply multiply the absolute values and add the arguments. This simplifies calculations considerably, particularly when we observe that it is valid for *any* arguments θ_1 and θ_2.

Example 9.2.5

Multiply $(1-i)(1+\sqrt{3}i)$ in two ways.

Solution

We have $|1-i| = \sqrt{2}$ and $|1+\sqrt{3}i| = 2$ so, from Figure 9.2.7,

$$1 - i = \sqrt{2}e^{-i\pi/4}$$
$$1 + \sqrt{3}i = 2e^{i\pi/3}$$

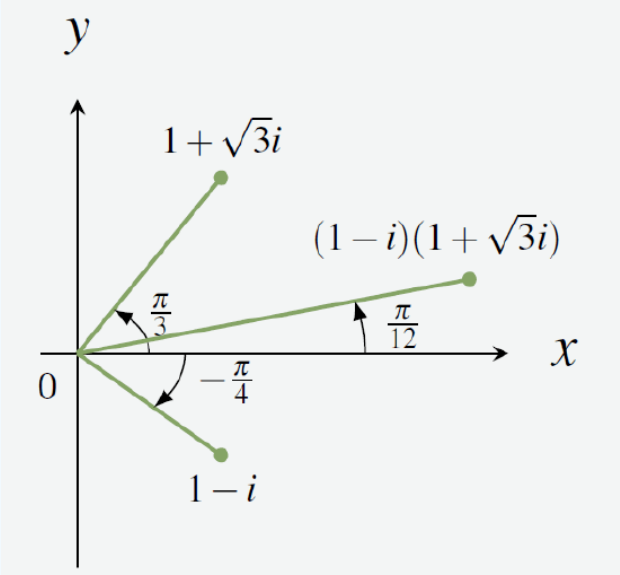


Figure 9.2.7

Hence, by the multiplication rule,

$$\begin{aligned}(1-i)(1+\sqrt{3}i) &= (\sqrt{2}e^{-i\pi/4})(2e^{i\pi/3}) \\ &= 2\sqrt{2}e^{i(-\pi/4+\pi/3)} \\ &= 2\sqrt{2}e^{i\pi/12}\end{aligned}$$

This gives the required product in polar form. Of course, direct multiplication gives $(1-i)(1+\sqrt{3}i) = (\sqrt{3}+1)+(\sqrt{3}-1)i$. Hence, equating real and imaginary parts gives the formulas $\cos(\frac{\pi}{12}) = \frac{\sqrt{3}+1}{2\sqrt{2}}$ and $\sin(\frac{\pi}{12}) = \frac{\sqrt{3}-1}{2\sqrt{2}}$.

Roots of Unity

If a complex number $z = re^{i\theta}$ is given in polar form, the powers assume a particularly simple form. In fact, $z^2 = (re^{i\theta})(re^{i\theta}) = r^2e^{2i\theta}$, $z^3 = z^2 \cdot z = (r^2e^{2i\theta})(re^{i\theta}) = r^3e^{3i\theta}$, and so on. Continuing in this way, it follows by induction that the following theorem holds for any positive integer n. The name honors Abraham De Moivre (1667–1754).

Theorem 9.2.2: De Moivre's Theorem

If θ is any angle, then $(e^{i\theta})^n = e^{in\theta}$ holds for all integers n.

Proof

The case $n > 0$ has been discussed, and the reader can verify the result for $n = 0$. To derive it for $n < 0$, first observe that

$$\text{if} \quad z = re^{i\theta} \neq 0 \quad \text{then} \quad z^{-1} = \frac{1}{r}\, e^{-i\theta}$$

In fact, $(re^{i\theta})(\frac{1}{r}e^{-i\theta}) = 1e^{i0} = 1$ by the multiplication rule. Now assume that n is negative and write it as $n = -m$, $m > 0$. Then

$$(re^{i\theta})^n = [(re^{i\theta})^{-1}]^m = (\frac{1}{r}\, e^{-i\theta})^m = r^{-m}e^{i(-m\theta)} = r^n e^{in\theta}$$

If $r = 1$, this is De Moivre's theorem for negative n.

□

Example 9.2.6

Verify that $(-1+\sqrt{3}i)^3 = 8$.

Solution

We have $|-1+\sqrt{3}i| = 2$, so $-1+\sqrt{3}i = 2e^{2\pi i/3}$ (see Figure 9.2.8).

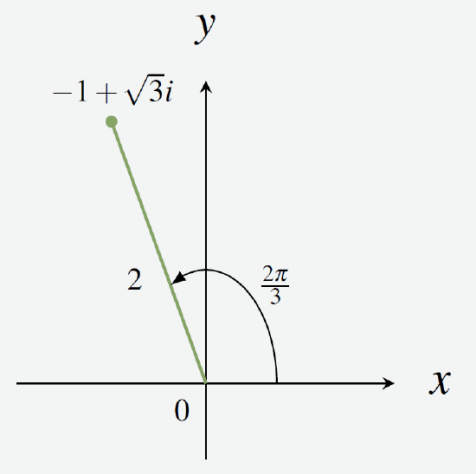


Figure 9.2.8

Hence De Moivre's theorem gives

$$(-1+\sqrt{3}i)^3 = (2e^{2\pi i/3})^3 = 8e^{3(2\pi i/3)} = 8e^{2\pi i} = 8$$

De Moivre's theorem can be used to find nth roots of complex numbers where n is positive. The next example illustrates this technique.

Example 9.2.7

Find the cube roots of unity; that is, find all complex numbers z such that $z^3 = 1$.

Solution

First write $z = re^{i\theta}$ and $1 = 1e^{i0}$ in polar form. We must use the condition $z^3 = 1$ to determine r and θ. Because $z^3 = r^3e^{3i\theta}$ by De Moivre's theorem, this requirement becomes

$$r^3e^{3i\theta} = 1e^{0i}$$

These two complex numbers are equal, so their absolute values must be equal and the arguments must either be equal or differ by an integral multiple of 2π:

$$\begin{aligned} r^3 &= 1 \\ 3\theta &= 0 + 2k\pi, \quad k \text{ some integer} \end{aligned}$$

Because r is real and positive, the condition $r^3 = 1$ implies that $r = 1$. However,

$$\theta = \frac{2k\pi}{3}, \quad k \text{ some integer}$$

seems at first glance to yield infinitely many different angles for z. However, choosing $k = 0, 1, 2$ gives three possible arguments θ (where $0 \le \theta < 2\pi$), and the corresponding roots are

$$\begin{aligned} 1e^{0i} &= 1 \\ 1e^{2\pi i/3} &= -\frac{1}{2} + \frac{\sqrt{3}}{2}i \\ 1e^{4\pi i/3} &= -\frac{1}{2} - \frac{\sqrt{3}}{2}i \end{aligned}$$

These are displayed in Figure [fig:0034128]. All other values of k yield values of θ that differ from one of these by a multiple of 2π—and so do not give new roots. Hence we have found all the roots.

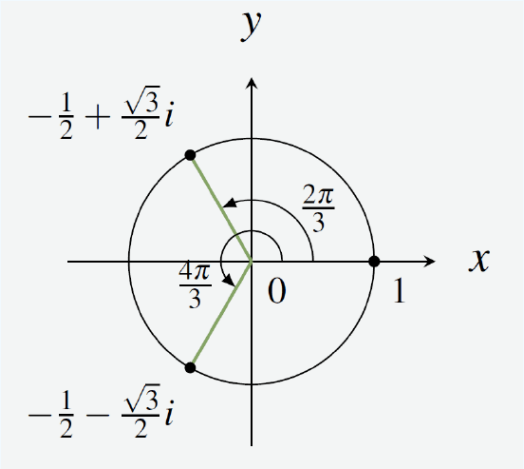


Figure 9.2.9

The same type of calculation gives all complex n**th roots of unity**; that is, all complex numbers z such that $z^n = 1$. As before, write $1 = 1e^{0i}$ and

$$z = re^{i\theta}$$

in polar form. Then $z^n = 1$ takes the form

$$r^n e^{ni\theta} = 1e^{0i}$$

using De Moivre's theorem. Comparing absolute values and arguments yields

$$\begin{aligned} r^n &= 1 \\ n\theta &= 0 + 2k\pi, \quad k \text{ some integer} \end{aligned}$$

Hence $r = 1$, and the n values

$$\theta = \frac{2k\pi}{n}, \quad k = 0, 1, 2, \ldots, n-1$$

of θ all lie in the range $0 \le \theta < 2\pi$. As in Example A.7, *every* choice of k yields a value of θ that differs from one of these by a multiple of 2π, so these give the arguments of *all* the possible roots.

Theorem 9.2.3: nth Roots of Unity

If $n \ge 1$ is an integer, the nth roots of unity (that is, the solutions to $z^n = 1$) are given by

$$z = e^{2\pi ki/n}, \quad k = 0, 1, 2, \ldots, n-1$$

The nth roots of unity can be found geometrically as the points on the unit circle that cut the circle into n equal sectors, starting at 1. The case $n = 5$ is shown in Figure 9.2.10, where the five fifth roots of unity are plotted.

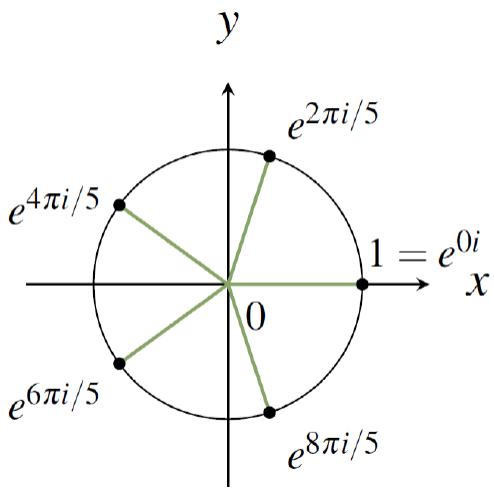


Figure 9.2.10

The method just used to find the nth roots of unity works equally well to find the nth roots of any complex number in polar form. We give one example.

Example 9.2.1

Find the fourth roots of $\sqrt{2} + \sqrt{2}i$.

Solution

First write $\sqrt{2}+\sqrt{2}i = 2e^{\pi i/4}$ in polar form. If $z = re^{i\theta}$ satisfies $z^4 = \sqrt{2}+\sqrt{2}i$, then De Moivre's theorem gives

$$r^4 e^{i(4\theta)} = 2e^{\pi i/4}$$

Hence $r^4 = 2$ and $4\theta = \frac{\pi}{4} + 2k\pi$, k an integer. We obtain four distinct roots (and hence all) by

$$r = \sqrt[4]{2}, \quad \theta = \frac{\pi}{16} = \frac{2k\pi}{16}, k = 0, 1, 2, 3$$

Thus the four roots are

$$\sqrt[4]{2}e^{\pi i/16} \quad \sqrt[4]{2}e^{9\pi i/16} \quad \sqrt[4]{2}e^{17\pi i/16} \quad \sqrt[4]{2}e^{25\pi i/16}$$

Of course, reducing these roots to the form $a + bi$ would require the computation of $\sqrt[4]{2}$ and the sine and cosine of the various angles.

An expression of the form $ax^2 + bx + c$, where the coefficients $a \neq 0$, b, and c are real numbers, is called a **real quadratic**. A complex number u is called a **root** of the quadratic if $au^2 + bu + c = 0$. The roots are given by the famous **quadratic formula**:

$$u = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

The quantity $d = b^2 - 4ac$ is called the **discriminant** of the quadratic $ax^2 + bx + c$, and there is no real root if and only if $d < 0$. In this case the quadratic is said to be **irreducible**. Moreover, the fact that $d < 0$ means that $\sqrt{d} = i\sqrt{|d|}$, so the two (complex) roots are conjugates of each other:

$$u = \frac{1}{2a}(-b + i\sqrt{|d|}) \quad \text{and} \quad \overline{u} = \frac{1}{2a}(-b - i\sqrt{|d|})$$

The converse of this is true too: Given any nonreal complex number u, then u and $\overline{u}$ are the roots of some real irreducible quadratic. Indeed, the quadratic

$$x^2 - (u + \overline{u})x + u\overline{u} = (x - u)(x - \overline{u})$$

has real coefficients ($u\overline{u} = |u|^2$ and $u + \overline{u}$ is twice the real part of u) and so is irreducible because its roots u and $\overline{u}$ are not real.

Example 9.2.1

Find a real irreducible quadratic with $u = 3 - 4i$ as a root.

Solution

We have $u + \overline{u} = 6$ and $|u|^2 = 25$, so $x^2 - 6x + 25$ is irreducible with u and $\overline{u} = 3 + 4i$ as roots.

Fundamental Theorem of Algebra

As we mentioned earlier, the complex numbers are the culmination of a long search by mathematicians to find a set of numbers large enough to contain a root of every polynomial. The fact that the complex numbers have this property was first proved by Gauss in 1797 when he was 20 years old. The proof is omitted.

Theorem 9.2.4: Fundamental Theorem of Algebra

Every polynomial of positive degree with complex coefficients has a complex root.

If $f(x)$ is a polynomial with complex coefficients, and if u_1 is a root, then the factor theorem (Section 6.5) asserts that

$$f(x) = (x - u_1)g(x)$$

where $g(x)$ is a polynomial with complex coefficients and with degree one less than the degree of $f(x)$. Suppose that u_2 is a root of $g(x)$, again by the fundamental theorem. Then $g(x) = (x - u_2)h(x)$, so

$$f(x) = (x - u_1)(x - u_2)h(x)$$

This process continues until the last polynomial to appear is linear. Thus $f(x)$ has been expressed as a product of linear factors. The last of these factors can be written in the form $u(x - u_n)$, where u and u_n are complex (verify this), so the fundamental theorem takes the following form.

Theorem 9.2.5

Every complex polynomial $f(x)$ of degree $n \geq 1$ has the form

$$f(x) = u(x - u_1)(x - u_2) \cdots (x - u_n)$$

where $u, u_1, \ldots, u_n$ are complex numbers and $u \neq 0$. The numbers $u_1, u_2, \ldots, u_n$ are the roots of $f(x)$ (and need not all be distinct), and u is the coefficient of x^n.

This form of the fundamental theorem, when applied to a polynomial $f(x)$ with *real* coefficients, can be used to deduce the following result.

Theorem 9.2.6

Every polynomial $f(x)$ of positive degree with real coefficients can be factored as a product of linear and irreducible quadratic factors.

In fact, suppose $f(x)$ has the form

$$f(x) = a_n x^n + a_{n-1}x^{n-1} + \cdots + a_1 x + a_0$$

where the coefficients a_i are real. If u is a complex root of $f(x)$, then we claim first that $\overline{u}$ is also a root. In fact, we have $f(u) = 0$, so

$$\begin{aligned} 0 = \overline{0} = \overline{f(u)} &= \overline{a_n u^n + a_{n-1}u^{n-1} + \cdots + a_1 u + a_0} \\ &= \overline{a_n u^n} + \overline{a_{n-1}u^{n-1}} + \cdots + \overline{a_1 u} + \overline{a_0} \\ &= \overline{a}_n \overline{u}^n + \overline{a}_{n-1}\overline{u}^{n-1} + \cdots + \overline{a}_1 \overline{u} + \overline{a}_0 \\ &= a_n \overline{u}^n + a_{n-1}\overline{u}^{n-1} + \cdots + a_1 \overline{u} + a_0 \\ &= f(\overline{u}) \end{aligned}$$

where $\overline{a}_i = a_i$ for each i because the coefficients a_i are real. Thus if u is a root of $f(x)$, so is its conjugate $\overline{u}$. Of course some of the roots of $f(x)$ may be real (and so equal their conjugates), but the nonreal roots come in pairs, u and $\overline{u}$. By Theorem A.6, we can thus write $f(x)$ as a product:

$$f(x) = a_n(x - r_1) \cdots (x - r_k)(x - u_1)(x - \overline{u}_1) \cdots (x - u_m)(x - \overline{u}_m)$$

where a_n is the coefficient of x^n in $f(x)$; $r_1, r_2, \ldots, r_k$ are the real roots; and $u_1, \overline{u}_1, u_2, \overline{u}_2, \ldots, u_m, \overline{u}_m$ are the nonreal roots. But the product

$$(x - u_j)(x - \overline{u}_j) = x^2 - (u_j + \overline{u}_j)x + (u_j \overline{u}_j)$$

is a real irreducible quadratic for each j (see the discussion preceding Example A.9). Hence () shows that $f(x)$ is a product of linear and irreducible quadratic factors, each with real coefficients. This is the conclusion in Theorem A.6.

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9.3: Proofs

Logic plays a basic role in human affairs. Scientists use logic to draw conclusions from experiments, judges use it to deduce consequences of the law, and mathematicians use it to prove theorems. Logic arises in ordinary speech with assertions such as "If John studies hard, he will pass the course," or "If an integer n is divisible by 6, then n is divisible by 3."[1] In each case, the aim is to assert that if a certain statement is true, then another statement must also be true. In fact, if p and q denote statements, most theorems take the form of an **implication**: "If p is true, then q is true." We write this in symbols as

$$p \Rightarrow q$$

and read it as "p implies q." Here p is the **hypothesis** and q the **conclusion** of the implication. The verification that $p \Rightarrow q$ is valid is called the **proof** of the implication. In this section we examine the most common methods of proof[2] and illustrate each technique with some examples.

Method of Direct Proof

To prove that $p \Rightarrow q$, demonstrate directly that q is true whenever p is true.

Example 9.3.1

If n is an odd integer, show that n^2 is odd.

Solution

If n is odd, it has the form $n = 2k + 1$ for some integer k. Then $n^2 = 4k^2 + 4k + 1 = 2(2k^2 + 2k) + 1$ also is odd because $2k^2 + 2k$ is an integer.

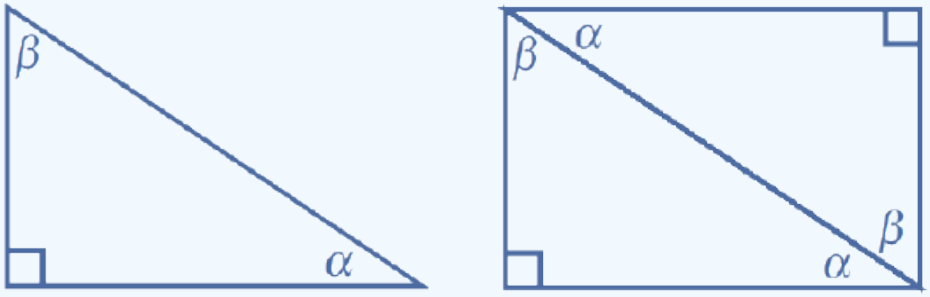
Note that the computation $n^2 = 4k^2 + 4k + 1$ in Example B.1 involves some simple properties of arithmetic that we did not prove. These properties, in turn, can be proved from certain more basic properties of numbers (called axioms)—more about that later. Actually, a whole body of mathematical information lies behind nearly every proof of any complexity, although this fact usually is not stated explicitly. Here is a geometrical example.

Example 9.3.2

In a right triangle, show that the sum of the two acute angles is 90 degrees.

Solution

The right triangle is shown in the diagram. Construct a rectangle with sides of the same length as the short sides of the original triangle, and draw a diagonal as shown. The original triangle appears on the bottom of the rectangle, and the top triangle is identical to the original (but rotated). Now it is clear that $\alpha + \beta$ is a right angle.



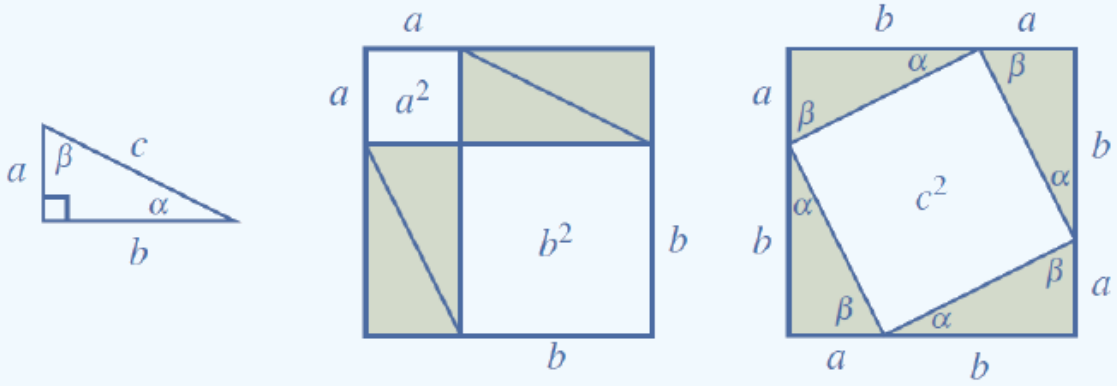
Geometry was one of the first subjects in which formal proofs were used—Euclid's *Elements* was published about 300 B.C. The *Elements* is the most successful textbook ever written, and contains many of the basic geometrical theorems that are taught in school today. In particular, Euclid included a proof of an earlier theorem (about 500 B.C.) due to Pythagoras. Recall that, in a right triangle, the side opposite the right angle is called the *hypotenuse* of the triangle.

Example 9.3.3: Pythagoras' Theorem

In a right-angled triangle, show that the square of the length of the hypotenuse equals the sum of the squares of the lengths of the other two sides.

Solution

Let the sides of the right triangle have lengths a, b, and c as shown.



Consider two squares with sides of length $a + b$, and place four copies of the triangle in these squares as in the diagram. The central rectangle in the second square shown is itself a square because the angles α and β add to 90 degrees (using Example B.2), so its area is c^2 as shown. Comparing areas shows that both $a^2 + b^2$ and c^2 each equal the area of the large square minus four times the area of the original triangle, and hence are equal.

Sometimes it is convenient (or even necessary) to break a proof into parts, and deal with each case separately. We formulate the general method as follows:

Method of Reduction to Cases

To prove that $p \Rightarrow q$, show that p implies at least one of a list $p_1, p_2, \ldots, p_n$ of statements (the cases) and then show that $p_i \Rightarrow q$ for each i.

Example 9.3.4

Show that $n^2 \geq 0$ for every integer n.

Solution

This statement can be expressed as an implication: If n is an integer, then $n^2 \geq 0$. To prove it, consider the following three cases:

$$(1)\ n > 0; \quad (2)\ n = 0; \quad (3)\ n < 0.$$

Then $n^2 > 0$ in Cases (1) and (3) because the product of two positive (or two negative) integers is positive. In Case (2) $n^2 = 0^2 = 0$, so $n^2 \geq 0$ in every case.

Example 9.3.5

If n is an integer, show that $n^2 - n$ is even.

Solution

We consider two cases:

$$(1)\ n \text{ is even}; \quad (2)\ n \text{ is odd}.$$

We have $n^2 - n = n(n-1)$, so this is even in Case (1) because any multiple of an even number is again even. Similarly, $n-1$ is even in Case (2) so $n(n-1)$ is again even for the same reason. Hence $n^2 - n$ is even in any case.

The statements used in mathematics are required to be either true or false. This leads to a proof technique which causes consternation in many beginning students. The method is a formal version of a debating strategy whereby the debater assumes the truth of an opponent's position and shows that it leads to an absurd conclusion.

Method of Proof by Contradiction

To prove that $p \Rightarrow q$, show that the assumption that both p is true and q is false leads to a contradiction. In other words, if p is true, then q must be true; that is, $p \Rightarrow q$.

Example 9.3.6

If r is a rational number (fraction), show that $r^2 \neq 2$.

Solution

To argue by contradiction, we assume that r is a rational number and that $r^2 = 2$, and show that this assumption leads to a contradiction. Let m and n be integers such that $r = \frac{m}{n}$ is in lowest terms (so, in particular, m and n are not both even). Then $r^2 = 2$ gives $m^2 = 2n^2$, so m^2 is even. This means m is even (Example B.1), say $m = 2k$. But then $2n^2 = m^2 = 4k^2$, so $n^2 = 2k^2$ is even, and hence n is even. This shows that n and m are both even, contrary to the choice of these numbers.

Example 9.3.7: Pigeonhole Principle

If $n+1$ pigeons are placed in n holes, then some hole contains at least 2 pigeons.

Solution

Assume the conclusion is false. Then each hole contains at most one pigeon and so, since there are n holes, there must be at most n pigeons, contrary to assumption.

The next example involves the notion of a *prime* number, that is an integer that is greater than 1 which cannot be factored as the product of two smaller positive integers both greater than 1. The first few primes are $2, 3, 5, 7, 11, \ldots$.

Example 9.3.8

If $2^n - 1$ is a prime number, show that n is a prime number.

Solution

We must show that $p \Rightarrow q$ where p is the statement "$2^n - 1$ is a prime", and q is the statement "n is a prime." Suppose that p is true but q is false so that n is not a prime, say $n = ab$ where $a \geq 2$ and $b \geq 2$ are integers. If we write $2^a = x$, then $2^n = 2^{ab} = (2^a)^b = x^b$. Hence $2^n - 1$ factors:

$$2^n - 1 = x^b - 1 = (x-1)(x^{b-1} + x^{b-2} + \cdots + x^2 + x + 1)$$

As $x \geq 4$, this expression is a factorization of $2^n - 1$ into smaller positive integers, contradicting the assumption that $2^n - 1$ is prime.

The next example exhibits one way to show that an implication is *not* valid.

Example 9.3.9

Show that the implication "n is a prime $\Rightarrow 2^n - 1$ is a prime" is false.

Solution

The first four primes are 2, 3, 5, and 7, and the corresponding values for $2^n - 1$ are 3, 7, 31, 127 (when $n = 2$, 3, 5, 7). These are all prime as the reader can verify. This result seems to be evidence that the implication is true. However, the next prime is 11 and $2^{11} - 1 = 2047 = 23 \cdot 89$, which is clearly *not* a prime.

We say that $n = 11$ is a **counterexample** to the (proposed) implication in Example B.9. Note that, if you can find even one example for which an implication is not valid, the implication is false. Thus disproving implications is in a sense easier than proving them.

The implications in Example B.8 and Example B.9 are closely related: They have the form $p \Rightarrow q$ and $q \Rightarrow p$, where p and q are statements. Each is called the **converse** of the other and, as these examples show, an implication can be valid even though its converse is not valid. If *both* $p \Rightarrow q$ and $q \Rightarrow p$ are valid, the statements p and q are called **logically equivalent**. This is written in symbols as

$$p \Leftrightarrow q$$

and is read "p if and only if q". Many of the most satisfying theorems make the assertion that two statements, ostensibly quite different, are in fact logically equivalent.

Example 9.3.10

If n is an integer, show that "n is odd $\Leftrightarrow n^2$ is odd."

Solution

In Example B.1 we proved the implication "n is odd $\Rightarrow n^2$ is odd." Here we prove the converse by contradiction. If n^2 is odd, we assume that n is not odd. Then n is even, say $n = 2k$, so $n^2 = 4k^2$, which is also even, a contradiction.

Many more examples of proofs can be found in this book and, although they are often more complex, most are based on one of these methods. In fact, linear algebra is one of the best topics on which the reader can sharpen his or her skill at constructing proofs. Part of the reason for this is that much of linear algebra is developed using the **axiomatic method**. That is, in the course of studying various examples it is observed that they all have certain properties in common. Then a general, abstract system is studied in which these basic properties are *assumed* to hold (and are called **axioms**). In this system, statements (called **theorems**) are deduced from the axioms using the methods presented in this appendix. These theorems will then be true in *all* the concrete examples, because the axioms hold in each case. But this procedure is more than just an efficient method for finding theorems in the examples. By reducing the proof to its essentials, we gain a better understanding of why the theorem is true and how it relates to analogous theorems in other abstract systems.

The axiomatic method is not new. Euclid first used it in about 300 B.C. to derive all the propositions of (euclidean) geometry from a list of 10 axioms. The method lends itself well to linear algebra. The axioms are simple and easy to understand, and there are only a few of them. For example, the theory of vector spaces contains a large number of theorems derived from only ten simple axioms.

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1. By an *integer* we mean a "whole number"; that is, a number in the set $0, \pm 1, \pm 2, \pm 3, \ldots$
2. For a more detailed look at proof techniques see D. Solow, How to Read and Do Proofs, 2nd ed. (New York: Wiley, 1990); or J. F. Lucas. *Introduction to Abstract Mathematics*, Chapter 2 (Belmont, CA: Wadsworth, 1986).

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9.4: Well Ordering and Induction

We begin this section with some important notation. Summation notation, written $\sum_{i=1}^{j} i$, represents a sum. Here, i is called the index of the sum, and we add iterations until $i = j$. For example,

$$\sum_{i=1}^{j} i = 1 + 2 + \cdots + j$$

Another example:

$$a_{11} + a_{12} + a_{13} = \sum_{i=1}^{3} a_{1i}$$

The following notation is a specific use of summation notation.

Notation : Summation Notation

Let be real numbers, and suppose while . These numbers can be listed in a rectangular array as given by

Then means to first sum the numbers in each column (using as the index) and then to add the sums which result (using as the index). Similarly, means to sum the vectors in each row (using as the index) and then to add the sums which result (using as the index).

Notice that since addition is commutative,

We now consider the main concept of this section. Mathematical induction and well ordering are two extremely important principles in math. They are often used to prove significant things which would be hard to prove otherwise.

Definition : Well Ordered

A set is **well ordered** if every nonempty subset contains a smallest element having the property that for all

In particular, the set of natural numbers defined as is well ordered.

Consider the following proposition.

Proposition : Well Ordered Sets

Any set of integers larger than a given number is well ordered.

This proposition claims that if a set has a lower bound which is a real number, then this set is well ordered.

Further, this proposition implies the principle of mathematical induction. The symbol denotes the set of all integers. Note that if is an integer, then there are no integers between and

Theorem : Mathematical Induction

A set having the property that and whenever , contains all integers such that

Proof available at the end of this section.

Mathematical induction is a very useful device for proving theorems about the integers. The procedure is as follows.

Procedure : Proof by Mathematical Induction

Suppose is a statement which is a function of the number , for , and we wish to show that is true for all . To do so using mathematical induction, use the following steps.

1. **Base Case:** Show is true.
2. Assume is true for some , which is the **induction hypothesis**. Then, using this assumption, show that is true.

Proving these two steps shows that is true for all .

We can use this procedure to solve the following examples.

Example : Proving by Induction

Prove by induction that .

Solution

By Procedure , we first need to show that this statement is true for . When , the statement says that

The sum on the left hand side also equals , so this equation is true for .

Now suppose this formula is valid for some where is an integer. Hence, the following equation is true.

We want to show that this is true for .

Suppose we add to both sides of Equation .

The step going from the first to the second line is based on the assumption that the formula is true for Now simplify the expression in the second line,

This equals and

Therefore, showing the formula holds for whenever it holds for This proves the formula by mathematical induction. In other words, this formula is true for all .

Consider another example.

Example : Proving an Inequality by Induction

Show that for all ,

Solution

Again we will use the procedure given in Procedure to prove that this statement is true for all . Suppose . Then the statement says which is true.

Suppose then that the inequality holds for In other words, is true.

Now multiply both sides of this inequality by . This yields

The theorem will be proved if this last expression is less than This happens if and only if which occurs if and only if and this is clearly true which may be seen from expanding both sides. This proves the inequality.

Let's review the process just used. If is the set of integers at least as large as for which the formula holds, the first step was to

show and then that whenever it follows Therefore, by the principle of mathematical induction, contains all positive integers. In doing an inductive proof of this sort, the set is normally not mentioned. One just verifies the steps above.

Answers

Theorem $9.4.1$**: Mathematical Induction**

Let T consist of all integers larger than or equal to a which are not in S. The theorem will be proved if $T = \emptyset$. If $T \neq \emptyset$ then by the well ordering principle, there would have to exist a smallest element of T, denoted as b. It must be the case that $b > a$ since by definition, $a \notin T$. Thus $b \geq a + 1$, and so $b - 1 \geq a$ and $b - 1 \notin S$ because if $b - 1 \in S$, then $b - 1 + 1 = b \in S$ by the assumed property of S. Therefore, $b - 1 \in T$ which contradicts the choice of b as the smallest element of T. ($b - 1$ is smaller.) Since a contradiction is obtained by assuming $T \neq \emptyset$, it must be the case that $T = \emptyset$ and this says that every integer at least as large as a is also in S.

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