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INTRODUCTION TO LINEAR ALGEBRA WITH APPLICATIONS

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To The Student

You are probably taking this course early in your undergraduate studies after two or three semesters of calculus, and most likely in your second year. Like calculus, linear algebra is a subject with elegant theory and many diverse applications. However, in this course you will be exposed to abstraction at a much higher level. To help with this transition, some colleges and universities offer a Bridge Course to Higher Mathematics. If you have not already taken such a course, this may likely be the first mathematics course where you will be expected to read and understand proofs of theorems, provide proofs of results as part of the exercise sets, and apply the concepts presented. All this is in the context of a specific body of knowledge. If you approach this task with an open mind and a willingness to read the text, some parts perhaps more than once, it will be an exciting an operating experience. Whether you are taking this course as part of a pair backs major or because linear algebra is applied in your specific theat (f) thely, a clear understanding of the theory is essential for applying in concepts of linear algorit that hematics or other fields of science. The solve Lexamples and exercises in the text are designed to prepare you for the types of problems you can expect to see in this course and other more advanced courses in mathematics The organization of the material is based on our philosophy that each op. South be fully developed before readers move onto the next. The image of a tree on the front cover of the text is a metaphor for this learning strategy. It is particularly applicable to the study of mathematics. The trunk of the tree represents the material that forms the basis for everything that comes afterward. In our text, this material is contained in Chaps. 1 through 4. All other branches of the tree, representing more advanced topics and applications, extend from the foundational material of the trunk or from the ancillary material of the intervening branches. We have specifically designed our text so that you can read it and learn the concepts of linear algebra in a sequential and thorough manner. If you remain committed to learning this beautiful subject, the rewards will be significant in other courses you may take, and in your professional career. Good luck!

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Preview

1.2 Matrices and Elementary Row Operations 19

DEFINITION 2

Echelon Form An $m \times n$ matrix is in row echelon form if

- **1.** Every row with all 0 entries is below every row with nonzero entries.
- **2.** If rows 1, 2, ..., k are the rows with nonzero entries and if the leading nonzero entry (**pivot**) in row *i* occurs in column c_i , for 1, 2, ..., k, then $c_1 < c_2 < \cdots < c_k$.

The matrix is in reduced row echelon form if, in addition,

- **3.** The first nonzero entry of each row is a 1.
- 4. Each column that contains a pivot has all other entries 0.

The process of transforming a matrix to reduced row echelon form is called *Gauss-Jordan elimination*.



To transform the matrix into reduced row echelon form, we first use the leading 1 in row 1 as a pivot to eliminate the terms in column 1 of rows 2, 3, and 4. To do this, we use the three row operations

$$\begin{array}{c} -2R_1 + R_2 \rightarrow R_2 \\ R_1 + R_3 \rightarrow R_3 \\ -R_1 + R_4 \rightarrow R_4 \end{array}$$

in succession, transforming the matrix

1	-1	-2	1	0		1	-1	-2	1	0	
2	-1	-3	2	-6	4.5	0	1	1	0	-6	
-1	2	1	3	2	10	0	1	-1	4	2	
1	1	-1	2	1		0	2	1	1	1	

For the second step we use the leftmost 1 in row 2 as the pivot and eliminate the term in column 2 above the pivot, and the two terms below the pivot. The required row operations are

$$R_2 + R_1 \rightarrow R_1$$
$$-R_2 + R_3 \rightarrow R_3$$
$$-2R_2 + R_4 \rightarrow R_4$$

1.3 Matrix Algebra 27

then

$a_{11} = -2$	$a_{12} = 1$	$a_{13} = 4$
$a_{21} = 5$	$a_{22} = 7$	$a_{23} = 11$
$a_{31} = 2$	$a_{32} = 3$	$a_{33} = 22$

A vector is an $n \times 1$ matrix. The entries of a vector are called its components. For a given matrix A, it is convenient to refer to its *row vectors* and its *column vectors*. For example, let



Then the column vectors of *A* are

DEFINITION 1

Addition and Scalar Multiplication If *A* and *B* are two $m \times n$ matrices, then the **sum** of the matrices A + B is the $m \times n$ matrix with the *ij* term given by $a_{ij} + b_{ij}$. The **scalar product** of the matrix *A* with the real number *c*, denoted by *cA*, is the $m \times n$ matrix with the *ij* term given by ca_{ij} .

EXAMPLE 1	Perform the operations on the matrices	
	$A = \begin{bmatrix} 2 & 0 & 1 \\ 4 & 3 & -1 \\ -3 & 6 & 5 \end{bmatrix} \text{and} B = \begin{bmatrix} -2 & 3 & -1 \\ 3 & 5 & 6 \\ 4 & 2 & 1 \end{bmatrix}$	
	a. $A + B$ b. $2A - 3B$	

28 Chapter 1 Systems of Linear Equations and Matrices

Solution a. We add the two matrices by adding their corresponding entries, so that

$$A + B = \begin{bmatrix} 2 & 0 & 1 \\ 4 & 3 & -1 \\ -3 & 6 & 5 \end{bmatrix} + \begin{bmatrix} -2 & 3 & -1 \\ 3 & 5 & 6 \\ 4 & 2 & 1 \end{bmatrix}$$
$$= \begin{bmatrix} 2 + (-2) & 0 + 3 & 1 + (-1) \\ 4 + 3 & 3 + 5 & -1 + 6 \\ -3 + 4 & 6 + 2 & 5 + 1 \end{bmatrix}$$
$$= \begin{bmatrix} 0 & 3 & 0 \\ 7 & 8 & 5 \\ 1 & 8 & 6 \end{bmatrix}$$

b. To evaluate this expression, we first multiply each entry of the matrix A by 2 and each entry of the matrix B by -3. Then we add the resulting matrices. This gives



In Example 1(a) reversing the order of the addition of the matrices gives the same result. That is, A + B = B + A. This is so because addition of real numbers is commutative. This result holds in general, giving us that matrix addition is also a commutative operation. Some other familiar properties that hold for real numbers also hold for matrices and scalars. These properties are given in Theorem 4.

THEOREM 4

Properties of Matrix Addition and Scalar Multiplication Let A, B, and C be $m \times n$ matrices and c and d be real numbers.

- **1.** A + B = B + A
- **2.** A + (B + C) = (A + B) + C
- **3.** c(A + B) = cA + cB
- **4.** (c+d)A = cA + dA
- **5.** c(dA) = (cd)A
- 6. The $m \times n$ matrix with all zero entries, denoted by 0, is such that A + 0 = 0 + A = A.
- 7. For any matrix A, the matrix -A, whose components are the negative of each component of A, is such that A + (-A) = (-A) + A = 0.

Chapter 1 Systems of Linear Equations and Matrices

Observe that the dot product of two vectors is a scalar. For example,

$$\begin{bmatrix} 2\\-3\\-1 \end{bmatrix} \cdot \begin{bmatrix} -5\\1\\4 \end{bmatrix} = (2)(-5) + (-3)(1) + (-1)(4) = -17$$

Now to motivate the concept and need for matrix multiplication we first introduce the operation of multiplying a vector by a matrix. As an illustration let

$$B = \begin{bmatrix} 1 & -1 \\ -2 & 1 \end{bmatrix} \quad \text{and} \quad \mathbf{v} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$$

The **product** of *B* and **v**, denoted by $B\mathbf{v}$, is a vector, in this case with two components. The first component of $B\mathbf{v}$ is the dot product of the first row vector of *B* with **v**, while the second component is the dot product of the second row vector of *B* with **v**, so that

$$B\mathbf{v} = \begin{bmatrix} 1 & -1 \\ -2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} (1)(1) + (-1)(3) \\ (-2)(1) + (1)(3) \end{bmatrix} \mathbf{v} \begin{bmatrix} -2 \\ 1 \end{bmatrix}$$
Using this operation, the matrix *B* reactions the vector $\mathbf{v} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$ to the vector
$$B\mathbf{v} = \begin{bmatrix} -2 \\ 1 \end{bmatrix}$$
If $\mathbf{v} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$ is another matrix, then the product of *A* and *B*v
is given by
$$\mathbf{A} = \begin{bmatrix} -1 & 2 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} -2 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 1 \end{bmatrix}$$
Restriction then arises, is there a single matrix which can be used to transform
the original vector $\begin{bmatrix} 1 \\ 3 \end{bmatrix}$ to $\begin{bmatrix} 4 \\ 1 \end{bmatrix}$? To answer this question, let
$$\mathbf{v} = \begin{bmatrix} x \\ y \end{bmatrix}$$

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$
and
$$B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

The product of B and \mathbf{v} is

$$B\mathbf{v} = \left[\begin{array}{c} b_{11}x + b_{12}y\\b_{21}x + b_{22}y\end{array}\right]$$

Now, the product of A and $B\mathbf{v}$ is

$$A(B\mathbf{v}) = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} b_{11}x + b_{12}y \\ b_{21}x + b_{22}y \end{bmatrix}$$
$$= \begin{bmatrix} a_{11}(b_{11}x + b_{12}y) + a_{12}(b_{21}x + b_{22}y) \\ a_{21}(b_{11}x + b_{12}y) + a_{22}(b_{21}x + b_{22}y) \end{bmatrix}$$
$$= \begin{bmatrix} (a_{11}b_{11} + a_{12}b_{21})x + (a_{11}b_{12} + a_{12}b_{22})y \\ (a_{21}b_{11} + a_{22}b_{21})x + (a_{21}b_{12} + a_{22}b_{22})y \end{bmatrix}$$
$$= \begin{bmatrix} a_{11}b_{11} + a_{12}b_{21} & a_{11}b_{12} + a_{12}b_{22} \\ a_{21}b_{11} + a_{22}b_{21} & a_{21}b_{12} + a_{22}b_{22} \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

30

- **37.** Suppose that *A* is an $n \times n$ matrix. Show that if for each vector **x** in \mathbb{R}^n , $A\mathbf{x} = \mathbf{0}$, then *A* is the zero matrix.
- **38.** For each positive integer n, let

 $A_n = \left[\begin{array}{cc} 1-n & -n \\ n & 1+n \end{array} \right]$

Show that $A_n A_m = A_{n+m}$.

Preview

- **39.** Find all 2×2 matrices that satisfy $AA^t = \mathbf{0}$.
- **40.** Suppose that A and B are symmetric matrices. Show that if AB = BA, then AB is symmetric.
- **41.** If A is an $m \times n$ matrix, show that AA^t and A^tA are both defined and are both symmetric.

- 1.4 The Inverse of a Square Matrix **39**
- **42.** An $n \times n$ matrix A is called *idempotent* provided that $A^2 = AA = A$. Suppose that A and B are $n \times n$ idempotent matrices. Show that if AB = BA, then the matrix AB is idempotent.
- **43.** An $n \times n$ matrix A is *skew-symmetric* provided $A^t = -A$. Show that if a matrix is skew-symmetric, then the diagonal entries are 0.
- 44. The trace of an $n \times n$ matrix A is the sum of the diagonal terms, denoted tr(A).
 - **a.** If A and B are $n \times n$ matrices, show that $\mathbf{tr}(A + B) = \mathbf{tr}(A) + \mathbf{tr}(B)$.
 - **b.** If A is an $n \times n$ matrix and c is a scalar, show that $\operatorname{tr}(cA) = c \operatorname{tr}(A)$

1.4 ► The Inverse of a Square Pater

In the real number of the number 1 is the multiplicative identity. That is, for any

We also know per followery number x with $x \neq 0$, there exists the number $\frac{1}{x}$, also write: O^{-1} , such that $x \cdot \frac{1}{x} = 1$

We seek a similar relationship for square matrices. For an $n \times n$ matrix A, we can check that the $n \times n$ matrix

	1	0	0	• • •	0]
	0	1	0	• • •	0
I =	0	0	1		0
1 -					.
	:	:	:	••	:
	0	0	0		1

is the **multiplicative identity**. That is, if A is any $n \times n$ matrix, then

$$AI = IA = A$$

This special matrix is called the **identity matrix**. For example, the 2×2 , 3×3 , and 4×4 identity matrices are, respectively,

	Γ1 (h	0]		1	0	0	0
$\begin{bmatrix} 1 & 0 \end{bmatrix}$) 1		1	0	1	0	0
0 1		1		and	0	0	1	0
		J			0	0	0	1

40 Chapter 1 Systems of Linear Equations and Matrices

DEFINITION 1 Inverse of a Square Matrix Let A be an $n \times n$ matrix. If there exists an $n \times n$ matrix B such that

$$AB = I = BA$$

then the matrix B is a (multiplicative) **inverse** of the matrix A.



Theorem 7 establishes the uniqueness, when it exists, of the multiplicative inverse.

THEOREM 7 The inverse of a matrix, if it exists, is unique.

Proof Assume that the square matrix A has an inverse and that B and C are both inverse matrices of A. That is, AB = BA = I and AC = CA = I. We show that B = C. Indeed,

$$B = BI = B(AC) = (BA)C = (I)C = C$$

Chapter 1 Systems of Linear Equations and Matrices

then

To illustrate the use of the formula, let

$$A^{-1} = \frac{1}{6 - (-1)} \begin{bmatrix} 3 & 1 \\ -1 & 2 \end{bmatrix} = \begin{bmatrix} \frac{3}{7} & \frac{1}{7} \\ -\frac{1}{7} & \frac{2}{7} \end{bmatrix}$$

 $A = \left[\begin{array}{cc} 2 & -1 \\ 1 & 3 \end{array} \right]$

For an example which underscores the necessity of the condition that $ad - bc \neq 0$, we consider the matrix

$$A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$$

 $\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 & x_2 \\ x_3 & x_4 \end{bmatrix} = \begin{bmatrix} \\ \end{bmatrix}$

Observe that in this case ad - bc = 1 - 1 = 0. Now, the matrix A is invertible if there is a $B = \begin{bmatrix} x_1 & x_2 \\ x_3 & x_4 \end{bmatrix}$ such that

This matrix equation yields the inconsistent syst m

Note

mvei ible

Preview Hence, A is not verse of larger square matrices, we extend the method of augrices. Let A be an $n \times n$ matrix. Let B be another $n \times n$ matrix, and let $\mathbf{B}_1, \mathbf{B}_2, \dots, \mathbf{B}_n$ denote the *n* column vectors of *B*. Since $A\mathbf{B}_1, A\mathbf{B}_2, \dots, A\mathbf{B}_n$ are the column vectors of AB, in order for B to be the inverse of A, we must have

$$A\mathbf{B}_{1} = \begin{bmatrix} 1\\0\\\vdots\\0 \end{bmatrix} \qquad A\mathbf{B}_{2} = \begin{bmatrix} 0\\1\\\vdots\\0 \end{bmatrix} \qquad \dots \qquad A\mathbf{B}_{n} = \begin{bmatrix} 0\\0\\\vdots\\1 \end{bmatrix}$$

That is, the matrix equations

$$A\mathbf{x} = \begin{bmatrix} 1\\0\\\vdots\\0 \end{bmatrix} \qquad A\mathbf{x} = \begin{bmatrix} 0\\1\\\vdots\\0 \end{bmatrix} \qquad \dots \qquad A\mathbf{x} = \begin{bmatrix} 0\\0\\\vdots\\1 \end{bmatrix}$$

must all have unique solutions. But all n linear systems can be solved simultaneously by row-reducing the $n \times 2n$ augmented matrix

a_{11}	a_{12}	• • •	a_{1n}	1	0		0
a_{21}	a_{22}		a_{2n}	0	1		0
÷	÷	۰.	÷	:	÷	۰.	÷
a_{n1}	a_{n2}		a_{nn}	0	0		1

42

On the left is the matrix A, and on the right is the matrix I. Then A will have an inverse if and only if it is row equivalent to the identity matrix. In this case, each of the linear systems can be solved. If the matrix A does not have an inverse, then the row-reduced matrix on the left will have a row of zeros, indicating at least one of the linear systems does not have a solution.

Example 2 illustrates the procedure.



[1	-1	2	1	0	0	٦
3	-3	1	0	1	0	
3	-3	1	0	0	1	

1.6 Determinants 57

Some examples of upper triangular matrices are $\begin{bmatrix} 1 & 1 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 2 & -1 & 0 \\ 0 & 0 & 3 \\ 0 & 0 & 2 \end{bmatrix} \text{ and } \begin{bmatrix} 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 \end{bmatrix}$ and some examples of lower triangular matrices are $\begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 2 \end{bmatrix} \text{ and } \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 3 & 1 & 0 \\ 0 & 1 & 2 & 1 \end{bmatrix}$ **THEOREM 13** If A is an $n \times n$ triangular matrix, then the determinant of A is the product of the terms on the diagonal. That is, $\det(A) = a_{11} \cdot a_{22} \cdots a_{nn}$ **Proof** We present the proof for an upper triangulat have. The proof for a lower triangular matrix is identical. The proof is by induction on n. If n = 2, then $det(A) = a_{11}a_{22} - 0$ and hence is the induction of the diagonal terms. Assume that the result of an $n \times n$ triangular matrix. We need to show $(n+1) \times (n+1)$ triangular matrix A. To this end let that the same Preview from Page 7 6 A =Using the cofactor expansion along row n + 1, we have

$$\det(A) = (-1)^{(n+1)+(n+1)} a_{n+1,n+1} \begin{vmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ 0 & a_{22} & a_{23} & \cdots & a_{2n} \\ 0 & 0 & a_{33} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & a_{nn} \end{vmatrix}$$

Since the determinant on the right is $n \times n$ and upper triangular, by the inductive hypothesis

 $det(A) = (-1)^{2n+2} (a_{n+1,n+1}) (a_{11}a_{22} \cdots a_{nn})$ = $a_{11}a_{22} \cdots a_{nn}a_{n+1,n+1}$

Properties of Determinants

Determinants for large matrices can be time-consuming to compute, so any properties of determinants that reduce the number of computations are useful. Theorem 14 shows how row operations affect the determinant.

EXAMPLE 6

Use Cramer's rule to solve the linear system.

$$2x + 3y = 2$$
$$-5x + 7y = 3$$

Solution The determinant of the coefficient matrix is given by

$$\begin{vmatrix} 2 & 3 \\ -5 & 7 \end{vmatrix} = 14 - (-15) = 29$$

and since the determinant is not zero, the system has a unique solution. The solution is given by

THEOREM 18

$$x = \frac{\begin{vmatrix} 2 & 3 \\ 3 & 7 \\ 29 \end{vmatrix}}{\begin{vmatrix} 29 \\ 29 \end{vmatrix}} = \frac{14 - 9}{29} = \frac{5}{29} \text{ and } y = \frac{\begin{vmatrix} 2 & 2 \\ -5 & 3 \\ 29 \\ 29 \end{vmatrix}}{=} \frac{6 - (-10)}{29} = \frac{16}{29}$$
THEOREM 18
Cramer's Rule Let **Lie and C** invertible matrix, and let **b** be a column vector with *n* components (1) to *i*_i be the matrix obtained by replacing the *i*th column of *A*
Where Note Constrained Where Constrained Constrained Where Constrained Constrained Constrained Where Constrained Where Constrained Where Constrained Constrained Constrained Where Constrained Constrained Where Constrained Constrain

Proof Let I_i be the matrix obtained by replacing the *i*th column of the identity matrix with **x**. Then the linear system is equivalent to the matrix equation

$$AI_i = A_i$$
 so $det(AI_i) = det(A_i)$

By Theorem 15, part 1, we have

$$\det(A) \det(I_i) = \det(AI_i) = \det(A_i)$$

Since A is invertible, $det(A) \neq 0$ and hence

$$\det(I_i) = \frac{\det(A_i)}{\det(A)}$$

Expanding along the *i*th row to find the determinant of I_i gives

$$\det(I_i) = x_i \det(I) = x_i$$

where I is the $(n-1) \times (n-1)$ identity. Therefore,

$$x_i = \frac{\det(A_i)}{\det(A)}$$

Chapter 1 Systems of Linear Equations and Matrices

39. a. Find the equation of the parabola in the form

$$Cy^2 + Dx + Ey + F = 0$$

that passes through the points (-2, -2), (3, 2), and (4, -3).

- **b.** Sketch the graph of the parabola.
- 40. a. Find the equation of the circle in the form

$$A(x^{2} + y^{2}) + Dx + Ey + F = 0$$

that passes through the points (-3, -3), (-1, 2), and (3, 0).

- **b.** Sketch the graph of the circle.
- 41. a. Find the equation of the hyperbola in the form

$$Ax^2 + Cy^2 + Dx + Ey + F = 0$$

that passes through the points (0, -4), (0, 4), (1, -2), and (2, 3).

- **b.** Sketch the graph of the hyperbola.
- 42. a. Find the equation of the ellipse

that has sets through the points (-2)(0, 1, 2)b. Sketch the graph of the ellipse.

43. a. Find the equation of the ellipse in the form

$$Ax^2 + Bxy + Cy^2 + Dx + Ey + F = 0$$

that passes through the points (-1, 0), (0, 1), (1, 0), (2, 2), and (3, 1).

b. Sketch the graph of the ellipse.

In Exercises 44–51, use Cramer's rule to solve the linear system.

44.
$$\begin{cases} 2x + 3y = 4\\ 2x + 2y = 4 \end{cases}$$

45.
$$\begin{cases} 5x - 5y = 7\\ 2x - 3y = 6 \end{cases}$$

46.
$$\begin{cases} 2x + 5y = 4\\ 4x + y = 3 \end{cases}$$

47.
$$\begin{cases} -9x - 4y = 3\\ -7x + 5y = -10 \end{cases}$$

48.
$$\begin{cases} -10x - 7y = -12\\ 12x + 11y = 5 \end{cases}$$

49.
$$\begin{cases} -x - 3y = 4\\ -8x + 4y = 3 \end{cases}$$

49.
$$\begin{cases} -x - 3y = 4\\ -8x + 4y = 3 \end{cases}$$

50.
$$\begin{cases} 4y + z = -8\\ 4y + z = -8\\ -x - 3y - z = -8 \end{cases}$$

51.
$$\begin{cases} 2x + 3y + 2z = -2\\ -x - 3y - 8z = -2\\ -3x + 2y - 7z = 2 \end{cases}$$

- **52.** An $n \times n$ matrix is *skew-symmetric* provided $A^t = -A$. Show that if A is skew-symmetric and n is an odd positive integer, then A is not invertible.
- **53.** If A is a 3×3 matrix, show that $det(A) = det(A^t)$.
- **54.** If A is an $n \times n$ upper triangular matrix, show that $det(A) = det(A^t)$.

1.7 Elementary Matrices and LU Factorization

In Sec. 1.2 we saw how the linear system $A\mathbf{x} = \mathbf{b}$ can be solved by using Gaussian elimination on the corresponding augmented matrix. Recall that the idea there was to use row operations to transform the coefficient matrix to row echelon form. The upper triangular form of the resulting matrix made it easy to find the solution by using back substitution. (See Example 1 of Sec. 1.2.) In a similar manner, if an augmented matrix is reduced to lower triangular form, then *forward substitution* can be used to find the solution of the corresponding linear system. For example, starting from the

68

Chapter 1 Systems of Linear Equations and Matrices

Using forward substitution, we solve the system Ly = b for y, obtaining $y_1 = 1$, $y_2 = 5$, and $y_3 = 10$. Next we solve the linear system $U\mathbf{x} = \mathbf{y}$. That is,

1	2	-1	$\begin{bmatrix} x_1 \end{bmatrix}$		1]
0	3	1	<i>x</i> ₂	=	5	
0	0	5	<i>x</i> ₃		10	

Using back substitution, we obtain $x_3 = 2$, $x_2 = 1$, and $x_1 = 1$.

The following steps summarize the procedure for solving the linear system $A\mathbf{x} = \mathbf{b}$ when A admits an LU factorization.

- **1.** Use Theorem 23 to write the linear system $A\mathbf{x} = \mathbf{b}$ as $L(U\mathbf{x}) = \mathbf{b}$.
- 2. Define the vector **y** by means of the equation $U\mathbf{x} = \mathbf{y}$.
- **3.** Use forward substitution to solve the system $L\mathbf{y} = \mathbf{b}$ for \mathbf{y} .
- 4. Use back substitution to solve the system $U\mathbf{x} = \mathbf{y}$ for \mathbf{x} . Note that \mathbf{x} is the solution e.co.uk to the original linear system.

PLU Factorization

We have seen that a matrix an LU factorization provided that it can be rowwithout it is charging rows. We conclude this section by noting that when a finite are required to reduce A a factorization is still possible. In this matrix A can be required as A = PLU, where P is a *permutation matrix*, a matrix that each provide the section of the identity matrix. As an reduced without

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

The matrix A can be reduced to

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

by means of the row operations \mathcal{R}_1 : $R_1 \leftrightarrow R_3$, \mathcal{R}_2 : $-R_1 + R_2 \longrightarrow R_2$, and $\mathcal{R}_3: -R_2 + R_3 \longrightarrow R_3$. The corresponding elementary matrices are given by

$$E_1 = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix} \qquad E_2 = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad \text{and} \qquad E_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix}$$

76

Preview

77 1.7 Elementary Matrices and LU Factorization

Observe that the elementary matrix E_1 is a permutation matrix while E_2 and E_3 are lower triangular. Hence,

$$A = E_1^{-1} \left(E_2^{-1} E_3^{-1} \right) U$$

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

Fact Summary

- **1.** A row operation on a matrix A can be performed by multiplying A by an elementary matrix.
- 2. An elementary matrix is invertible, and the inverse that elementary matrix.
- 3. An $n \times n$ matrix A is invertible if and only if it is the product of elementary matrices.

then L is it

- **4.** An $m \times n$ matrix A-has an factorization if it can be reduced to an with no row interchanges. upper tria
- eview fro. An LU factorization ercise Set 1929 of A provides an efficient method for solving $A\mathbf{x} = \mathbf{b}$.

In Exercises 1-4:

Exercise Set

- **a.** Find the 3×3 elementary matrix *E* that performs the row operation.
- **b.** Compute EA, where

$$A = \left[\begin{array}{rrrr} 1 & 2 & 1 \\ 3 & 1 & 2 \\ 1 & 1 & -4 \end{array} \right]$$

1. $2R_1 + R_2 \longrightarrow R_2$

2.
$$R_1 \leftrightarrow R_2$$

3.
$$-3R_2 + R_3 \longrightarrow R_3$$

4.
$$-R_1 + R_3 \longrightarrow R_3$$

In Exercises 5–10:

a. Find the elementary matrices required to reduce A to the identity.

b. Write A as the product of elementary matrices.

5.
$$A = \begin{bmatrix} 1 & 3 \\ -2 & 4 \end{bmatrix}$$

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

1.8 Applications of Systems of Linear Equations

85

8. Find the traffic flow pattern for the network in the figure. Flow rates are in cars per half-hour. What is the smallest possible value for x_8 ?



9. The table lists the number of milligrams of vitamin A, vitamin B, ettamin C, and niacin contrared at a g of four different foods. A detectant wants to prepare a meal that provides 250 mg of vitamin A, 300 mg of vitamin B, 400 mg at Paamin C, and 70 mg of niacin. Determine 100 many grams of each food must be included, and describe any limitations on the quantities of each food that can be used.

	Group 1	Group 2	Group 3	Group 4
Vitamin A	20	30	40	10
Vitamin B	40	20	35	20
Vitamin C	50	40	10	30
Niacin	5	5	10	5

10. The table lists the amounts of sodium, potassium, carbohydrates, and fiber in a single serving of three food groups. Also listed are the daily recommended amounts based on a 2000-calorie diet. Is it possible to prepare a diet using the three food groups alone that meets the recommended amounts?



6. Find the traffic flow pattern for the network in the figure. Flow rates are in cars per hour. Give one specific solution.



7. Find the traffic flow pattern for the network in the figure. Flow rates are in cars per half-hour. What is the current status of the road labeled *x*₅?



Chapter 1 Systems of Linear Equations and Matrices

7. a. Explain why the matrix

$$A = \begin{vmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{vmatrix}$$

is invertible.

- **b.** Determine the maximum number of 1's that can be added to *A* such that the resulting matrix is invertible.
- 8. Show that if A is invertible, then A^t is invertible and $(A^t)^{-1} = (A^{-1})^t$.

9. A matrix A is skew-symmetric provided A^t = −A.
a. Let A be an n × n matrix and define

 $B = A + A^t$ and $C = A - A^t$

Show that B is symmetric and C is skew-symmetric.

- **b.** Show that every $n \times n$ matrix can be written as the sum of a symmetric and a skew-symmetric matrix.
- **10.** Suppose **u** and **v** are solutions to the linear system $A\mathbf{x} = \mathbf{b}$. Show that if scalars α and β satisfy $\alpha + \beta = 1$, then $\alpha \mathbf{u} + \beta \mathbf{v}$ is also a solution to the linear system $A\mathbf{x} = \mathbf{b}$.

0 2

-2

4

Chapter 1: Chapter Test

In Exercises 1-45, determine whether the statement true or false.

 A 2 × 2 linear system has the solution, solutions, or infinitely many solutions.
 A 3 × 3 linear system has no solutions.

solution, two solutions three valuons, or infinitely many solutions.

- **3.** If A and B are $n \times n$ matrices with no zero entries, then $AB \neq 0$.
- **4.** Homogeneous linear systems always have at least one solution.
- 5. If A is an $n \times n$ matrix, then $A\mathbf{x} = \mathbf{0}$ has a nontrivial solution if and only if the matrix A has an inverse.
- 6. If A and B are $n \times n$ matrices and $A\mathbf{x} = B\mathbf{x}$ for every $n \times 1$ matrix \mathbf{x} , then A = B.
- 7. If A, B, and C are invertible $n \times n$ matrices, then $(ABC)^{-1} = A^{-1}B^{-1}C^{-1}$.
- 8. If A is an invertible $n \times n$ matrix, then the linear system $A\mathbf{x} = \mathbf{b}$ has a unique solution.
- 9. If A and B are $n \times n$ invertible matrices and AB = BA, then A commutes with B^{-1} .
- **10.** If A and B commute, then $A^2B = BA^2$.

does not have an inverse.

0

0

0

12. Interchanging two rows of a matrix changes the sign of its determinant.

0

- **13.** Multiplying a row of a matrix by a nonzero constant results in the determinant being multiplied by the same nonzero constant.
- **14.** If two rows of a matrix are equal, then the determinant of the matrix is 0.
- **15.** Performing the operation $aR_i + R_j \rightarrow R_j$ on a matrix multiplies the determinant by the constant *a*.

16. If
$$A = \begin{bmatrix} 1 & 2 \\ 4 & 6 \end{bmatrix}$$
, then $A^2 - 7A = 2I$.

- 17. If A and B are invertible matrices, then A + B is an invertible matrix.
- **18.** If *A* and *B* are invertible matrices, then *AB* is an invertible matrix.

1.8 Applications of Systems of Linear Equations 9

32. The solution to the system is given by the matrix

91

- 19. If A is an $n \times n$ matrix and A does not have an inverse, then the linear system $A\mathbf{x} = \mathbf{b}$ is inconsistent.
- **20.** The linear system

[1	2	3]	x		[1]	
6	5	4	y	=	2	
0	0	0			3	
isten	t.					

is inconsistent.

21. The inverse of the matrix

$$\begin{bmatrix} 2 & -1 \\ 3 & 1 \end{bmatrix} \quad \text{is} \quad \begin{bmatrix} 1 & 1 \\ -3 & 2 \end{bmatrix}$$

 $-1 \\ -2$

Q

22. The matrix

does not have an inverse.

- **23.** If the $n \times n$ matrix A is idempotent and invertible, then A = I.
- **24.** If A and B commute, then A^t and B
- **25.** If A is an $n \times n$ matrix at 1 = (A) =
- det($A^{T}A$) = 9 In Figure 20-32, use the linear extent 2x + 2y = 3x - y = 1
 - **26.** The coefficient matrix is

$$A = \left[\begin{array}{cc} 2 & 2 \\ 1 & -1 \end{array} \right]$$

27. The coefficient matrix *A* has determinant

 $\det(A) = 0$

- 28. The linear system has a unique solution.
- **29.** The only solution to the linear system is x = -7/4 and y = -5/4.
- **30.** The inverse of the coefficient matrix A is

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

31. The linear system is equivalent to the matrix equation

$$\begin{bmatrix} 2 & 2 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \end{bmatrix}$$

equation $\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \frac{1}{4} & \frac{1}{2} \\ \frac{1}{4} & -\frac{1}{2} \end{bmatrix} \begin{bmatrix} 3 \\ 1 \end{bmatrix}$

In Exercises 33–36, use the linear system

$(x_1 + 2x_2 - 3x_3 =$	1
$2x_1 + 5x_2 - 8x_3 =$	4
$(-2x_1 - 4x_2 + 6x_3 = -$	-2

33. The determinant of the coefficient matrix is

$$\begin{vmatrix} 5 & -8 \\ -4 & 6 \end{vmatrix} + \begin{vmatrix} 2 & -8 \\ -2 & 6 \end{vmatrix} + \begin{vmatrix} 2 & 5 \\ -2 & -4 \end{vmatrix}$$

- 34. The determinant of the coefficient matrix is 0.
 35. A solution control includes system is x₁ = −4, x₂ = 0, and x₃ = −1.
 - The linear system has infinitely many solutions, and the reneral solution is given by x_3 is free,

$$x_1 = -3 - x_3$$
, and $x_1 = -3 - x_3$.

In Exercises 37–41, use the matrix

	-1	-2	1	3]	
A =	1	0	1	-1	
	2	1	2	1	

37. After the operation $R_1 \leftrightarrow R_2$ is performed, the matrix becomes

-	1	0	1	-1]
_	-1	-2	1	3
_	2	1	2	1

38. After the operation $-2R_1 + R_3 \longrightarrow R_3$ is performed on the matrix found in Exercise 37, the matrix becomes

39. The matrix A is row equivalent to

1	0	1	-1
0	-2	2	2
0	0	1	4

Chapter 2 Linear Combinations and Linear Independence

- 3. Additive identity: The vector 0 satisfies 0 + u = u + 0 = u.
 4. Additive inverse: For every vector u, the vector -u satisfies u + (-u) = -u + u = 0.
 5. c(u + v) = cu + cv
 6. (c + d)u = cu + du
 7. c(du) = (cd)u
- **8.** (1)**u** = **u**

By the associative property, the vector sum $\mathbf{u}_1 + \mathbf{u}_2 + \cdots + \mathbf{u}_n$ can be computed unambiguously, without the need for parentheses. This will be important in Sec. 2.2.



The properties given in Theorem 1 can be used to establish other useful properties of vectors in \mathbb{R}^n . For example, if $\mathbf{u} \in \mathbb{R}^n$ and *c* is a scalar, then

$$0\mathbf{u} = 0 \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \mathbf{0} \quad \text{and} \quad c\mathbf{0} = \mathbf{0}$$

98



In three-dimensional Euclidean space \mathbb{R}^3 the *coordinate vectors* that define the three axes are the vectors

$$\mathbf{e}_1 = \begin{bmatrix} 1\\0\\0 \end{bmatrix} \qquad \mathbf{e}_2 = \begin{bmatrix} 0\\1\\0 \end{bmatrix} \qquad \text{and} \qquad \mathbf{e}_3 = \begin{bmatrix} 0\\0\\1 \end{bmatrix}$$

Every vector in \mathbb{R}^3 can then be obtained from these three coordinate vectors, for example, the vector

$$\mathbf{v} = \begin{bmatrix} 2\\3\\3 \end{bmatrix} = 2 \begin{bmatrix} 1\\0\\0 \end{bmatrix} + 3 \begin{bmatrix} 0\\1\\0 \end{bmatrix} + 3 \begin{bmatrix} 0\\0\\1 \end{bmatrix}$$

Geometrically, the vector \mathbf{v} is obtained by adding scalar multiples of the coordinate vectors, as shown in Fig. 1. The vectors \mathbf{e}_1 , \mathbf{e}_2 , and \mathbf{e}_3 are not unique in this respect. For example, the vector \mathbf{v} can also be written as a combination of the vectors

$$\mathbf{v}_1 = \begin{bmatrix} 1\\1\\1 \end{bmatrix} \qquad \mathbf{v}_2 = \begin{bmatrix} 0\\1\\1 \end{bmatrix} \qquad \text{and} \qquad \mathbf{v}_3 = \begin{bmatrix} -1\\1\\1 \end{bmatrix}$$



In Exercises 13-16, find all the ways that v can be written as a linear combination of the given vectors. $\mathbf{v}_k, c\mathbf{v}_k$, where *c* is a nonzero scalar. Show that $S_1 = S_2$.

- **36.** Let S_1 be the set of all linear combinations of the vectors $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k$ in \mathbb{R}^n , and S_2 be the set of all linear combinations of the vectors $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k, \mathbf{v}_1 + \mathbf{v}_2$. Show that $S_1 = S_2$.
- **37.** Suppose that $A\mathbf{x} = \mathbf{b}$ is a 3 × 3 linear system that is consistent. If there is a scalar *c* such that $\mathbf{A}_3 = c\mathbf{A}_1$, then show that the linear system has infinitely many solutions.
- **38.** Suppose that $A\mathbf{x} = \mathbf{b}$ is a 3 × 3 linear system that is consistent. If $\mathbf{A}_3 = \mathbf{A}_1 + \mathbf{A}_2$, then show that the linear system has infinitely many solutions.
- **39.** The equation

$$2y'' - 3y' + y = 0$$

is an example of a *differential equation*. Show that $y = f(x) = e^x$ and $y = g(x) = e^{\frac{1}{2}x}$ are solutions to the equation. Then show that any linear combination of f(x) and g(x) is another solution to the differential equation.

2.3 Linear Independence

In Sec. 2.2 we saw that given a set S of vectors in \mathbb{R}^{1} is not always possible to express every vector in \mathbb{R}^n as a linear contribution of vectors from S. At the other extreme, there are infinitely much lift out subsets S such that the collection of all linear combinations of extra from S is \mathbb{R}^n . For example, the collection of all linear combination of the set of coordinate vectors $S = {\bf e}_1, ..., {\bf e}_n$ is \mathbb{R}^n , but so is the effection of linear combinations of $T = {\bf e}_1, ..., {\bf e}_n, {\bf e}_1 + {\bf e}_2$. In this way S and V both generate \mathbb{R}^n . To characterize those minimal sets S that generate \mathbb{R}^n , we require the concept of *linear independence*. As motivation let two vectors **u** and **v** in \mathbb{R}^2 . on the case ine, as shown in Fig. 1. Thus, there is a nonzero scalar c such Figure 1 $\mathbf{u} = c\mathbf{v}$ This condition can also be written as $\mathbf{u} - c\mathbf{v} = \mathbf{0}$ u In this case we say that the vectors \mathbf{u} and \mathbf{v} are *linearly dependent*. Evidently we have that two vectors \mathbf{u} and \mathbf{v} are linearly dependent provided that the zero vector is a nontrivial (not both scalars 0) linear combination of the vectors. On the other hand, the vectors shown in Fig. 2 are not linearly dependent. This concept is generalized to sets of vectors in \mathbb{R}^n . Figure 2 **DEFINITION 1 Linearly Indpendent and Linearly Dependent** The set of vectors S = $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m\}$ in \mathbb{R}^n is **linearly independent** provided that the only solution to the equation

> $c_1\mathbf{v}_1 + c_2\mathbf{v}_2 + \dots + c_m\mathbf{v}_m = \mathbf{0}$ is the trivial solution $c_1 = c_2 = \dots = c_m = 0$. If the above linear combination has a nontrivial solution, then the set *S* is called **linearly dependent**.

Chapter 2 Linear Combinations and Linear Independence

c. Show that the matrix

$$M = \left[\begin{array}{cc} 0 & 3 \\ 3 & 1 \end{array} \right]$$

cannot be written as a linear combination of M_1 , M_2 , and M_3 .

In Exercises 25 and 26, for the given matrix A determine if the linear system $A\mathbf{x} = \mathbf{b}$ has a unique solution.

$$25. A = \begin{bmatrix} 1 & 2 & 0 \\ -1 & 0 & 3 \\ 2 & 1 & 2 \end{bmatrix}$$
$$26. A = \begin{bmatrix} 3 & 2 & 4 \\ 1 & -1 & 4 \\ 0 & 2 & -4 \end{bmatrix}$$

provided

F

In Exercises 27-30, determine whether the set of polynomials is linearly independent or linearly dependent. A set of polynomials $S = \{p_1(x), p_2(x), \dots, p_n(x)\}$ is linearly independent

$$c_1 p_1(x) + c_2 p_2(x) + 1 + ... p_n(x)$$

for all x insplies for
 $c_1 = c_1 = c_2 = 0 = 0$

27.
$$p_1(x) = 1 p_2(x) = -2 + 4x^2$$

 $p_3(x) = 2x p_4(x) = -12x + 8x^3$

28.
$$p_1(x) = 1$$
 $p_2(x) = x$
 $p_3(x) = 5 + 2x - x^2$

29.
$$p_1(x) = 2 p_2(x) = x p_3(x) = x^2$$

 $p_4(x) = 3x - 1$

30.
$$p_1(x) = x^3 - 2x^2 + 1$$
 $p_2(x) = 5x$
 $p_3(x) = x^2 - 4$ $p_4(x) = x^3 + 2x$

In Exercises 31-34, show that the set of functions is linearly independent on the interval [0, 1]. A set of functions $S = \{f_1(x), f_2(x), \dots, f_n(x)\}$ is linearly independent on the interval [a, b] provided

$$c_1 f_1(x) + c_2 f_2(x) + \dots + c_n f_n(x) = 0$$

for all $x \in [a, b]$ implies that

$$c_1=c_2=\cdots=c_n=0$$

31. $f_1(x) = \cos \pi x \ f_2(x) = \sin \pi x$

32.
$$f_1(x) = e^x f_2(x) = e^{-x}$$

 $f_3(x) = e^{2x}$

33. $f_1(x) = x f_2(x) = x^2 f_3(x) = e^x$

34.
$$f_1(x) = x f_2(x) = e^{x}$$

 $f_3(x) = \sin \pi x$

- **35.** Verify that two vectors **u** and **v** in \mathbb{R}^n are linearly dependent if and only if one is a scalar multiple of the other.
- **36.** Suppose that $S = {\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3}$ is linearly independent and

$$\mathbf{w}_1 = \mathbf{v}_1 + \mathbf{v}_2 + \mathbf{v}_3 \qquad \mathbf{w}_2 = \mathbf{v}_2 + \mathbf{v}_3$$

and
$$\mathbf{C} \mathbf{W}_3 = \mathbf{v}_3$$

the tran $T = {\mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3}$ is linearly
independent.

Suppose the $S = {\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3}$ is linearly independent and

$$\mathbf{w_1} = \mathbf{v}_1 + \mathbf{v}_2 \qquad \mathbf{w_2} = \mathbf{v}_2 - \mathbf{v}_3$$

and

$$\mathbf{w}_3 = \mathbf{v}_2 + \mathbf{v}_3$$

Show that $T = {\mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3}$ is linearly independent.

38. Suppose that $S = {\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3}$ is linearly independent and

$$\mathbf{w_1} = \mathbf{v_2} \qquad \mathbf{w_2} = \mathbf{v_1} + \mathbf{v_3}$$

and

$$\mathbf{w}_3 = \mathbf{v}_1 + \mathbf{v}_2 + \mathbf{v}_3$$

Determine whether the set $T = {\mathbf{w_1}, \mathbf{w_2}, \mathbf{w_3}}$ is linearly independent or linearly dependent.

- **39.** Suppose that the set $S = {\mathbf{v}_1, \mathbf{v}_2}$ is linearly independent. Show that if v_3 cannot be written as a linear combination of \mathbf{v}_1 and \mathbf{v}_2 , then $\{v_1, v_2, v_3\}$ is linearly independent.
- **40.** Let $S = {\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3}$, where $\mathbf{v}_3 = \mathbf{v}_1 + \mathbf{v}_2$.
 - **a.** Write \mathbf{v}_1 as a linear combination of the vectors in S in three different ways.



A polynomial of degree *n* is an expression of the form

$$p(x) = a_0 + a_1 x + a_2 x^2 + \dots + a_{n-1} x^{n-1} + a_n x^n$$

where a_0, \ldots, a_n are real numbers and $a_n \neq 0$. The degree of the **zero polynomial** is undefined since it can be written as $p(x) = 0x^n$ for any positive integer *n*. Polynomials comprise one of the most basic sets of functions and have many applications in mathematics.

EXAMPLE 6

Vector Space of Polynomials Let *n* be a fixed positive integer. Denote by \mathcal{P}_n the set of all polynomials of degree *n* or less. Define addition by adding like terms. That is, if

$$p(x) = a_0 + a_1 x + a_2 x^2 + \dots + a_{n-1} x^{n-1} + a_n x^n$$

- **29.** Let V be the set of all real-valued functions defined on \mathbb{R} with the standard operations that satisfy f(0) = 1. Determine whether V is a vector space.
- **30.** Let V be the set of all real-valued functions defined on \mathbb{R} .

Define $f \oplus g$ by

$$(f \oplus g)(x) = f(x) + g(x)$$

and define $c \odot f$ by

$$(c \odot f)(x) = f(x+c)$$

Determine whether V is a vector space.

31. Let
$$f(x) = x^3$$
 defined on \mathbb{R} and let

 $V = \{ f(x+t) \mid t \in \mathbb{R} \}$

Define

$$f(x+t_1) \oplus f(x+t_2) = f(x+t_1+t_2)$$

 $c \odot f(x+t) = f(x+ct)$

- **a.** Determine the additive identity and additive inverses.
- **b.** Show that V is a vector space.

3.2 Subspaces

Many interesting examples of vector spaces are subsets of a given vector space V that are vector spaces in their own right. For paraple, where xy plane in \mathbb{R}^3 given by

Preview Preview Prev

DEFINITION 1

Subspace A subspace W of a vector space V is a nonempty subset that is itself a vector space with respect to the inherited operations of vector addition and scalar multiplication on V.

The first requirement for a subset $W \subseteq V$ to be a subspace is that W be closed under the operations of V. For example, let V be the vector space \mathbb{R}^2 with the standard definitions of addition and scalar multiplication. Let $W \subseteq \mathbb{R}^2$ be the subset defined by

$$W = \left\{ \left[\begin{array}{c} a \\ 0 \end{array} \right] \middle| a \in \mathbb{R} \right\}$$

Observe that the sum of any two vectors in W is another vector in W, since

 $\left[\begin{array}{c}a\\0\end{array}\right]\oplus\left[\begin{array}{c}b\\0\end{array}\right]=\left[\begin{array}{c}a+b\\0\end{array}\right]$

3.2 Subspaces 141

In this way we say that W is closed under addition. The subset W is also closed under scalar multiplication since for any real number c,

$$c \odot \left[\begin{array}{c} a \\ 0 \end{array} \right] = \left[\begin{array}{c} ca \\ 0 \end{array} \right]$$

which is again in W.

On the other hand, the subset

$$W = \left\{ \left[\begin{array}{c} a \\ 1 \end{array} \right] \middle| a \in \mathbb{R} \right\}$$

is not closed under addition, since

$$\left[\begin{array}{c}a\\1\end{array}\right]\oplus\left[\begin{array}{c}b\\1\end{array}\right]=\left[\begin{array}{c}a+b\\2\end{array}\right]$$

which is not in W. See Fig. 1. The subset W is also not closed under scalar multiplication since



which is not in W for all values ρ

Now let us suppose that a charpet subset W is closed under both of the operations on V. For letering, whether W is subspace, we must show that each of the remaining even of space axioms foll. For inately, our task is simplified as most of these properties are inherited from the vector space V. For example, to show that the commutative poperty helds in W, let \mathbf{u} and \mathbf{v} be vectors in W. Since \mathbf{u} and \mathbf{v} are also in V, then

 $\mathbf{u} \oplus \mathbf{v} = \mathbf{v} \oplus \mathbf{u}$

Similarly, any three vectors in W satisfy the associative property, as this property is also inherited from V. To show that W contains the zero vector, let w be any vector in W. Since W is closed under scalar multiplication, $0 \odot \mathbf{w} \in W$. Now, by Theorem 2 of Sec. 3.1, we have $0 \odot \mathbf{w} = \mathbf{0}$. Thus, $\mathbf{0} \in W$. Similarly, for any $\mathbf{w} \in W$,

$$(-1) \odot \mathbf{w} = -\mathbf{w}$$

is also in W. All the other vector space properties, axioms 7 through 10, are inherited from V. This shows that W is a subspace of V. Conversely, if W is a subspace of V, then it is necessarily closed under addition and scalar multiplication. This proves Theorem 3.

THEOREM 3

Let W be a nonempty subset of the vector space V. Then W is a subspace of V if and only if W is closed under addition and scalar multiplication.

By Theorem 3, the first of the examples above with

$$W = \left\{ \left[\begin{array}{c} a \\ 0 \end{array} \right] \middle| a \in \mathbb{R} \right\}$$



W is not a subspace of V Figure 1

Preview

We now consider what happens when subspaces are combined. In particular, let W_1 and W_2 be subspaces of a vector space V. Then the intersection $W_1 \cap W_2$ is also a subspace of V. To show this, let \mathbf{u} and \mathbf{v} be elements of $W_1 \cap W_2$ and let cbe a scalar. Since W_1 and W_2 are both subspaces, then by Theorem 4, $\mathbf{u} \oplus (c \odot \mathbf{v})$ is in W_1 and is in W_2 , and hence is in the intersection. Applying Theorem 4 again, we have that $W_1 \cap W_2$ is a subspace.

The extension to an arbitrary number of subspaces is stated in Theorem 5.



Example 6 shows that the union of two subspaces need not be a subspace.



Chapter 3 Vector Spaces

spans \mathbb{R}^3 . These vectors are also linearly independent. To see this, observe that the matrix

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

whose column vectors are the vectors of S, is row equivalent to the 3×3 identity matrix, as seen in the solution to Example 9. [Another way of showing that S is linearly independent is to observe that $det(A) = 1 \neq 0$.] Consequently, by Theorem 7 of Sec. 2.3, we have that every vector in \mathbb{R}^3 can be written in only one way as a linear combination of the vectors of S.

On the other hand, the span of the set of vectors

$$S' = \left\{ \mathbf{v}_1', \ \mathbf{v}_2', \ \mathbf{v}_3' \right\} = \left\{ \begin{bmatrix} -1\\2\\1 \end{bmatrix}, \begin{bmatrix} 4\\1\\-3 \end{bmatrix}, \begin{bmatrix} -6\\3\\1 \end{bmatrix} \right\}$$

ot Example 10 is a plane passing through the origin Decke, not every vector in \mathbb{R}^3 can be written as a linear combination of the vectors in S'. As we expect, these vectors are linearly dependent since \mathbf{O} $det \begin{pmatrix} -\mathbf{r} & \mathbf{O} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} & \mathbf{3} \\ \mathbf{1} & -\mathbf{3} & \mathbf{5} \end{bmatrix} = 0$ In particular, $\mathbf{v}_3' = 2\mathbf{v}_1' - \mathbf{v}_2'$. The vectors \mathbf{v}_1' and \mathbf{v}_2 are linearly independent inde

To pursue these notions a bit further, there are many sets of vectors which span \mathbb{R}^3 . For example, the set

$$B = \{\mathbf{e}_1, \ \mathbf{e}_2, \ \mathbf{e}_3, \mathbf{v}\} = \left\{ \begin{bmatrix} 1\\0\\0 \end{bmatrix}, \begin{bmatrix} 0\\1\\0 \end{bmatrix}, \begin{bmatrix} 0\\0\\1 \end{bmatrix}, \begin{bmatrix} 1\\2\\3 \end{bmatrix} \right\}$$

spans \mathbb{R}^3 , but by Theorem 3 of Sec. 2.3 must necessarily be linearly dependent. The ideal case, in terms of minimizing the number of vectors, is illustrated in Example 9 where the three linearly independent vectors of S span \mathbb{R}^3 . In Sec. 3.3 we will see that S is a basis for \mathbb{R}^3 , and that every basis for \mathbb{R}^3 consists of exactly three linearly independent vectors.

EXAMPLE 11 Show that the set of matrices

$$S = \left\{ \begin{bmatrix} -1 & 0 \\ 2 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} \right\}$$

does not span $M_{2\times 2}$. Describe span(S).

150

152 Chapter 3 Vector Spaces

Hence, the linear system has the unique solution $c_1 = 2a - c$, $c_2 = -a + c$, and $c_3 = -4a + b + 2c$, for all a, b, and c. Therefore, span $(S) = \mathcal{P}_2$.

The Null Space and Column Space of a Matrix

Two special subspaces associated with every matrix A are the *null space* and *column* space of the matrix.



EXAMPLE 13	Let
------------	-----

	1	-1	-2			3]
A =	-1	2	3	and	b =	1
	2	-2	-2		l	2]

a. Determine whether **b** is in col(A).

b. Find N(A).

Solution

a. By Theorem 6, the vector **b** is in col(A) if and only if there is a vector **x** such that $A\mathbf{x} = \mathbf{b}$. The corresponding augmented matrix is given by

$$\begin{bmatrix} 1 & -1 & -2 & 3 \\ -1 & 2 & 3 & 1 \\ 2 & -2 & -2 & -2 \end{bmatrix} \text{ which reduces to } \begin{bmatrix} 1 & 0 & 0 & 3 \\ 0 & 1 & 0 & 8 \\ 0 & 0 & 1 & -4 \end{bmatrix}$$

This leads to the concept of a basis for an abstract vector space. As a first step, we generalize the concept of linear independence to abstract vector spaces introduced in Sec. 3.1.

DEFINITION 1

Linear Independence and Linear Dependence The set of vectors $S = {\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_m}$ in a vector space V is called **linearly independent** provided that the only solution to the equation

$$c_1\mathbf{v}_1+c_2\mathbf{v}_2+\cdots+c_m\mathbf{v}_m=\mathbf{0}$$

is the trivial solution $c_1 = c_2 = \cdots = c_m = 0$. If the equation has a nontrivial solution, then the set S is called **linearly dependent**.



 $= (c_1 - 3c_3)\mathbf{v}_1 + (c_2 + 2c_3)\mathbf{v}_2$

Solution By using the methods presented in Chap. 2 it can be shown that the the column vectors of the matrix A are linearly independent. Since the column vectors of B consist of a set of five vectors in \mathbb{R}^4 , by Theorem 3 of Sec. 2.3, the vectors are linearly dependent. In addition, the first four column vectors of B are the same as the linearly independent column vectors of A, hence by Theorem 5 of Sec. 2.3 the fifth column vector of B must be a linear combination of the other four vectors. Finally by Theorem 8, we know that col(A) = col(B).

As a consequence of Theorem 8, a set of vectors $\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ such that $V = \mathbf{span}\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ is minimal, in the sense of the number of spanning vectors, when they are linearly independent. We also saw in Chap. 2 that when a vector in \mathbb{R}^n can be written as a linear combination of vectors from a linearly independent set, then the representation is unique. The same result holds for abstract vector spaces.

THEOREM 9
If B = {v₁, v₂, ..., v_m} is a linearly independent strop vectors in a vector space V, then every vector in span(B) can be deter uniquely as a linearly combination of vectors from B.
Observated by these ident, we low define what we mean by a basis of a vector space.
DEFINITION: The provided that
I. B is a linearly independent set of vectors in V

2. span(B) = V

As an example, the set of coordinate vectors

$$S = \{\mathbf{e}_1, \ldots, \mathbf{e}_n\}$$

spans \mathbb{R}^n and is linearly independent, so that S is a basis for \mathbb{R}^n . This particular basis is called the **standard basis** for \mathbb{R}^n . In Example 3 we give a basis for \mathbb{R}^3 , which is not the standard basis.

EXAMPLE 3 S

Show that the set

$$B = \left\{ \begin{bmatrix} 1\\1\\0 \end{bmatrix}, \begin{bmatrix} 1\\1\\1 \end{bmatrix}, \begin{bmatrix} 0\\1\\-1 \end{bmatrix} \right\}$$

is a basis for \mathbb{R}^3 .

164 Chapter 3 Vector Spaces

Dimension

We have already seen in Theorem 3 of Sec. 2.3 that any set of m vectors from \mathbb{R}^n , with m > n, must necessarily be linearly dependent. Hence, any basis of \mathbb{R}^n contains at most n vectors. It can also be shown that any linearly independent set of m vectors, with m < n, does not span \mathbb{R}^n . For example, as we have already seen, two linearly independent vectors in \mathbb{R}^3 span a plane. Hence, any basis of \mathbb{R}^n must contain exactly *n* vectors. The number *n*, an invariant of \mathbb{R}^n , is called the *dimension* of \mathbb{R}^n . Theorem 11 shows that this holds for abstract vector spaces.

THEOREM 11

If a vector space V has a basis with n vectors, then every basis has n vectors. **Proof** Let $B = {\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n}$ be a basis for V, and let $T = {\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_m}$

be a subset of V with m > n. We claim that T is linearly dependent. To establish this result, observe that since B is a basis, then every vector in T can be written as a linear combination of the vectors from B. That is,

Preview from he equations above, we can write this last equation in terms of the basis vectors. After collecting like terms, we obtain

 $c_1\mathbf{u}_1+c_2\mathbf{u}_2+\cdots+c_m\mathbf{u}_m=\mathbf{0}$

$$(c_1\lambda_{11} + c_2\lambda_{21} + \dots + c_m\lambda_{m1})\mathbf{v}_1$$

+ $(c_1\lambda_{12} + c_2\lambda_{22} + \dots + c_m\lambda_{m2})\mathbf{v}_2$
:
+ $(c_1\lambda_{1n} + c_2\lambda_{2n} + \dots + c_m\lambda_{mn})\mathbf{v}_n = \mathbf{0}$

Since *B* is a basis, it is linearly independent, hence

101

the e ua.

$$c_1\lambda_{11} + c_2\lambda_{21} + \dots + c_m\lambda_{m1} = 0$$

$$c_1\lambda_{12} + c_2\lambda_{22} + \dots + c_m\lambda_{m2} = 0$$

$$\vdots$$

$$c_1\lambda_{1n} + c_2\lambda_{2n} + \dots + c_m\lambda_{mn} = 0$$

This last linear system is not square with *n* equations in the *m* variables c_1, \ldots, c_m . Since m > n, by Theorem 3 of Sec. 2.3 the linear system has a nontrivial solution, and hence T is linearly dependent.

168 Chapter 3 Vector Spaces

The details of these observations are made clearer by considering a specific example. Let

$$S = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \mathbf{v}_4, \mathbf{v}_5\} = \left\{ \begin{bmatrix} 1\\1\\0 \end{bmatrix}, \begin{bmatrix} 1\\0\\1 \end{bmatrix}, \begin{bmatrix} 2\\1\\2 \end{bmatrix}, \begin{bmatrix} 2\\1\\1 \end{bmatrix}, \begin{bmatrix} 3\\1\\3 \end{bmatrix} \right\}$$

We begin by considering the equation

$$c_{1}\begin{bmatrix}1\\1\\0\end{bmatrix}+c_{2}\begin{bmatrix}1\\0\\1\end{bmatrix}+c_{3}\begin{bmatrix}2\\1\\2\end{bmatrix}+c_{4}\begin{bmatrix}2\\1\\1\end{bmatrix}+c_{5}\begin{bmatrix}3\\1\\3\end{bmatrix}=\begin{bmatrix}0\\0\\0\end{bmatrix}$$

To solve this system, we reduce the corresponding augmented matrix to reduced echelon form. That is,

1	1	2	2	3	0]		[1	0	0	1	0	0]
1	0	1	1	1	0	reduces to	0	1	0	1	1	0
0	1	2	1	3	0		0	0	1	K	1	0

In the general solution, the variables c_1, c_2 , and c_3 is the dependent variables corresponding to the leading ones in the red c_2 matrix, while c_4 and c_5 are free. Thus, the solution is given by 5

$$\mathbf{C} = \{(-s, -s - \mathbf{C}, t) \mid s, t \in \mathbb{R}\}$$

d a basis for sparse, we ubstitute these values into the original vector

Preview Autor to obtain $+(-s-t)\begin{bmatrix}1\\0\\1\end{bmatrix}+(-t)\begin{bmatrix}2\\1\\2\end{bmatrix}+s\begin{bmatrix}2\\1\\1\end{bmatrix}+t\begin{bmatrix}3\\1\\3\end{bmatrix}=\begin{bmatrix}0\\0\\0\end{bmatrix}$

We claim that each of the vectors corresponding to a free variable is a linear combination of the others. To establish the claim in this case, let s = 1 and t = 0. The above vector equation now becomes

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

that is,

$$\mathbf{v}_1 - \mathbf{v}_2 + \mathbf{v}_4 = \mathbf{0}$$

Thus, \mathbf{v}_4 is a linear combination of \mathbf{v}_1 and \mathbf{v}_2 . Also, to see that \mathbf{v}_5 is a linear combination of \mathbf{v}_1 , \mathbf{v}_2 , and \mathbf{v}_3 , we let s = 0 and t = 1.

In light of Theorem 8 we eliminate \mathbf{v}_4 and \mathbf{v}_5 from S to obtain $S' = {\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3}$. Observe that S' is linearly independent since each of these vectors corresponds to a column with a leading 1. Thus, the equation

$$c_1 \begin{bmatrix} 1\\1\\0 \end{bmatrix} + c_2 \begin{bmatrix} 1\\0\\1 \end{bmatrix} + c_3 \begin{bmatrix} 2\\1\\2 \end{bmatrix} = \begin{bmatrix} 0\\0\\0 \end{bmatrix}$$

has only the trivial solution.

3.5 Application: Differential Equations 185

23. Let $S = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right\}$

$$= \left\{ \begin{bmatrix} 0 \end{bmatrix}, \begin{bmatrix} 1 \end{bmatrix} \right\}$$

be the standard ordered basis for \mathbb{R}^2 and let

$$B = \left\{ \begin{bmatrix} 1\\0 \end{bmatrix}, \begin{bmatrix} -\frac{1}{2}\\\frac{1}{2} \end{bmatrix} \right\}$$

be a second ordered basis.

a. Find $[I]_S^B$

b. Find the coordinates of

$$\left[\begin{array}{c}1\\2\end{array}\right]\left[\begin{array}{c}1\\4\end{array}\right]\left[\begin{array}{c}4\\2\end{array}\right]\left[\begin{array}{c}4\\4\end{array}\right]$$

relative to the ordered basis B.

- **c.** Draw the rectangle in the plane with vertices (1, 2), (1, 4), (4, 1), and (4, 4).
- **d.** Draw the polygon in the plane with v given by the coordinates found in p h

```
24. Fix a real number \theta and denne the transition matrix for a the standard ordered basis S on \mathbb{R}^2 to
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a second ordered basis B by

$$[I]_{S}^{B} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$

a. If $[\mathbf{v}]_{S} = \begin{bmatrix} x \\ y \end{bmatrix}$, then find $[\mathbf{v}]_{B}$.

- **b.** Draw the rectangle in the plane with vertices
 - $\left[\begin{array}{c}0\\0\end{array}\right]\left[\begin{array}{c}0\\1\end{array}\right]\left[\begin{array}{c}1\\0\end{array}\right]\left[\begin{array}{c}1\\1\end{array}\right]$
- c. Let $\theta = \frac{\pi}{2}$. Draw the rectangle in the plane with vertices the coordinates of the vectors, given in part (b), relative to the ordered basis *B*.

25. Suppose that $\mathbf{A} = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3\}$ and $\mathbf{v}_2 = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\}$ are ordered bases for a vector space V such that $\mathbf{u}_1 = -\mathbf{v}_1 + 2\mathbf{v}_2, \mathbf{u}_2 = -\mathbf{v}_1 + 2\mathbf{v}_2 - \mathbf{v}_3$, and $\mathbf{u}_3 = -\mathbf{v}_2 + \mathbf{v}_3$.

b. Find
$$[2u_1 - 3u_2 + u_3]_{B_2}$$

Application: Differential Equations

Differential equations arise naturally in virtually every branch of science and technology. They are used extensively by scientists and engineers to solve problems concerning growth, motion, vibrations, forces, or any problem involving the rates of change of variable quantities. Not surprisingly, mathematicians have devoted a great deal of effort to developing methods for solving differential equations. As it turns out, linear algebra is highly useful to these efforts. However, linear algebra also makes it possible to attain a deeper understanding of the theoretical foundations of these equations and their solutions. In this section and in Sec. 5.3 we give a brief introduction to the connection between linear algebra and differential equations.

As a first step, let y be a function of a single variable x. An equation that involves x, y, y', y'', ..., $y^{(n)}$, where n is a fixed positive integer, is called an **ordinary differential equation of order** n. We will henceforth drop the qualifier *ordinary* since none of the equations we investigate will involve partial derivatives. Also, for obvious reasons we will narrow the scope of our discussion and consider only equations of a certain type.

3.5 Application: Differential Equations 187

second derivatives $y' = re^{rx}$ and $y'' = r^2e^{rx}$, we see that $y = e^{rx}$ is a solution of the second-order equation if and only if

$$r^2 e^{rx} + are^{rx} + be^{rx} = 0$$

that is,

$$e^{rx}(r^2 + ar + b) = 0$$

Since $e^{rx} > 0$ for every choice of r and x, we know e^{rx} is a solution of y'' + ay' + by = 0 if and only if

$$r^2 + ar + b = 0$$

This equation is called the **auxiliary equation**. As this equation is quadratic there are three possibilities for the roots r_1 and r_2 . This in turn yields three possible variations for the solution of the differential equation. The auxiliary equation can have two distinct real roots, one real root, or two distinct complex roots. These cases are considered in order.



 $y_1(x) = e^x$ and $y_2(x) = e^{2x}$

Case 2 There is one repeated root r. Although the auxiliary equation has only one root, there are still two distinct solutions, given by

$$y_1(x) = e^{rx}$$
 and $y_2(x) = xe^{rx}$

EXAMPLE 2

Find two distinct solutions to the differential equation y'' - 2y' + y = 0.

Solution

Let $y = e^{rx}$. Since the auxiliary equation $r^2 - 2r + 1 = (r - 1)^2 = 0$ has the repeated root r = 1, two distinct solutions of the differential equation are

$$y_1(x) = e^x$$
 and $y_2(x) = xe^x$

194 Chapter 3 Vector Spaces

b. Assume there exists a particular solution to the nonhomogeneous equation of the form

$$y_p(x) = A\cos 2x + B\sin 2x$$

Substitute $y_p(x)$ into the differential equation to find conditions on the coefficients A and B.

- **c.** Verify that $y_c(x) + y_p(x)$ is a solution to the differential equation.
- **9.** Let *w* be the weight of an object attached to a spring, *g* the constant acceleration due to gravity of 32 ft/s², *k* the spring constant, and *d* the distance in feet that the spring is stretched by the

weight. Then the mass of the object is $m = \frac{w}{g}$ and $k = \frac{w}{d}$. Suppose that a 2-lb weight stretches a spring by 6-in. Find the equation of the motion of the weight if the object is pulled down by 3-in and then released. Notice that this system is *undamped*; that is, the damping coefficient is 0.

10. Suppose an 8-lb object is attached to a spring with a spring constant of 4 lb/ft and that the damping force on the system is twice the velocity. Find the equation of the motion if the object is pulled down 1-ft and given an upward velocity of 2 ft/s.


- **24.** If V is a vector space of dimension n and H is a subspace of dimension n, then H = V.
- **25.** If B_1 and B_2 are bases for the vector space V, then the transition matrix from B_1 to B_2 is the inverse of the transition matrix from B_2 to B_1 .

In Exercises 26–29, use the bases of \mathbb{R}^2

$$B_1 = \left\{ \left[\begin{array}{c} 1 \\ -1 \end{array} \right], \left[\begin{array}{c} 0 \\ 2 \end{array} \right] \right\}$$



In Exercises 30–35, use the bases of \mathcal{P}_3 ,

$$B_1 = \{1, x, x^2, x^3\}$$

and

$$B_{2} = \{x, x^{2}, 1, x^{3}\}$$
30. $[x^{3} + 2x^{2} - x]_{B_{1}} = \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}$
31. $[x^{3} + 2x^{2} - x]_{B_{1}} = \begin{bmatrix} 0 \\ -1 \\ 2 \\ 1 \end{bmatrix}$
32. $[x^{3} + 2x^{2} - x]_{B_{2}} = \begin{bmatrix} 0 \\ -1 \\ 2 \\ 1 \end{bmatrix}$
33. $[x^{3} + 2x^{2} - x]_{B_{2}} = \begin{bmatrix} -1 \\ 2 \\ 0 \\ 1 \end{bmatrix}$
34. $[(1 + x)^{2} - 3(x^{2} + x - 1) + x^{3}]_{B_{2}}$

$$= \begin{bmatrix} 4 \\ -1 \\ -2 \\ 1 \end{bmatrix}$$
35. The transition matrix from B_{1} to B_{2} is

$$[I]_{B_1}^{B_2} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$T\left(\left[\begin{array}{c}7\\-1\\5\end{array}\right]\right) = \left[\begin{array}{cc}1&2&-1\\-1&3&2\end{array}\right]\left[\begin{array}{c}7\\-1\\5\end{array}\right] = \left[\begin{array}{c}0\\0\end{array}\right]$$



and

Operations with Linear Transformations

Linear transformations can be combined by using a natural addition and scalar multiplication to produce new linear transformations. For example, let $S, T: \mathbb{R}^2 \to \mathbb{R}^2$ be defined by

$$S\left(\begin{bmatrix}x\\y\end{bmatrix}\right) = \begin{bmatrix}x+y\\-x\end{bmatrix}$$
 and $T\left(\begin{bmatrix}x\\y\end{bmatrix}\right) = \begin{bmatrix}2x-y\\x+3y\end{bmatrix}$

We then define

$$(S+T)(\mathbf{v}) = S(\mathbf{v}) + T(\mathbf{v}) \quad \text{and} \quad (cS)(\mathbf{v}) = c(S(\mathbf{v}))$$

To illustrate this definition, let $\mathbf{v} = \begin{bmatrix} 2\\-1 \end{bmatrix}$; then
$$(S+T)(\mathbf{v}) = S(\mathbf{v}) + T(\mathbf{v}) = \begin{bmatrix} 2+(-1)\\-2 \end{bmatrix} \bigoplus \begin{bmatrix} \mathbf{x} \\ \mathbf{z} + \mathbf{3}(-1) \end{bmatrix} = \begin{bmatrix} 6\\-3 \end{bmatrix}$$

For scalar multiplication is $\mathbf{z} = \mathbf{z} = \mathbf{z}$

THEOREM 1

Let V and W be vector spaces and let $S, T: V \to W$ be linear transformations. The function S + T defined by

$$(S+T)(\mathbf{v}) = S(\mathbf{v}) + T(\mathbf{v})$$

is a linear transformation from V into W. If c is any scalar, the function cS defined by

$$(cS)(\mathbf{v}) = cS(\mathbf{v})$$

is a linear transformation from V into W.

Proof Let $\mathbf{u}, \mathbf{v} \in V$ and let *d* be any scalar. Then

$$(S+T)(d\mathbf{u} + \mathbf{v}) = S(d\mathbf{u} + \mathbf{v}) + T(d\mathbf{u} + \mathbf{v})$$

= $S(d\mathbf{u}) + S(\mathbf{v}) + T(d\mathbf{u}) + T(\mathbf{v})$
= $dS(\mathbf{u}) + S(\mathbf{v}) + dT(\mathbf{u}) + T(\mathbf{v})$
= $d(S(\mathbf{u}) + T(\mathbf{u})) + S(\mathbf{v}) + T(\mathbf{v})$
= $d(S+T)(\mathbf{u}) + (S+T)(\mathbf{v})$

 $\cdot + c_n T(\mathbf{v}_n)$

Fact Summary

- Let V, W, and Z be vector spaces and S and T functions from V into W.
 - **1.** The function T is a linear transformation provided that for all \mathbf{u}, \mathbf{v} in V and all scalars $c, T(c\mathbf{u} + \mathbf{v}) = cT(\mathbf{u}) + T(\mathbf{v})$.
 - **2.** If A is an $m \times n$ matrix and T is defined by $T(\mathbf{x}) = A\mathbf{x}$, then T is a linear transformation from \mathbb{R}^n into \mathbb{R}^m .
 - 3. If T is a linear transformation, then the zero vector in V is mapped to the zero vector in W, that is, T(0) = 0.
 - 4. If $B = {\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n}$ is an ordered basis for V and $W = \mathbb{R}^n$, then the coordinate mapping $T(\mathbf{v}) = [\mathbf{v}]_B$ is a linear transformation.
 - **5.** If $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$ is a set of vectors in V and T is a linear transformation, then

 $T(c_1\mathbf{v}_1 + c_2\mathbf{v}_2 + \dots + c_n\mathbf{v}_n) = c_1T(\mathbf{v}_1) + c_1T(\mathbf{v}_2)$

for all scalars c₁,..., c_n.
6. If S and T are linear transformations and c is a scalar, then S + T and cT are linear transformations.

W is a linear area social tion and $L: W \longrightarrow Z$ is a linear n, then $x \to T: V \longrightarrow Z$ is a linear transformation.

Exercise Set 1-6, determine whether the function $T: \mathbb{R}^2 \rightarrow \mathbb{R}^2$ is a linear transformation.

1.
$$T\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = \begin{bmatrix} y \\ x \end{bmatrix}$$

2. $T\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = \begin{bmatrix} x+y \\ x-y+2 \end{bmatrix}$
3. $T\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = \begin{bmatrix} x \\ y^2 \end{bmatrix}$
4. $T\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = \begin{bmatrix} 2x-y \\ x+3y \end{bmatrix}$
5. $T\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = \begin{bmatrix} x \\ 0 \end{bmatrix}$
6. $T\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = \begin{bmatrix} \frac{x+y}{2} \\ \frac{x+y}{2} \end{bmatrix}$

In Exercises 7–16, determine whether the function is a linear transformation between vector spaces.

7.
$$T: \mathbb{R} \to \mathbb{R}, T(x) = x^2$$

8. $T: \mathbb{R} \to \mathbb{R}, T(x) = -2x$
9. $T: \mathbb{R}^2 \to \mathbb{R}, T\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = x^2 + y^2$
10. $T: \mathbb{R}^3 \to \mathbb{R}^2,$
 $T\left(\begin{bmatrix} x \\ y \\ z \end{bmatrix}\right) = \begin{bmatrix} x \\ y \end{bmatrix}$
11. $T: \mathbb{R}^3 \to \mathbb{R}^3,$
 $T\left(\begin{bmatrix} x \\ y \\ z \end{bmatrix}\right) = \begin{bmatrix} x + y - z \\ 2xy \\ x + z + 1 \end{bmatrix}$

214 Chapter 4 Linear Transformations

b. Let
$$\mathbf{w} = \begin{bmatrix} 7 \\ -6 \\ -9 \end{bmatrix}$$
. Determine whether there is a vector \mathbf{v} in \mathbb{R}^3 such that $T(\mathbf{v}) = \mathbf{w}$.

34. Define $T: \mathcal{P}_2 \to \mathcal{P}_2$ by

$$T(p(x)) = p'(x) - p(0)$$

- **a.** Find all vectors that are mapped to **0**.
- **b.** Find two polynomials p(x) and q(x) such that T(p(x)) = T(q(x)) = 6x 3.

c. Is T a linear operator?

35. Suppose $T_1: V \to \mathbb{R}$ and $T_2: V \to \mathbb{R}$ are linear transformations. Define $T: V \to \mathbb{R}^2$ by

$$T(\mathbf{v}) = \left[\begin{array}{c} T_1(\mathbf{v}) \\ T_2(\mathbf{v}) \end{array} \right]$$

Show that T is a linear transformation.

- 36. Define T: M_{n×n} → R by T(A → r A). Show that T is a linear transformation.
 37. Suppose that b is a fixed n × n (Parix Define 7, M_{n×n} → M_{n×n} b) (A = 0 b BA. Show that T is a linear operator.
- **38.** Define $T: \mathbb{R} \to \mathbb{R}$ by T(x) = mx + b. Determine when *T* is a linear operator.

39. Define
$$T: C^{(0)}[0, 1] \to \mathbb{R}$$
 by

$$T(f) = \int_0^1 f(x) \, dx$$

for each function f in $C^{(0)}[0, 1]$. **a.** Show that T is a linear operator. **b.** Find $T(2x^2 - x + 3)$.

- **40.** Suppose that $T: V \to W$ is a linear transformation and $T(\mathbf{u}) = \mathbf{w}$. If $T(\mathbf{v}) = \mathbf{0}$, then find $T(\mathbf{u} + \mathbf{v})$.
- **41.** Suppose that $T: \mathbb{R}^n \to \mathbb{R}^m$ is a linear transformation and $\{\mathbf{v}, \mathbf{w}\}$ is a linearly independent subset of \mathbb{R}^n . If $\{T(\mathbf{v}), T(\mathbf{w})\}$ is linearly dependent, show that $T(\mathbf{u}) = \mathbf{0}$ has a nontrivial solution.
- **42.** Suppose that $T: V \to V$ in the inear operator and $\{v_1, \ldots, v_n\}$ is linearly dependent. Show that $\{T_1, \ldots, T_n\}$ is linearly dependent.

- **44.** Suppose that $T_1: V \to V$ and $T_2: V \to V$ are linear operators and $\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ is a basis for *V*. If $T_1(\mathbf{v}_i) = T_2(\mathbf{v}_i)$, for each $i = 1, 2, \ldots, n$, show that $T_1(\mathbf{v}) = T_2(\mathbf{v})$ for all \mathbf{v} in *V*.
- **45.** Verify that $\pounds(U, V)$ is a vector space.

4.2 The Null Space and Range

In Sec. 3.2, we defined the null space of an $m \times n$ matrix to be the subspace of \mathbb{R}^n of all vectors **x** with A**x** = **0**. We also defined the column space of A as the subspace of \mathbb{R}^m of all linear combinations of the column vectors of A. In this section we extend these ideas to linear transformations.

DEFINITION 1

Null Space and Range Let V and W be vector spaces. For a linear transformation $T: V \longrightarrow W$ the **null space** of T, denoted by N(T), is defined by

$$N(T) = \{ \mathbf{v} \in V \mid T(\mathbf{v}) = \mathbf{0} \}$$

The **range** of *T*, denoted by R(T), is defined by

 $R(T) = \{T(\mathbf{v}) \mid \mathbf{v} \in V\}$

The null space of a linear transformation is then the set of all vectors in V that are mapped to the zero vector, with the range being the set of all images of the mapping, as shown in Fig. 1.



EXAMPLE 1

Define the linear transformation $T: \mathbb{R}^4 \longrightarrow \mathbb{R}^3$ by

$$T\left(\left[\begin{array}{c}a\\b\\c\\d\end{array}\right]\right) = \left(\left[\begin{array}{c}a+b\\b-c\\a+d\end{array}\right]\right)$$

a. Find a basis for the null space of *T* and its dimension.

232 Chapter 4 Linear Transformations

Applying
$$A^{-1}$$
 to **w**, we obtain

$$\begin{bmatrix} 0 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} v_1 + v_2 \\ -v_1 \end{bmatrix} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = T^{-1}(\mathbf{w})$$

THEOREM 11

If V and W are vector spaces of dimension n, then V and W are isomorphic.

Proof By Theorem 10, there are isomorphisms $T_1: V \longrightarrow \mathbb{R}^n$ and $T_2: W \longrightarrow \mathbb{R}^n$, as shown in Fig. 1. Let $\phi = T_2^{-1} \circ T_1: V \longrightarrow W$. To show that ϕ is linear, we first note that T_2^{-1} is linear by Proposition 3. Next by Theorem 2 of Sec. 4.1, the composition $T_2^{-1} \circ T_1$ is linear. Finally, by Theorem 4 of Sec. A.2, the mapping ϕ is one-to-one and onto and is therefore a vector space isomorphism.



EXAMPLE 4

Find an explicit isomorphism from \mathcal{P}_2 onto the vector space of 2×2 symmetric matrices $S_{2\times 2}$.

Solution To use the method given in the proof of Theorem 11, first let

$$B_1 = \{1, x, x^2\}$$
 and $B_2 = \left\{ \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \right\}$

be ordered bases for \mathcal{P}_2 and $S_{2\times 2}$, respectively. Let T_1 and T_2 be the respective coordinate maps from \mathcal{P}_2 and $S_{2\times 2}$ into \mathbb{R}^3 . Then

$$T_1(ax^2 + bx + c) = \begin{bmatrix} c \\ b \\ a \end{bmatrix}$$
 and $T_2\left(\begin{bmatrix} a & b \\ b & c \end{bmatrix}\right) = \begin{bmatrix} c \\ b \\ a \end{bmatrix}$



4.4 Matrix Representation of a Linear Transformation

Matrices have played an important role in our study of linear algebra. In this section we establish the connection between matrices and linear transformations. To illustrate the idea, recall from Sec. 4.1 that given any $m \times n$ matrix A, we can define a linear transformation $T: \mathbb{R}^n \longrightarrow \mathbb{R}^m$ by

$$T(\mathbf{v}) = A\mathbf{v}$$

In Example 8 of Sec. 4.1, we showed how a linear transformation $T: \mathbb{R}^3 \longrightarrow \mathbb{R}^2$ is completely determined by the images of the coordinate vectors $\mathbf{e}_1, \mathbf{e}_2$, and \mathbf{e}_3 of \mathbb{R}^3 .

The key was to recognize that a vector $\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix}$ can be written as $\mathbf{v} = v_1 \mathbf{e}_1 + v_2 \mathbf{e}_2 + v_3 \mathbf{e}_3$ so that $T(\mathbf{v}) = v_1 T(\mathbf{e}_1) + v_2 T(\mathbf{e}_2) + v_3 T(\mathbf{e}_3)$

236 Chapter 4 Linear Transformations

In that example, T was defined so that

$$T(\mathbf{e}_1) = \begin{bmatrix} 1\\1 \end{bmatrix}, T(\mathbf{e}_2) = \begin{bmatrix} -1\\2 \end{bmatrix} \qquad T(\mathbf{e}_3) = \begin{bmatrix} 0\\1 \end{bmatrix}$$

Now let *A* be the 2 × 3 matrix whose column vectors are $T(\mathbf{e}_1)$, $T(\mathbf{e}_2)$, and $T(\mathbf{e}_3)$. Then

$$T(\mathbf{v}) = \begin{bmatrix} 1 & -1 & 0\\ 1 & 2 & 1 \end{bmatrix} \mathbf{v} = A\mathbf{v}$$

That is, the linear transformation T is given by a matrix product. In general, if $T: \mathbb{R}^n \longrightarrow \mathbb{R}^m$ is a linear transformation, then it is possible to write

$$T(\mathbf{v}) = A\mathbf{v}$$

where A is the $m \times n$ matrix whose *j*th column vector is $T(\mathbf{e}_j)$ for j = 1, 2, ..., n. The matrix A is called the **matrix representation of** T **relative to the standard bases** of \mathbb{R}^n and \mathbb{R}^m .

In this section we show that every linear transformation between finite dimensional vector spaces can be written as a matrix multiplicative. Specifically, let V and W be finite dimensional vector spaces with the key ordered bases B and B', respectively. If $T: V \longrightarrow W$ is a linear transformation, then there exists a matrix A such that

$$[T\mathbf{v}]\mathbf{v} = \mathcal{A}[\mathbf{v}]_B$$

In the case for which $V = \mathbb{R}^m$, and B and B' are, respectively, the standard bases, the last equation is equivalent to
 $T(\mathbf{v}) = A\mathbf{v}$

as above. We now present the details.

Let V and W be vector spaces with ordered bases $B = {\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n}$ and $B' = {\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_m}$, respectively, and let $T: V \longrightarrow W$ be a linear transformation. Now let **v** be any vector in V and let

$$[\mathbf{v}]_B = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix}$$

be the coordinate vector of v relative to the basis B. Thus,

$$\mathbf{v} = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2 + \dots + c_n \mathbf{v}_n$$

Applying T to both sides of this last equation gives

$$T(\mathbf{v}) = T(c_1\mathbf{v}_1 + c_2\mathbf{v}_2 + \dots + c_n\mathbf{v}_n)$$

= $c_1T(\mathbf{v}_1) + c_2T(\mathbf{v}_2) + \dots + c_nT(\mathbf{v}_n)$

Note that for each i = 1, 2, ..., n the vector $T(\mathbf{v}_i)$ is in W. Thus, there are unique scalars a_{ij} with $1 \le i \le m$ and $1 \le j \le n$ such that





246

4.6 Application: Computer Graphics 255

to show directly that the matrices $[T]_{B_1}$ and $[T]_{B_2}$ are similar.

- 16. Let $T: \mathcal{P}_2 \longrightarrow \mathcal{P}_2$ be the linear operator defined by T(p(x)) = xp'(x) + p''(x). Find the matrix representation $[T]_{B_1}$ relative to the basis $B_1 = \{1, x, x^2\}$ and the matrix representation $[T]_{B_2}$ relative to $B_2 = \{1, x, 1 + x^2\}$. Find the transition matrix $P = [I]_{B_2}^{B_1}$, and use Theorem 15 to show directly that the matrices $[T]_{B_1}$ and $[T]_{B_2}$ are similar.
- **17.** Show that if *A* and *B* are similar matrices and *B* and *C* are similar matrices, then *A* and *C* are similar matrices.

Preview

- **18.** Show that if A and B are similar matrices, then det(A) = det(B).
- **19.** Show that if A and B are similar matrices, then $\mathbf{tr}(A) = \mathbf{tr}(B)$.
- **20.** Show that if A and B are similar matrices, then A^t and B^t are similar matrices.
- **21.** Show that if A and B are similar matrices, then A^n and B^n are similar matrices for each positive integer n.
- 22. Show that if A and B are similar matrices and λ is any scalar, then det $(A \lambda I) = det(B \lambda I)$.

4.6 ► Application: Computer Graphics

The rapid development of increasingly were powerful computers has led to the explosive growth of digital the powerful computer-generated visual content is ubiquitous, found in almost every unity from advertising and entertainment to science and medicine. The brack of computer science end vi as *computer graphics* is devoted to the study of the generation and manipulation of digital images. Computer graphics are based on displaying two or three-dimensional objects in two-dimensional space. Images displayed on a computer screen are stored in memory using data items called **pixels**, then is short for picture elements. A single picture can be comprised of millions of pixels, which collectively determine the image. Each pixel contains information on how to color the corresponding point on a computer screen, as shown in Fig. 1. If an image contains curves or lines, the pixels which describe the object may be connected by a mathematical formula. The saddle shown in Fig. 1 is an example.





Figure 1



260 Chapter 4 Linear Transformations

Reflection

The **reflection** of a geometric object through a line produces the *mirror image* of the object across the line. The linear operator that reflects a vector through the x axis is given by

$$R_{x}\left(\left[\begin{array}{c}x\\y\end{array}\right]\right)=\left[\begin{array}{c}x\\-y\end{array}\right]$$

A reflection through the y axis is given by

$$R_{y}\left(\left[\begin{array}{c}x\\y\end{array}\right]\right) = \left[\begin{array}{c}-x\\y\end{array}\right]$$

and a reflection through the line y = x is given by

ote

$$R_{y=x}\left(\left[\begin{array}{c}x\\y\end{array}\right]\right) = \left[\begin{array}{c}y\\x\end{array}\right]$$

The matrix representations, relative to the standard basis B, for each of these are given by

 $[R_{y=x}]_B = \begin{bmatrix} 0 & 1\\ 1 & 0 \end{bmatrix}$

EXAMPLE 3 Perform the following reflection on the triangle T of Fig. 4.
a. Reflection through the x axis.
b. reflection mrough the y axis.
c. reflection through the line y = x.

 $[R_x]_B =$

Solution

on a. The vertices of the triangle in Fig. 4 are given by

$$\mathbf{v}_1 = \begin{bmatrix} 0\\1 \end{bmatrix} \qquad \mathbf{v}_2 = \begin{bmatrix} 2\\1 \end{bmatrix} \qquad \mathbf{v}_3 = \begin{bmatrix} 1\\3 \end{bmatrix}$$

Applying the matrix $[R_x]_B$ to the vertices of the original triangle, we obtain

$$\mathbf{v}_1' = \begin{bmatrix} 0\\-1 \end{bmatrix} \qquad \mathbf{v}_2' = \begin{bmatrix} 2\\-1 \end{bmatrix} \qquad \mathbf{v}_3' = \begin{bmatrix} 1\\-3 \end{bmatrix}$$

The image of the triangle is shown in Fig. 9(a).

b. Applying the matrix $[R_y]_B$ to the vertices of the original triangle, we obtain

$$\mathbf{v}_1' = \begin{bmatrix} 0\\1 \end{bmatrix} \qquad \mathbf{v}_2' = \begin{bmatrix} -2\\1 \end{bmatrix} \qquad \mathbf{v}_3' = \begin{bmatrix} -1\\3 \end{bmatrix}$$

The image of the triangle with this reflection is shown in Fig. 9(b).

c. Finally, applying the matrix $[R_{x=y}]_B$ to the vertices of the original triangle, we obtain

$$\mathbf{v}_1' = \begin{bmatrix} 1\\0 \end{bmatrix} \quad \mathbf{v}_2' = \begin{bmatrix} 1\\2 \end{bmatrix} \quad \mathbf{v}_3' = \begin{bmatrix} 3\\1 \end{bmatrix}$$

The image of the triangle is shown in Fig. 9(c).

265 4.6 Application: Computer Graphics



$$S_{\theta}\left(\left[\begin{array}{c}x\\y\end{array}\right]\right) = \left[\begin{array}{c}x\cos\theta - y\sin\theta\\x\sin\theta + y\cos\theta\end{array}\right]$$

The matrix of S_{θ} relative to the standard basis $B = \{\mathbf{e}_1, \mathbf{e}_2\}$ for \mathbb{R}^2 is given by

$$S_{\theta}]_{B} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$

When using homogeneous coordinates, we apply the matrix

$\cos \theta$	$-\sin\theta$	0
$\sin \theta$	$\cos \theta$	0
0	0	1





$$\mathbf{v}_{1}' = \begin{bmatrix} \frac{\sqrt{3}}{2} \\ \frac{1}{2} \\ 1 \end{bmatrix} \qquad \mathbf{v}_{2}' = \begin{bmatrix} \frac{3\sqrt{3}}{2} \\ \frac{3}{2} \\ 1 \end{bmatrix} \qquad \text{and} \qquad \mathbf{v}_{3}' = \begin{bmatrix} \sqrt{3} - 1 \\ \sqrt{3} + 1 \\ 1 \end{bmatrix}$$

Figure 13

The resulting triangle is shown in Fig. 13.

Projection

v

Rendering a picture of a three-dimensional object on a flat computer screen requires projecting points in 3-space to points in 2-space. We discuss only one of many methods to project points in \mathbb{R}^3 to points in \mathbb{R}^2 that preserve the natural appearance of an object.



vertex of the cube into \mathbb{R}^2 . Connecting the images by line segments gives the picture shown in Fig. 16. The projected points are given in Table 1.

Table 1	
Vertex	Projected Point
(0,0,1)	(0.433, 0.25)
(1,0,1)	(1.433, 0.25)
(1,0,0)	(1,0)
(0,0,0)	(0, 0)
(0,1,1)	(0.433, 1.25)
(1,1,1)	(1.433, 1.25)
(1,1,0)	(1, 1)
(0,1,0)	(0, 1)

280 Chapter 5 Eigenvalues and Eigenvectors

Alternatively, the set

$$V_{\lambda} = \{ \mathbf{v} \in \mathbb{R}^n \mid A\mathbf{v} = \lambda \mathbf{v} \} = \{ \mathbf{v} \in \mathbb{R}^n \mid (A - \lambda I)\mathbf{v} = 0 \} = N(A - \lambda I)$$

Since V_{λ} is the null space of the matrix $A - \lambda I$, by Theorem 3 of Sec. 4.2 it is a subspace of \mathbb{R}^n .

EXAMPLE 2	Find the eigenvalues and corresponding eigenvectors of
	$A = \left[\begin{array}{cc} 2 & -12 \\ 1 & -5 \end{array} \right]$
	Give a description of the eigenspace corresponding to each eigenvalue.
Solution	By Theorem 1 to find the eigenvalues, we solve the characteristic equation
	$det(A - \lambda I) = \begin{vmatrix} 2 - \lambda & -12 \\ 1 & -5 \\ -5 \\ -5 \\ -5 \\ -5 \\ -5 \\ -5 \\ -5$
preview	Thus the eigenvalues are $\lambda_1 = 11$ and $\lambda_2 = -2$. To find the eigenvectors, we need to find all normal becomes holder null spaces of $A - \lambda_1 I$ and $A - \lambda_2 I$. First, for $\lambda_1 = -1$,
The P	$A - \lambda_1 I = A + I = \begin{bmatrix} 2 & -12 \\ 1 & -5 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 3 & -12 \\ 1 & -4 \end{bmatrix}$
	The null space of $A + I$ is found by row-reducing the augmented matrix
	$\begin{bmatrix} 3 & -12 & & 0 \\ 1 & -4 & & 0 \end{bmatrix} \text{to} \begin{bmatrix} 1 & -4 & & 0 \\ 0 & 0 & & 0 \end{bmatrix}$
	The solution set for this linear system is given by $S = \left\{ \begin{bmatrix} 4t \\ t \end{bmatrix} t \in \mathbb{R} \right\}$. Choosing
	$t = 1$, we obtain the eigenvector $\mathbf{v}_1 = \begin{bmatrix} 4\\1 \end{bmatrix}$. Hence, the eigenspace corresponding
	to $\lambda_1 = -1$ is $V_{\lambda_1} = \left\{ t \begin{bmatrix} 4\\1 \end{bmatrix} \middle t \text{ is any real number} \right\}$
	For $\lambda_2 = -2$, $A - \lambda_2 I = \begin{bmatrix} 4 & -12 \\ 1 & -3 \end{bmatrix}$
	In a similar way we find that the vector $\mathbf{v}_2 = \begin{bmatrix} 3\\1 \end{bmatrix}$ is an eigenvector corresponding
	to $\lambda_2 = -2$. The corresponding eigenspace is

292 Chapter 5 Eigenvalues and Eigenvectors

THEOREM 3

Preview

Let A be an $n \times n$ matrix, and let $\lambda_1, \lambda_2, \ldots, \lambda_n$ be distinct eigenvalues with corresponding eigenvectors $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n$. Then the set $\{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n\}$ is linearly independent.

Proof The proof is by contradiction. Assume that $\lambda_1, \lambda_2, \ldots, \lambda_n$ are distinct eigenvalues of *A* with corresponding eigenvectors $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n$, and assume that the set of eigenvectors is linearly dependent. Then by Theorem 5 of Sec. 2.3, at least one of the vectors can be written as a linear combination of the others. Moreover, the eigenvectors can be reordered so that $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_m$, with m < n, are linearly independent, but $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_{m+1}$ are linearly dependent with \mathbf{v}_{m+1} a nontrivial linear combination of the first *m* vectors. Therefore, there are scalars c_1, \ldots, c_m , not all 0, such that

 $\mathbf{v}_{m+1} = c_1 \mathbf{v}_1 + \dots + c_m \mathbf{v}_m$

This is the statement that will result in a contradiction. We multiply the last equation by A to obtain

$$A\mathbf{v}_{m+1} = A(c_1\mathbf{v} + \mathbf{c}_m \cdot \mathbf{v}_m)$$

= $c_1 t_1 \cdot \mathbf{v}_m \cdot \mathbf{v}_m + c_m A(\mathbf{v}_m)$

Further, since \mathbf{v}_i is a fight vector corresponding to the eigenvalue λ_i , then $A\mathbf{v}_i = \lambda_i \mathbf{v}_i$, and a Θ substitution in the provides equation, we have

 $\mathbf{v}_{+1} = c_1 \lambda_1 \mathbf{v}_1 + \dots + c_m \lambda_m \mathbf{v}_m$

multiplying both sides of $\mathbf{v}_{m+1} = c_1 \mathbf{v}_1 + \cdots + c_m \mathbf{v}_m$ by λ_{m+1} , we also have

$$\lambda_{m+1}\mathbf{v}_{m+1} = c_1\lambda_{m+1}\mathbf{v}_1 + \dots + c_m\lambda_{m+1}\mathbf{v}_n$$

By equating the last two expressions for $\lambda_{m+1}\mathbf{v}_{m+1}$ we obtain

$$c_1\lambda_1\mathbf{v}_1+\cdots+c_m\lambda_m\mathbf{v}_m=c_1\lambda_{m+1}\mathbf{v}_1+\cdots+c_m\lambda_{m+1}\mathbf{v}_m$$

or equivalently,

$$c_1(\lambda_1 - \lambda_{m+1})\mathbf{v}_1 + \cdots + c_m(\lambda_m - \lambda_{m+1})\mathbf{v}_m = \mathbf{0}$$

Since the vectors $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_m$ are linearly independent, the only solution to the previous equation is the trivial solution, that is,

$$c_1(\lambda_1 - \lambda_{m+1}) = 0$$
 $c_2(\lambda_2 - \lambda_{m+1}) = 0$... $c_m(\lambda_m - \lambda_{m+1}) = 0$

Since all the eigenvalues are distinct, we have

 c_1

$$\lambda_1 - \lambda_{m+1} \neq 0$$
 $\lambda_2 - \lambda_{m+1} \neq 0$... $\lambda_m - \lambda_{m+1} \neq 0$

and consequently

$$= 0 \qquad c_2 = 0 \qquad \dots \qquad c_m = 0$$

This contradicts the assumption that the nonzero vector \mathbf{v}_{m+1} is a nontrivial linear combination of $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_m$.

5.2 Diagonalization 293

COROLLARY 1

If A is an $n \times n$ matrix with n distinct eigenvalues, then A is diagonalizable.

EXAMPLE 4

Show that every 2×2 real symmetric matrix is diagonalizable.

Solution

n Recall that the matrix A is symmetric if and only if $A = A^t$. Every 2×2 symmetric matrix has the form

$$A = \left[\begin{array}{cc} a & b \\ b & d \end{array} \right]$$

See Example 5 of Sec. 1.3. The eigenvalues are found by solving the characteristic equation

$$det(A - \lambda I) = \begin{vmatrix} a - \lambda & b \\ b & d - \lambda \end{vmatrix} = \lambda^2 - (a + d)\lambda + ad - b^2 = 0$$

By the quadratic formula, the eigenvalues ar **CO**
$$G = \frac{Gdd \pm \sqrt{(a - d)^2 + 4b^2}}{2}$$

Since the discriminant $(a - a)^2 + ab(1)$ by the characteristic equation has either one on wo real roots. If $a - a^2 + ab(1)$ by the characteristic equation has either one on wo real roots. If $a - a^2 + ab(1) + 4b^2 = 0$, then $(a - d)^2 = 0$ and $b^2 = 0$, which holds if and $ab(1) + b^2 = d$ and $b = 0$. Hence, the matrix A is diagonal. If $(a - a^2 + ab^2 > 0)$, then A has two distinct eigenvalues; so by Corollary 1, the known A is diagonalizable.

By Theorem 2, if A is diagonalizable, then A is similar to a diagonal matrix whose eigenvalues are the same as the eigenvalues of A. In Theorem 4 we show that the same can be said about any two similar matrices.

THEOREM 4

Let A and B be similar $n \times n$ matrices. Then A and B have the same eigenvalues.

Proof Since A and B are similar matrices, there is an invertible matrix P such that $B = P^{-1}AP$. Now

$$det(B - \lambda I) = det(P^{-1}AP - \lambda I)$$

= det(P^{-1}(AP - P(\lambda I)))
= det(P^{-1}(AP - \lambda IP))
= det(P^{-1}(A - \lambda I)P)

 $T\left(\left[\begin{array}{c} x_1\\ x_2\\ x_3\end{array}\right]\right) = \left[\begin{array}{c} 3x_1 - x_2 + 2x_3\\ 2x_1 + 2x_3\\ x_1 + 3x_2\end{array}\right]$ Show that *T* is diagonalizable. Solution Let $B = \{\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3\}$ be the standard basis for \mathbb{R}^3 . Then the matrix for *T* relative to B is $[T]_B = \left[\begin{array}{c} 3 & -1 & 2\\ 2 & 0 & 2\\ 1 & 3 & 0\end{array}\right]$ Observe that the eigenvalues of $[T]_B$ are $\lambda_1 = -2, \lambda_2 = 4$, and $\lambda_3 = 1$ with corresponding eigenvectors, respectively, $\mathbf{v}_1 = \left[\begin{array}{c} 1\\ 1\\ -2\end{array}\right] \quad \mathbf{v}_2 = \left[\begin{array}{c} 1\\ 1\\ -2\end{array}\right] \quad \mathbf{c} = \mathbf{c} \cdot \mathbf{c} \cdot \mathbf{c} = \begin{bmatrix} -5\\ 4\\ 7 \end{bmatrix}$ Now let $B' = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\} = \mathbf{c} = \mathbf{c} = \mathbf{c} \cdot \mathbf{c} = \begin{bmatrix} -5\\ 4\\ 7 \end{bmatrix}$ Now let $B' = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\} = \mathbf{c} =$

Define the linear operator $T: \mathbb{R}^3 \longrightarrow \mathbb{R}^3$ by

Fact Summary

EXAMPLE 6

Let A be an $n \times n$ matrix.

- 1. If A is diagonalizable, then $A = PDP^{-1}$ or equivalently $D = P^{-1}AP$. The matrix D is a diagonal matrix with diagonal entries the eigenvalues of A. The matrix P is invertible whose column vectors are the corresponding eigenvectors.
- 2. If A is diagonalizable, then the diagonalizing matrix P is not unique. If the columns of P are permuted, then the diagonal entries of D are permuted in the same way.
- **3.** The matrix *A* is diagonalizable if and only if *A* has *n* linearly independent eigenvectors.
- **4.** If A has n distinct eigenvalues, then A is diagonalizable.

- **300** Chapter 5 Eigenvalues and Eigenvectors
 - **b.** Find the matrix *B* for *T* relative to the basis $\{x, x 1, x^2\}$.
 - **c.** Show the eigenvalues of *A* and *B* are the same.
 - **d.** Explain why T is not diagonalizable.
- **36.** Define a vector space $V = \text{span}\{\sin x, \cos x\}$ and a linear operator $T: V \to V$ by T(f(x)) = f'(x). Show that T is diagonalizable.
- **37.** Define a linear operator $T: \mathbb{R}^3 \to \mathbb{R}^3$ by

Preview

	[]	x_1	$\left \right\rangle$		$2x_1 + 2x_2 + 2x_3$
Τ		x_2		=	$-x_1 + 2x_2 + x_3$
	$\langle $	<i>x</i> ₃]/		$x_1 - x_2$

Show that T is not diagonalizable.

38. Define a linear operator $T: \mathbb{R}^3 \to \mathbb{R}^3$ by

$$T\left(\left[\begin{array}{c} x_1\\ x_2\\ x_3 \end{array}\right]\right) = \left[\begin{array}{c} 4x_1 + 2x_2 + 4x_3\\ 4x_1 + 2x_2 + 4x_3\\ 4x_3 \end{array}\right]$$

Show that T is diagonalizable.

39. Let *T* be a linear operator on a finite dimensional vector space, *A* the matrix for *T* relative to a basis B_1 , and *B* the matrix for *T* relative to a basis B_2 . Show that *A* is diagonalizable if and only if *B* is diagonalizable.

5.3 Application: Systems of Linear Differential Equations

In Sec. 3.5 we considered only a rank differential equation where the solution involved a single function, revever, in many modeling applications, an equation that involves the derivatives of only one takes ion is not sufficient. It is more likely involves the derivatives of only one takes ion is not sufficient. It is more likely that there are of change of a variable of mixed will be linked to other functions outside solf. This is the function of a dynamical system. One of the most familiar examples of this is the *predator-prey* model. For example, suppose we take of create a model to predict the number of foxes and rabbits in some habitat. (It are with rate of the foxes is dependent on not only the number of foxes but also the number of rabbits in their territory. Likewise, the growth rate of the rabbit population in part is dependent on their current number, but is obviously mitigated by the number of foxes in their midst. The mathematical model required to describe this relationship is a system of differential equations of the form

$$\begin{cases} y_1'(t) &= f(t, y_1, y_2) \\ y_2'(t) &= g(t, y_1, y_2) \end{cases}$$

In this section we consider systems of linear differential equations. Problems such as predator-prey problems involve systems of *nonlinear* differential equations.

Uncoupled Systems

At the beginning of Sec. 3.5 we saw that the differential equation given by

$$y' = ay$$

has the solution $y(t) = Ce^{at}$, where C = y(0). An extension of this to two dimensions is the system of differential equations

$$\begin{cases} y_1' &= ay_1 \\ y_2' &= by_2 \end{cases}$$

5.3 Application: Systems of Linear Differential Equations **305**

In Example 2 we describe the solution for a system when the eigenvalues have the same sign.

EXAMPLE 2 Find the general solution to the system of differential equations

$$\begin{cases} y_1' = y_1 + 3y_2 \\ y_2' = 2y_2 \end{cases}$$

Solution The system of differential equations is given in matrix form by

$$\mathbf{y}' = A\mathbf{y} = \begin{bmatrix} 1 & 3\\ 0 & 2 \end{bmatrix}$$

The eigenvalues of A are $\lambda_1 = 1$ and $\lambda_2 = 2$ with corresponding eigenvectors

with general solution

The matrix that diagonalizes A is then 9 with $P^{-1} = \begin{bmatrix} 1 & -3 \\ 0 & 1 \end{bmatrix}$ with $P^{-1} = \begin{bmatrix} 1 & -3 \\ 0 & 1 \end{bmatrix}$

$$\mathbf{w}(t) = \begin{bmatrix} e^t \end{bmatrix}$$

 $= \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \mathbf{w}$

 $\mathbf{w}(t) = \begin{bmatrix} e^t & 0\\ 0 & e^{2t} \end{bmatrix} \mathbf{w}(0)$

 $\mathbf{w}' = \begin{bmatrix} 1 & -3 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 3 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 1 & 3 \\ 0 & 1 \end{bmatrix} \mathbf{w}$

Hence, the solution to the original system is given by

$$\mathbf{y}(t) = \begin{bmatrix} 1 & 3\\ 0 & 1 \end{bmatrix} \begin{bmatrix} e^t & 0\\ 0 & e^{2t} \end{bmatrix} \begin{bmatrix} 1 & -3\\ 0 & 1 \end{bmatrix} \mathbf{y}(0)$$
$$= \begin{bmatrix} e^t & -3e^t + 3e^{2t}\\ 0 & e^{2t} \end{bmatrix} \mathbf{y}(0)$$

The general solution can also be written in the form

$$y_1(t) = [y_1(0) - 3y_2(0)]e^t + 3y_2(0)e^{2t}$$
 and $y_2(t) = y_2(0)e^{2t}$

309 5.3 Application: Systems of Linear Differential Equations

Hence, the solution to the original system is given by

$$\mathbf{y}(t) = \begin{bmatrix} -1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} e^{-\frac{3}{20}t} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} -\frac{2}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} \end{bmatrix} \mathbf{y}(0)$$
$$= \frac{1}{3} \begin{bmatrix} 2e^{-\frac{3}{20}t} + 1 & -e^{-\frac{3}{20}t} + 1 \\ -2e^{-\frac{3}{20}t} + 2 & e^{-\frac{3}{20}t} + 2 \end{bmatrix} \begin{bmatrix} 8 \\ 0 \end{bmatrix}$$
$$= \frac{8}{3} \begin{bmatrix} 2e^{-\frac{3}{20}t} + 1 \\ -2e^{-\frac{3}{20}t} + 2 \end{bmatrix}$$

c. The solution to the system in equation form is given by

$$y_1(t) = \frac{8}{3} \left(2e^{-\frac{3}{20}t} + 1 \right)$$
 and $y_2(t) = \frac{8}{3} \left(-2e^{-\frac{3}{20}t} + 2 \right)$

To find the amount of salt in each tank as t goes to infinity, we compute the limits

and

 $(0+2) = \frac{16}{3}$ 3 Preview from tanks of a retion we expect that the 8 lb of salt should re in rithe value expect that the 8 lb of salt should i mic d, and divided proportionally between the two re nake sen oro B

Exercise Set 5.3

In Exercises 1-6, find the general solution to the system of differential equations.

1.
$$\begin{cases} y_1' = -y_1 + y_2 \\ y_2' = -2y_2 \end{cases}$$

2.
$$\begin{cases} y_1' = -y_1 + 2y_2 \\ y_2' = y_1 \end{cases}$$

3.
$$\begin{cases} y_1' = y_1 - 3y_2 \\ y_2' = -3y_1 + y_2 \end{cases}$$

4.
$$\begin{cases} y_1' = y_1 - y_2 \\ y_2' = -y_1 + y_2 \end{cases}$$

5.
$$\begin{cases} y_1' = -4y_1 - 3y_2 - 3y_3\\ y_2' = 2y_1 + 3y_2 + 2y_3\\ y_3' = 4y_1 + 2y_2 + 3y_3 \end{cases}$$

6.
$$\begin{cases} y_1' = -3y_1 - 4y_2 - 4y_3\\ y_2' = 7y_1 + 11y_2 + 13y_3\\ y_3' = -5y_1 - 8y_2 - 10y_3 \end{cases}$$

,

In Exercises 7 and 8, solve the initial-value problem.

3

7.
$$\begin{cases} y_1' = -y_1 & y_1(0) = 1 \\ y_2' = 2y_1 + y_2 \end{cases} \quad y_2(0) = -1$$

For reasons that will soon be clear, we scale \mathbf{v}_1 (by the reciprocal of the sum of its components) so that it becomes a probability vector. Observe that this new vector

$$\widehat{\mathbf{v}}_1 = \begin{bmatrix} \frac{5}{8} \\ \frac{3}{8} \end{bmatrix}$$

is also an eigenvector since it is in the eigenspace V_{λ_1} . Since the 2 × 2 transition matrix has two distinct eigenvalues, by Corollary 1 of Sec. 5.2, T is diagonalizable and, by Theorem 2 of Sec. 5.2, can be written as





By Exercise 27 of Sec. 5.2, the powers of T are given by

as n gets large. This suggests that the eigenvector corresponding to $\lambda = 1$ is useful in determining the limiting proportion of sunny days to cloudy days far into the future.

Steady-State Vector

Given an initial state vector \mathbf{v} , of interest is the long-run behavior of this vector in a Markov chain, that is, the tendency of the vector $T^n \mathbf{v}$ for large n. If for any initial state vector **v** there is some vector **s** such that T^n **v** approaches **s**, then **s** is called a steady-state vector for the Markov process.

In our weather model we saw that the transition matrix T has an eigenvalue $\lambda = 1$ and a corresponding probability eigenvector given by

$$\widehat{\mathbf{v}}_1 = \begin{bmatrix} \frac{5}{8} \\ \frac{3}{8} \end{bmatrix} = \begin{bmatrix} 0.625 \\ 0.375 \end{bmatrix}$$

314 Chapter 5 Eigenvalues and Eigenvectors

We claim that this vector is a steady-state vector for the weather model. As verification,

0.4 let \boldsymbol{u} be an initial probability vector, say, $\boldsymbol{u}=$. We then compute 0.6

$$T^{10}\mathbf{u} = \begin{bmatrix} 0.6249999954\\ 0.3750000046 \end{bmatrix} \text{ and } T^{20}\mathbf{u} = \begin{bmatrix} 0.6250000002\\ 0.3750000002 \end{bmatrix}$$

which suggests that $T^n \mathbf{u}$ approaches $\hat{\mathbf{v}}_1$. That this is in fact the case is stated in Theorem 6. Before doing so, we note that a **regular** transition matrix T is a transition matrix such that for some n, all the entries of T^n are positive.

THEOREM 6

If a Markov chain has a regular stochastic transition matrix T, then there is a unique probability vector s with Ts = s. Moreover, s is the steady-state vector for any initial probability vector.

EXAMPLE 1

A group insurance plan allows three different options for variationants, plan A, B, or C. Suppose that the percentages of the total function participants enrolled in each plan are 25 percent, 30 percent, a did verticed, respectively. Also, from past experience assume that partic pans change plans as shown in the table.

Preview from 0.4 0.4 0.1 0.3

percent of participants enrolled in each plan after 5 years. End the steady-state vector for the system.

Solution Let *T* be the matrix given by

$$T = \begin{bmatrix} 0.75 & 0.25 & 0.2 \\ 0.15 & 0.45 & 0.4 \\ 0.1 & 0.3 & 0.4 \end{bmatrix}$$

a. The number of participants enrolled in each plan after 5 years is approximated by the vector

	0.49776	0.46048	0.45608	0.25		0.47	
$T^5 \mathbf{v} =$	0.28464	0.30432	0.30664	0.30	=	0.30	
	0.21760	0.23520	0.23728	0.45		0.22	

so approximately 47 percent will be enrolled in plan A, 30 percent in plan B, and 22 percent in plan C.

b. The steady-state vector for the system is the probability eigenvector corresponding to the eigenvalue $\lambda = 1$, that is,

	0.48	
5 =	0.30	
	0.22	
		-

318 Chapter 5 Eigenvalues and Eigenvectors

a. Let *D* be the diagonal matrix

$$D = \begin{bmatrix} \lambda_1 & 0 & 0 & \dots & 0 \\ 0 & \lambda_2 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & & \vdots \\ 0 & \dots & \dots & \lambda_n \end{bmatrix}$$

and find e^D .

Chapter 5: Chapter Test

b. Suppose A is diagonalizable and $D = P^{-1}AP$. Show that $e^A = P e^D P^{-1}$.

c. Use parts (a) and (b) to compute e^A for the matrix

$$A = \left[\begin{array}{cc} 6 & -1 \\ 3 & 2 \end{array} \right]$$

In Exercises 1-40, determine whether the statement is 6. The eigenvectors of true or false. 1. The matrix $P = \left[\begin{array}{cc} 1 & 1 \\ 0 & 1 \end{array} \right]$ diagonalizes the matrix m Notes $\begin{array}{ccc}
-1 & 1 \\
0 & -2
\end{array}$ $\begin{bmatrix} 3 & -2 \\ 2 & -1 \end{bmatrix}$ A =han eg a dimension 1. value $\lambda_1 = 1$ and V_{λ_1} has 2. The matrix 8. If $A = \begin{vmatrix} -\frac{1}{2} & \frac{\sqrt{3}}{2} \\ \frac{\sqrt{3}}{2} & \frac{1}{2} \end{vmatrix}$ then $AA^t = I$. 3. The matrix **9.** If A is a 2×2 matrix with det(A) < 0, then A has two real eigenvalues. $A = \begin{bmatrix} -1 & 0 & 0\\ 0 & 1 & 0\\ -1 & -1 & 1 \end{bmatrix}$ 10. If A is a 2×2 matrix that has two distinct

is diagonalizable.

4. The eigenvalues of

$$A = \left[\begin{array}{rr} -1 & 0\\ -4 & -3 \end{array} \right]$$

are
$$\lambda_1 = -3$$
 and $\lambda_2 = -1$

5. The characteristic polynomial of

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

is $\lambda^3 + 2\lambda^2 + \lambda - 4$.

- eigenvalues λ_1 and λ_2 , then $\mathbf{tr}(A) = \lambda_1 + \lambda_2$.
- **11.** If $A = \begin{bmatrix} a & b \\ b & a \end{bmatrix}$, then the eigenvalues of A are $\lambda_1 = a + b$ and $\lambda_2 = b - a$.
- **12.** For all integers k the matrix $A = \begin{bmatrix} 1 & k \\ 1 & 1 \end{bmatrix}$ has only one eigenvalue.
- **13.** If A is a 2×2 invertible matrix, then A and A^{-1} have the same eigenvalues.
- 14. If A is similar to B, then tr(A) = tr(B).
- **15.** The matrix $A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$ is diagonalizable.

6.1 The Dot Product on \mathbb{R}^n **329**

PROPOSITION 2

Two nonzero vectors \mathbf{u} and \mathbf{v} in \mathbb{R}^n are orthogonal if and only if $\mathbf{u} \cdot \mathbf{v} = 0$. The zero vector is orthogonal to every vector in \mathbb{R}^n .

One consequence of Proposition 2 is that if \mathbf{u} and \mathbf{v} are orthogonal, then

$$\|\mathbf{u} + \mathbf{v}\|^{2} = (\mathbf{u} + \mathbf{v}) \cdot (\mathbf{u} + \mathbf{v}) = \|\mathbf{u}\|^{2} + 2\mathbf{u} \cdot \mathbf{v} + \|\mathbf{v}\|^{2}$$
$$= \|\mathbf{u}\|^{2} + \|\mathbf{v}\|^{2}$$

This is a generalization of the Pythagorean theorem to \mathbb{R}^n . Theorem 3 gives several useful properties of the norm in \mathbb{R}^n .



Figure 4

Geometrically, part 4 of Theorem 3 confirms our intuition that the shortest distance between two points is a straight line, as seen in Fig. 4.

PROPOSITION 3

Let **u** and **v** be vectors in \mathbb{R}^n . Then $\|\mathbf{u} + \mathbf{v}\| = \|\mathbf{u}\| + \|\mathbf{v}\|$ if and only if the vectors have the same direction.

Proof First suppose that the vectors have the same direction. Then the angle between the vectors is 0, so that $\cos \theta = 1$ and $\mathbf{u} \cdot \mathbf{v} = \|\mathbf{u}\| \|\mathbf{v}\|$. Therefore,

$$\mathbf{u} + \mathbf{v} \|^{2} = (\mathbf{u} + \mathbf{v}) \cdot (\mathbf{u} + \mathbf{v})$$

= $\|\mathbf{u}\|^{2} + 2(\mathbf{u} \cdot \mathbf{v}) + \|\mathbf{v}\|^{2}$
= $\|\mathbf{u}\|^{2} + 2\|\mathbf{u}\|\|\mathbf{v}\| + \|\mathbf{v}\|^{2}$
= $(\|\mathbf{u}\| + \|\mathbf{v}\|)^{2}$

Taking square roots of both sides of the previous equation gives $||\mathbf{u} + \mathbf{v}|| =$ $||\mathbf{u}|| + ||\mathbf{v}||.$

Conversely, suppose that $\|\mathbf{u} + \mathbf{v}\| = \|\mathbf{u}\| + \|\mathbf{v}\|$. After squaring both sides, we obtain



Fact Summary

All vectors are in \mathbb{R}^n .

- 1. The length of a vector and the distance between two vectors are natural extensions of the same geometric notions in \mathbb{R}^2 and \mathbb{R}^3 .
- 2. The dot product of a vector with itself gives the square of its length and is 0 only when the vector is the zero vector. The dot product of two vectors is commutative and distributes through vector addition.
- **3.** By using the Cauchy-Schwartz inequality $|\mathbf{u} \cdot \mathbf{v}| \le ||\mathbf{u}|| ||\mathbf{v}||$, the angle between vectors is defined by

$$\cos \theta = \frac{\mathbf{u} \cdot \mathbf{v}}{\|\mathbf{u}\| \|\mathbf{v}\|}$$

4. Two vectors are orthogonal if and only if the dot product of the vectors is 0.

330

In Exercises 19–22, let

$$\mathbf{v_1} = \begin{bmatrix} 1\\ 2\\ -1 \end{bmatrix} \qquad \mathbf{v_2} = \begin{bmatrix} 6\\ -2\\ 2 \end{bmatrix}$$
$$\mathbf{v_3} = \begin{bmatrix} -1\\ -2\\ 1 \end{bmatrix} \qquad \mathbf{v_4} = \begin{bmatrix} -1/\sqrt{3}\\ 1/\sqrt{3}\\ 1/\sqrt{3} \end{bmatrix}$$
$$\mathbf{v_5} = \begin{bmatrix} 3\\ -1\\ 1 \end{bmatrix}$$

- 19. Determine which of the vectors are orthogonal.
- **20.** Determine which of the vectors are in the same direction.
- **21.** Determine which of the vectors are in the opposite direction.

22. Determine which of the vectors are unit vectors 23-28, find the projection of one of given by

The vector **w** is called the *orthogonal projection* of **u**

TI O

onto v. Sketch the three vectors \mathbf{u} , \mathbf{v} , and \mathbf{w} .

23.
$$\mathbf{u} = \begin{bmatrix} 2\\ 3 \end{bmatrix} \mathbf{v} = \begin{bmatrix} 4\\ 0 \end{bmatrix}$$

24. $\mathbf{u} = \begin{bmatrix} -2\\ 3 \end{bmatrix} \mathbf{v} = \begin{bmatrix} 4\\ 0 \end{bmatrix}$
25. $\mathbf{u} = \begin{bmatrix} 4\\ 3 \end{bmatrix} \mathbf{v} = \begin{bmatrix} 3\\ 1 \end{bmatrix}$
26. $\mathbf{u} = \begin{bmatrix} 5\\ 2\\ 1 \end{bmatrix} \mathbf{v} = \begin{bmatrix} 1\\ 0\\ 0 \end{bmatrix}$
27. $\mathbf{u} = \begin{bmatrix} 1\\ 0\\ 0 \end{bmatrix} \mathbf{v} = \begin{bmatrix} 5\\ 2\\ 1 \end{bmatrix}$

28.
$$\mathbf{u} = \begin{bmatrix} 2\\ 3\\ -1 \end{bmatrix} \mathbf{v} = \begin{bmatrix} 0\\ 2\\ 3 \end{bmatrix}$$

- **29.** Let $S = {\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n}$ and suppose $\mathbf{v} \cdot \mathbf{u}_i = 0$ for each $i = 1, \dots, n$. Show that \mathbf{v} is orthogonal to every vector in **span**(*S*).
- **30.** Let **v** be a fixed vector in \mathbb{R}^n and define $S = \{\mathbf{u} \mid \mathbf{u} \cdot \mathbf{v} = 0\}$. Show that S is a subspace of \mathbb{R}^n .
- **31.** Let $S = {\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n}$ be a set of nonzero vectors which are pairwise orthogonal. That is, if $i \neq j$, then $\mathbf{v}_i \cdot \mathbf{v}_j = 0$. Show that *S* is linearly independent.
- **32.** Let A be an $n \times n$ invertible matrix. Show that if $i \neq i$, the row vector i of A and column vector $i \neq i^{n}$ are orthogonal.
 - the **u** r all vectors **u** and **v** in \mathbb{R}^n ,

|| u +

$$\mathbf{v} \|^{2} + \| \mathbf{u} - \mathbf{v} \|^{2}$$
$$= 2 \| \mathbf{u} \|^{2} + 2 \| \mathbf{v} \|^{2}$$

- **34.** a. Find a vector that is orthogonal to every vector in the plane P: x + 2y z = 0.
 - **b.** Find a matrix A such that the null space N(A) is the plane x + 2y z = 0.
- **35.** Suppose that the column vectors of an $n \times n$ matrix *A* are pairwise orthogonal. Find $A^t A$.
- **36.** Let *A* be an $n \times n$ matrix and **u** and **v** vectors in \mathbb{R}^n . Show that

$$\mathbf{u} \cdot (A\mathbf{v}) = (A^t \mathbf{u}) \cdot \mathbf{v}$$

37. Let *A* be an $n \times n$ matrix. Show that *A* is symmetric if and only if

$$(A\mathbf{u}) \cdot \mathbf{v} = \mathbf{u} \cdot (A\mathbf{v})$$

for all **u** and **v** in \mathbb{R}^n . *Hint*: See Exercise 36.

and linearly independent. Theorem 5 relates the notions of orthogonality and linear independence in an inner product space.

THEOREM 5

If $S = {\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n}$ is an orthogonal set of nonzero vectors in an inner product space *V*, then *S* is linearly independent.

Proof Since the set S is an orthogonal set of nonzero vectors,

 $\langle \mathbf{v}_i, \mathbf{v}_j \rangle = 0$ for $i \neq j$ and $\langle \mathbf{v}_i, \mathbf{v}_i \rangle = \|\mathbf{v}_i\|^2 \neq 0$ for all i

Now suppose that

$$c_1\mathbf{v}_1 + c_2\mathbf{v}_2 + \cdots + c_n\mathbf{v}_n = \mathbf{0}$$

The vectors are linearly independent if and only if the only solution to the previous equation is the trivial solution $c_1 = c_2 = \cdots = c_n = 0$. Now let \mathbf{v}_j be an element of S. Take the inner product on both sides of the previous equation with \mathbf{v}_i so that

 $\langle \mathbf{v}_j, (c_1\mathbf{v}_1 + c_2\mathbf{v}_2 + \dots + c_{j-1}\mathbf{v}_{j-1} + c_j\mathbf{v}_j + c_{j+1}\mathbf{v}_{j+1} + \dots + c_n\mathbf{v}_n) \rangle = \langle \mathbf{v}_j, \mathbf{0} \rangle$ By the linearity of the inner product and the fact that $\mathbf{v}_j = \langle \mathbf{v}_j, \mathbf{0} \rangle$ Now deterposition 4 and the fact that $\mathbf{v}_j \parallel \neq 0$, we have $\langle \mathbf{v}_j \mathbf{v}_j \parallel^2 = 0$ so that $c_j = 0$ Since this bodies for each $j = 1, \dots, n$, then $c_1 = c_2 = \dots = c_n = 0$ and therefore $\mathbf{v}_j \mathbf{v}_j \parallel \mathbf{v}_j$ independent.

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If V is an inner product space of dimension n, then any orthogonal set of n nonzero vectors is a basis for V.

The proof of this corollary is a direct result of Theorem 12 of Sec. 3.3. Theorem 6 provides us with an easy way to find the coordinates of a vector relative to an orthonormal basis. This property underscores the usefulness and desirability of orthonormal bases.

THEOREM 6

If $B = {\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n}$ is an ordered orthonormal basis for an inner product space *V* and $\mathbf{v} = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2 + \dots + c_n \mathbf{v}_n$, then the coordinates of \mathbf{v} relative to *B* are given by $c_i = \langle \mathbf{v}_i, \mathbf{v} \rangle$ for each $i = 1, 2, \dots, n$.

Proof Let \mathbf{v}_i be a vector in *B*. Taking the inner product on both sides of

 $\mathbf{v} = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2 + \cdots + c_{i-1} \mathbf{v}_{i-1} + c_i \mathbf{v}_i + c_{i+1} \mathbf{v}_{i+1} + \cdots + c_n \mathbf{v}_n$

To justify this substitution, note that $\mathbf{w}_1 \cdot \mathbf{w}_2 = 0$; that is, multiplying \mathbf{w}_2 by a scalar does not change the fact that it is orthogonal to \mathbf{w}_1 . To find \mathbf{w}_3 , we use the computation



Fact Summary

- **1.** Every finite dimensional inner product space has an orthonormal basis.
- **2.** The Gram-Schmidt process is an algorithm to construct an orthonormal basis from any basis of the vector space.

Exercise Set 6.3

In Exercises 1–8, use the standard inner product on \mathbb{R}^n .

- **a.** Find proj_v **u**.
- **b.** Find the vector $\mathbf{u} \text{proj}_{\mathbf{v}}\mathbf{u}$ and verify this vector is orthogonal to \mathbf{v} .

1.
$$\mathbf{u} = \begin{bmatrix} -1 \\ 2 \end{bmatrix} \mathbf{v} = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

2. $\mathbf{u} = \begin{bmatrix} 3 \\ -2 \end{bmatrix} \mathbf{v} = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$

6.3 Orthonormal Bases 353

13.
$$B = \left\{ \begin{bmatrix} 1 \\ -1 \end{bmatrix}, \begin{bmatrix} 1 \\ -2 \end{bmatrix} \right\}$$

14.
$$B = \left\{ \begin{bmatrix} 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ -2 \end{bmatrix} \right\}$$

15.
$$B = \left\{ \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ -1 \end{bmatrix} \right\}$$

$$\langle p,q\rangle = \int_0^1 p(x)q(x)\,dx$$

to find an orthonormal basis for the subspace span(W).

23.
$$W = \{x, 2x + 1\}$$

24.
$$W = \{1, x + 2, x^3 - 1\}$$

Solution a. Let

$$\mathbf{w}_1 = \begin{bmatrix} 1\\0\\-1\\-1 \end{bmatrix} \quad \text{and} \quad \mathbf{w}_2 = \begin{bmatrix} 0\\1\\-1\\1 \end{bmatrix}$$

Notice that \mathbf{w}_1 and \mathbf{w}_2 are orthogonal and hence by Theorem 5 of Sec. 6.2 are linearly independent. Thus, $\{\mathbf{w}_1, \mathbf{w}_2\}$ is a basis for W.

b. Now by Proposition 5, the vector

$$= \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix}$$

is in W^{\perp} if and only if $\mathbf{v} \cdot \mathbf{w}_1 = 0$ and $\mathbf{v} \cdot \mathbf{w}_2 = 0$. This requirement leads to the linear system

w = 0The two parameters surfice set for this linear system is **Preview from 378 of** = $\begin{cases} 0 \\ s \\ t \\ t \end{cases} | s, t \in \mathbb{R} \end{cases}$ **Preview of the solution to this system, in vector form, provides a description of the orthogonal complement of W and is given by**

orthogonal complement of W and is given by

$$W^{\perp} = \operatorname{span} \left\{ \begin{bmatrix} 1\\1\\1\\0 \end{bmatrix}, \begin{bmatrix} 1\\-1\\0\\1 \end{bmatrix} \right\}$$

Let

$$\mathbf{v}_1 = \begin{bmatrix} 1\\1\\1\\0 \end{bmatrix} \quad \text{and} \quad \mathbf{v}_2 = \begin{bmatrix} 1\\-1\\0\\1 \end{bmatrix}$$

Since \mathbf{v}_1 and \mathbf{v}_2 are orthogonal, by Theorem 5 of Sec. 6.2 they are linearly independent and hence a basis for W^{\perp} .

c. Let B be the set of vectors $B = {\mathbf{w}_1, \mathbf{w}_2, \mathbf{v}_1, \mathbf{v}_2}$. Since B is an orthogonal set of four vectors in \mathbb{R}^4 , then by Corollary 1 of Sec. 6.2, B is a basis for \mathbb{R}^4 . Dividing each of these vectors by its length, we obtain the (ordered) orthonormal basis for \mathbb{R}^4 given by

a function in W

symmetric}

to the

2

Chapter 6 Inner Product Spaces

22.
$$W = \operatorname{span} \left\{ \begin{bmatrix} 1 \\ 2 \end{bmatrix} \right\} \mathbf{v} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

23. $W = \operatorname{span} \left\{ \begin{bmatrix} 3 \\ -1 \end{bmatrix} \right\} \mathbf{v} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$
24. $W = \operatorname{span} \left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \right\}$
24. $W = \operatorname{span} \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \end{bmatrix} \right\}$
 $\mathbf{v} = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$
25. $W = \operatorname{span} \left\{ \begin{bmatrix} 1 \\ 1 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 2 \\ 4 \end{bmatrix} \right\}$
 $\mathbf{v} = \begin{bmatrix} 2 \\ 1 \\ 1 \\ 1 \end{bmatrix}$
 $\mathbf{v} = \begin{bmatrix} 2 \\ 1 \\ 1 \\ 1 \end{bmatrix}$
 $\mathbf{v} = \begin{bmatrix} 2 \\ 1 \\ 1 \\ 1 \end{bmatrix}$
25. $W = \operatorname{span} \left\{ \begin{bmatrix} 1 \\ -1 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 2 \\ 4 \end{bmatrix} \right\}$
 $\mathbf{v} = \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix}$
 $\mathbf{v} = \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix}$
 $\mathbf{v} = \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix}$
26. Show that if V is an inner product space, $\mathbf{v} = \mathbf{v}$
27. Show that if V is an inner product space, $\mathbf{v} = \mathbf{v}$
28. Let $V = C^{(0)}[-1, 1]$ with the mner product $\langle f, g \rangle = \int_{-1}^{-1} f(x)g(x) dx$
and $W = \{f \in V \mid f(-x) = f(x)\}$.
a. Show that W is a subspace of V.
b. Show $W^{\perp} = \{f \in V \mid f(-x) = -f(x)\}$.
a. Show that W is a subspace of V.
b. Show $W^{\perp} = \{f \in V \mid f(-x) = -f(x)\}$.
a. Show that $(W^{\perp}) = W$.
30. In \mathbb{R}^2 with the terms of a vector to the standard basis for the orthogonal projection of \mathbb{R}^2 onto W.
b. Let $\mathbf{v} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$. Find proj_W v and verify the result is the same by applying the matrix P found in part (a).
c. Show $P^2 = P$.
31. If W is a finite dimensional subspace of an inner product space, show that $(W^{\perp})^{\perp} = W$.

6.5 Application: Least Squares Approximation

There are many applications in mathematics and science where an exact solution to a problem cannot be found, but an approximate solution exists that is sufficient to satisfy the demands of the application. Consider the problem of finding the equation of a line going through the points (1, 2), (2, 1), and (3, 3). Observe from Fig. 1 that this problem has no solution as the three points are noncollinear.

This leads to the problem of finding the line that is the best fit for these three points based on some criteria for measuring goodness of fit. There are different ways of solving this new problem. One way, which uses calculus, is based on the idea

366

- **1.** Find the eigenvalues and corresponding eigenvectors of *A*.
- 2. Since A is diagonalizable, there are n linearly independent eigenvectors. If necessary, use the Gram-Schmidt process to find an orthonormal set of eigenvectors.
- 3. Form the orthogonal matrix P with column vectors determined in Step 2.
- 4. The matrix $P^{-1}AP = P^{t}AP = D$ is a diagonal matrix.

EXAMPLE 3 Let $A = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}$ Find an orthogonal matrix *P* such that $P^{-1}AP$ is a diagonal matrix. **Solution**The characteristic equation for *A* is given by $det(A - \lambda I) = -\lambda^3 + 3\lambda + 2 = -(\lambda - 2)(\lambda + 1)^2 = 0$ Thus, the eigenvalues are $\lambda_1 = -1$ and $\lambda_2 = 2$. The operating eigenspaces are $V_{\lambda_1} = \operatorname{span} \left\{ \begin{bmatrix} -1 \\ 0 \\ 0 \end{bmatrix} \right\} \text{ and } V_{\lambda_2} = \operatorname{span} \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \right\}$ For $A = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\} = \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \right\}$ Since *B* is a linearly independent set of three vectors, by Theorem 2 of Sec. 5.2,

Since *B* is a linearly independent set of three vectors, by Theorem 2 of Sec. 5.2, *A* is diagonalizable. To find an orthogonal matrix *P* which diagonalizes *A*, we use the Gram-Schmidt process on *B*. This was done in Example 3 of Sec. 6.3, yielding the orthonormal basis

$$B' = \left\{ \frac{1}{\sqrt{3}} \begin{bmatrix} 1\\1\\1 \end{bmatrix}, \frac{1}{\sqrt{2}} \begin{bmatrix} -1\\1\\0 \end{bmatrix}, \frac{1}{\sqrt{6}} \begin{bmatrix} -1\\-1\\2 \end{bmatrix} \right\}$$

Now let *P* be the matrix given by

$$P = \begin{bmatrix} \frac{\sqrt{3}}{3} & -\frac{\sqrt{2}}{2} & -\frac{\sqrt{6}}{6} \\ \frac{\sqrt{3}}{3} & \frac{\sqrt{2}}{2} & -\frac{\sqrt{6}}{6} \\ \frac{\sqrt{3}}{3} & 0 & \frac{\sqrt{6}}{3} \end{bmatrix}$$

Observe that P is an orthogonal matrix with $P^{-1} = P^t$. Morevover,

$$P^{t}AP = \begin{bmatrix} 2 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix}$$

Since the eigenvalues have opposite sign, the conic section C is a hyperbola. To describe the hyperbola, we first diagonalize A. Using the unit eigenvectors, the orthogonal matrix that diagonalizes A is

$$P = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & -2\\ 2 & 1 \end{bmatrix} \quad \text{with} \quad \begin{bmatrix} -2 & 0\\ 0 & 3 \end{bmatrix} = P^t A P$$

Making the substitution $\mathbf{x} = P\mathbf{x}'$ in the equation $\mathbf{x}^t A\mathbf{x} + \mathbf{b}^t \mathbf{x} + f = 0$ gives

$$\begin{bmatrix} x' \ y' \end{bmatrix} \begin{bmatrix} -2 & 0 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} x' \\ y' \end{bmatrix} + \begin{bmatrix} -4 & -8 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{-2}{\sqrt{5}} \\ \frac{2}{\sqrt{5}} & \frac{1}{\sqrt{5}} \end{bmatrix} \begin{bmatrix} x' \\ y' \end{bmatrix} + 14 = 0$$

After simplification of this equation we obtain

$$-2(x')^2 - 4\sqrt{5}x' + 3(y')^2 + 14 = 0$$

that is,

$$-2[(x')^2 + 2\sqrt{5}(x')] + 3(y')^2 + 14 = 0$$

After completing the square on x', we obtain

that is,

Preview

erbola with x' as the major axis. An additional C the x' axis allows us to simplify the result even further. transformation S

-

-14 - 10

$$x'' = x' + \sqrt{5}$$
 and $y'' = y'$

then the equation now becomes

$$\frac{(x'')^2}{12} - \frac{(y'')^2}{8} = 1$$

The graph is shown in Fig. 3.



390



For certain matrices, some of the singular values may be z ro. As an illustration, . For this matrix, we have col(A) = spanconsider the matrix A = $\begin{bmatrix} 1 & 2 \\ 0 & 0 \end{bmatrix}$, which has only one PtopAs the matrix The reduced row echelon to The eigenvalues of $A^t A$ are $\lambda_1 = 50$ pivot column Hei conthe rank of A wh corresponding onit Preview and $\mathbf{v}_2 = \begin{bmatrix} -2/\sqrt{5} \\ 1/\sqrt{5} \end{bmatrix}$ igular values of A are given by $\sigma_1 = 5\sqrt{2}$ and $\sigma_2 = 0$. Now, multiplying \mathbf{v}_1

and \mathbf{v}_2 by A gives

$$A\mathbf{v}_1 = \begin{bmatrix} \sqrt{5} \\ 3\sqrt{5} \end{bmatrix}$$
 and $A\mathbf{v}_2 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

Observe that $A\mathbf{v}_1$ spans the one dimensional column space of A. In this case, the linear transformation $T: \mathbb{R}^2 \longrightarrow \mathbb{R}^2$ defined by $T(\mathbf{x}) = A\mathbf{x}$ maps the unit circle to the line segment

$$\left\{ t \left[\begin{array}{c} \sqrt{5} \\ 3\sqrt{5} \end{array} \right] \middle| -1 \le t \le 1 \right\}$$

as shown in Fig. 2.

Singular Value Decomposition (SVD)

We now turn our attention to the problem of finding a singular value decomposition of an $m \times n$ matrix A.

THEOREM 18

SVD Let A be an $m \times n$ matrix of rank r, with r nonzero singular values $\sigma_1, \sigma_2, \ldots, \sigma_r$. Then there exists an $m \times n$ matrix Σ , an $m \times m$ orthogonal matrix


398 Chapter 6 Inner Product Spaces

Then

$$U\Sigma = \begin{bmatrix} \mathbf{u}_1 & \mathbf{u}_2 & \cdots & \mathbf{u}_m \end{bmatrix} \Sigma$$
$$= \begin{bmatrix} \sigma_1 \mathbf{u}_1 & \cdots & \sigma_r \mathbf{u}_r & \mathbf{0} & \cdots & \mathbf{0} \end{bmatrix}$$
$$= AV$$

Since V is orthogonal, then $V^t = V^{-1}$, and hence, $A = U \Sigma V^t$.



$$\mathbf{v}_1 = \begin{bmatrix} -1/\sqrt{2} \\ 1/\sqrt{2} \end{bmatrix}$$
 and $\mathbf{v}_2 = \begin{bmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{bmatrix}$

Since the column vectors of V are given by the orthonormal eigenvectors of $A^t A$, the matrix V is given by

$$V = \left[\begin{array}{cc} -1/\sqrt{2} & 1/\sqrt{2} \\ 1/\sqrt{2} & 1/\sqrt{2} \end{array} \right]$$

Step 2. Find the singular values of A and define the matrix Σ . The singular values of A are the square roots of the eigenvalues of A^tA , so that

$$\sigma_1 = \sqrt{\lambda_1} = 2\sqrt{3}$$
 and $\sigma_2 = \sqrt{\lambda_2} = 0$

Since Σ has the same dimensions as A, then Σ is 3×2 . In this case,

$$\Sigma = \left[\begin{array}{cc} 2\sqrt{3} & 0\\ 0 & 0\\ 0 & 0 \end{array} \right]$$

402 Chapter 6 Inner Product Spaces

singular values) has the SVD $A = U\Sigma V^t$. That is,

$$A = U\Sigma V^{t} = \begin{bmatrix} \sigma_{1}\mathbf{u}_{1} & \cdots & \sigma_{r}\mathbf{u}_{r} & \mathbf{0} & \cdots & \mathbf{0} \end{bmatrix} V^{t}$$

$$= \sigma_{1}\mathbf{u}_{1}\mathbf{v}_{1}^{t} + \sigma_{2}\mathbf{u}_{2}\mathbf{v}_{2}^{t} + \cdots + \sigma_{r}\mathbf{u}_{r}\mathbf{v}_{r}^{t}$$

$$= \sigma_{1}\left(\frac{1}{\sigma_{1}}A\mathbf{v}_{1}\right)\mathbf{v}_{1}^{t} + \sigma_{2}\left(\frac{1}{\sigma_{2}}A\mathbf{v}_{2}\right)\mathbf{v}_{2}^{t} + \cdots + \sigma_{r}\left(\frac{1}{\sigma_{r}}A\mathbf{v}_{r}\right)\mathbf{v}_{r}^{t}$$

$$= (A\mathbf{v}_{1})\mathbf{v}_{1}^{t} + (A\mathbf{v}_{2})\mathbf{v}_{2}^{t} + \cdots + (A\mathbf{v}_{r})\mathbf{v}_{r}^{t}$$

Figure 4

Preview

Observe that each of the terms $A\mathbf{v}_i\mathbf{v}_i^t$ is a matrix of rank 1. Consequently, the sum of the first *k* terms of the last equation is a matrix of rank $k \le r$, which gives an approximation to the matrix *A*. This factorization of a matrix has application in many areas.

As an illustration of the utility of such an approximation, suppose that A is the 356×500 matrix, where each entry is a numeric value for a pixel, of the gray scale image of the surface of Mars shown in Fig. 4. A simple algorithe using the method above for approximating the image stored in the matrix A is given by the following:

1. Find the eigenvectors of the ~ 0 ymmetric matrix $A^t A$.

2. Compute A with k = r = rank(A).

3. The matrix $(A\mathbf{v}_1)\mathbf{v}_1' + (A\mathbf{v}_2)\mathbf{v}_2'$ is an approximation of the original image.

To transmit the kth approximation of the image and reproduce it back on earth representation $\mathbf{v}_1, \ldots, \mathbf{v}_k$ of A'A and the vectors $A\mathbf{v}_1, \ldots, A\mathbf{v}_k$.

images in Fig. 5 are produced using matrices of ranks 1, 4, 10, 40, 80, and 100, respectively.



Figure 5

The storage requirements for each of the images are given in Table 1.

read as "Q implies P" or "P is necessary for Q." For example, let P be the statement Mary lives in Iowa and Q the statement that Mary lives in the United States. Then certainly $P \implies Q$ is a theorem since every resident of Iowa is a resident of the United States. But $Q \implies P$ is not a theorem since, for example, if Mary is a resident of California, then she is a resident of the United States but not a resident of Iowa. So the statement $Q \implies P$ is not always true given that Q is true. In terms of sets, if A is the set of residents of Iowa and B is the set of residents of the United States, then the statement P is Mary is in A and Q is Mary is in B. Then Mary is in A implies Mary is in B. It is also clear that if Mary is in $B \setminus A$, then Mary is in B does not imply that Mary is in A.

A statement that is equivalent to the theorem $P \implies Q$ is the **contrapositive** statement $\sim Q \implies \sim P$, that is, *not* Q *implies not* P. In the example above, if Mary is not a resident of the United States, then Mary is not a resident of Iowa. An equivalent formulation of the statement, in the terminology of sets, is that if Mary $\notin B$, then it implies Mary $\notin A$.

There are other statements in mathematics that require roof. **Lemmas** are preliminary results used to prove theorems, **propositions** a coresults not as important as theorems, and **corollaries** are special cases of a theorem. A statement that is not yet proven is called a **conjecture**. Dre of the most famous conjectures is the celebrated Riemann hypothesis. A single **counterexample** is enough to refute a false conjecture. For example, the statement *all move ave green eyes* is rendered invalid by the discovery of a single blue-effect no.

In this section we write introduce three main types of proof. A fourth type, called matter researchduction, is discussed in Sec. A.4.

Preview Called mathematical and Papert Argument

In a **direct argument**, a sequence of logical steps links the hypotheses P to the conclusion Q. Example 1 provides an illustration of this technique.

EXAMPLE 1

Prove that if p and q are odd integers, then p + q is an even integer.

Solution

To prove this statement with a direct argument, we assume that p and q are odd integers. Then there are integers m and n such that

$$p = 2m + 1$$
 and $q = 2n + 1$

Adding p and q gives

$$p + q = 2m + 1 + 2n + 1$$

= 2(m + n) + 2
= 2(m + n + 1)

Since p + q is a multiple of 2, it is an even integer.

Since for every natural number $n \ge 1$ it is also the case that $n + 1 \ge 2$, we have $(n+1)! \ge (n+1)2^{n-1} \ge 2 \cdot 2^{n-1} = 2^n$ Consequently, the statement $n! \ge 2^{n-1}$ is true for every natural number n.

EXAMPLE 4

For any natural number n, find the sum of the odd natural numbers from 1 to 2n - 1.

Solution The first five cases are given in Table 3.



$$1 + 3 + 5 + 7 + \dots + (2n - 1) = n^2$$

Starting with the case for n = 1, we see that the left-hand side is 1 and the expression on the right is $1^2 = 1$. Hence, the statement holds when n = 1. Next, we assume that $1 + 3 + 5 + \dots + (2n - 1) = n^2$. For the next case when the index is n + 1, we consider the sum

$$1 + 3 + 5 + \dots + (2n - 1) + [2(n + 1) - 1] = 1 + 3 + 5 + \dots + (2n - 1) + (2n + 1)$$

Using the inductive hypothesis, we get

$$\underbrace{1+3+5+\dots+(2n-1)}_{n^2} + [2(n+1)-1] = n^2 + (2n+1)$$
$$= n^2 + 2n + 1$$
$$= (n+1)^2$$

Therefore, by induction the statement holds for all natural numbers.

Answers to Odd-Numbered Exercises 4



455



466 Answers to Odd-Numbered Exercises

39. Since *A* and *B* are matrix representations for the same linear operator, they are similar. Let $A = Q^{-1}BQ$. The matrix *A* is diagonalizable if and only if $D = P^{-1}AP$ for some invertible matrix *P* and diagonal matrix *D*. Then

$$D = P^{-1}(Q^{-1}BQ)P = (QP)^{-1}B(QP)$$

so B is diagonalizable. The proof of the converse is identical.

3. $T = \begin{bmatrix} 0.5 & 0.4 & 0.1 \\ 0.4 & 0.4 & 0.2 \\ 0.1 & 0.2 & 0.7 \end{bmatrix}$

 $T^{3} \begin{bmatrix} 0\\1\\0 \end{bmatrix} \approx \begin{bmatrix} 0.36\\0.35\\0.29 \end{bmatrix}$

 $T^{10} \begin{bmatrix} 0\\1 \end{bmatrix} \approx \begin{bmatrix} 0.33\\0.33 \end{bmatrix}$

b. $\lambda_1 = a + b$, $\lambda_2 = a - b$ **c.** $\mathbf{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $\mathbf{v}_2 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$

1. a.
$$T = \begin{bmatrix} 0.85 & 0.08 \\ 0.15 & 0.92 \end{bmatrix}$$

b. $T^{10} \begin{bmatrix} 0.7 \\ 0.3 \end{bmatrix} \approx \begin{bmatrix} 0.37 \\ 0.63 \end{bmatrix}$
c. $\begin{bmatrix} 0.35 \\ 0.65 \end{bmatrix}$



common factors.

21. If $7xy < 3x^2 + 2y^2$, then $3x^2 - 7xy + 2y^2 =$

 $(3x - y)(x - 2y) \ge 0$. There are two cases: either both

factors are greater than or equal to 0, or both are less

476

Answers to Odd-Numbered Exercises

 $\Leftrightarrow 2x_1 - 1 = 2x_2 - 1$

 $\Leftrightarrow x_1 = x_2$

b. Since the exponential function is always positive,

f is not onto \mathbb{R} .

478 Answers to Odd-Numbered Exercises

Base case: n = 1 : 2 = 1(2)Inductive hypothesis: Assume the summation formula holds for the natural number *n*. Consider

$$2+4+6+\dots+2n+2(n+1) = n(n+1)+2(n+1) = (n+1)(n+2)$$

13. Base case: $n = 5: 32 = 2^5 > 25 = 5^2$ Inductive hypothesis: Assume $2^n > n^2$ holds for the natural number *n*.

Consider $2^{n+1} = 2(2^n) > 2n^2$. But since $2n^2 - (n+1)^2 = n^2 - 2n - 1 = (n-1)^2 - 2 > 0$, for all $n \ge 5$, we have $2^{n+1} > (n+1)^2$.

- **15.** Base case: $n = 1: 1^2 + 1 = 2$, which is divisible by 2. Inductive hypothesis: Assume $n^2 + n$ is divisible by 2. Consider $(n + 1)^2 + (n + 1) = n^2 + n + 2n + 2$. By the inductive hypothesis, $n^2 + n$ is divisible by 2, so since both terms on the right are divisible by 2, then $(n + 1)^2 + (n + 1)$ is divisible by 2. Alternatively, observe that $n^2 + n = n(n + 1)$, which is the product of the solution consecutive integers and is therefore even
- 17. Base case: $n = 1: 1 = \frac{r-1}{r-1}$ Inductive hypothesis: Assume the Commula holds for the formula holds for the Community Contraction

 $=\frac{r^{n+1}-1}{r-1}$

 $=\frac{r^{n}-1+r^{n}(r-1)}{r-1}$

19. Base case: n = 2 : A ∩ (B₁ ∪ B₂) = (A ∩ B₁) ∪ (A ∩ B₂), by Theorem 1 of Sec. A.1 Inductive hypothesis: Assume the formula holds for the natural number n. Consider

$$A \cap (B_1 \cup B_2 \cup \dots \cup B_n \cup B_{n+1})$$

= $A \cap [(B_1 \cup B_2 \cup \dots \cup B_n) \cup B_{n+1}]$
= $[A \cap (B_1 \cup B_2 \cup \dots \cup B_n)] \cup (A \cap B_{n+1})$
= $(A \cap B_1) \cup (A \cap B_2) \cup \dots \cup (A \cap B_n) \cup (A \cap B_{n+1})$

21.

$$\binom{n}{r} = \frac{n!}{r!(n-r)!}$$

$$= \frac{n!}{(n-r)!(n-(n-r))!}$$

$$= \binom{n}{n-r}$$
23. By the binomial use real, a
$$2^{n} = (1+1)^{n} = \sum_{k=0}^{n} \binom{n}{k}$$

2 Index

Preview

Gram-Schmidt process examples of, 349-352explanation of, 344, 347-348, 394geometric interpretation of, 348-349Graphics operations in \mathbb{R}^2 reflection, 260, 261 reversing, 261-262 rotation, 264-265 scaling and shearing, 256-259 translation, 262-264 Graphs of conic sections, 61 of functions, 416

н

Hamming, Richard, 127 Hamming's code, 127, 129 Homogeneous coordinates, 262–264 Homogeneous linear systems, 49–51, 113 Horizontal line tests 110 Horizontal coming, 56, 257 Horizontal

Images explanation of, 415, 418 inverse, 416, 418 Imaginary part, complex numbers, 134 Inconsistent linear systems explanation of, 2, 10 reduced matrix for, 21-22 Independence, linear. See Linear independence Inequality, Cauchy-Schwartz, 326–327 Infinite dimensional vector space, 165 Initial point, vector, 95 Initial probability vectors, 275 Initial-value problems, 186, 192-193 Injective mapping. See One-to-one mapping Injective functions, 419 Inner product examples of, 334-336

explanation of, 333 that is not dot product, 335 Inner product spaces diagonalization of symmetric matrices and, 377-383 explanation of, 333-334 facts about, 340 least squares approximation and, 366-375 orthogonal complements and, 355-364 orthogonal sets and, 338-340 orthonormal bases and, 342-352 properties of norm in, 336-337 quadratic forms and, 385-391 singular value decomposition and, 392-403 subspaces of, 355 Input-output matrix Integers, et fr 40 Internal demand, 83 Intersection, of sets, 410, 411 verse functions kplanation of, 418–420 unique nature of, 421 Inverse images, 416, 418 Inverse of elementary matrix, 71-72 Inverse of square matrix definition of, 40 explanation of, 40-45 facts about, 45 Inverse transformations, 230-231 Invertible functions, 418-420 Invertible matrix elementary matrices and, 72 explanation of, 41, 54 inverse of product of, 44-45 square, 60-61 Isomorphisms definition of, 229 explanation of, 226 inverse and, 230-231 linear transformations as, 229-231 one-to-one and onto mappings and, 226-230 vector space, 232-233

Κ

Kepler, Johannes, 61 Kirchhoff's laws, 88 484

Index

Preview

Markov chains applications of, 310-314 explanation of, 275-276 Markov process, 310 Mathematical induction base case, 430 binomial coefficients and binomial theorem and, 435-438 examples of, 431-435 inductive hypothesis, 430 introduction to, 429-430 principle of, 430-431 Matrices addition of, 27-29 augmented, 15-17, 22, 23 check, 128 coefficient, 15 condition number of, 403 definition of, 14 sale determinants of, 54-65 diagonal, 56 discussion of, 1 echelon tput. 83 nverse of product of invertible, 44–45 inverse of square, 39-45 linear independence of, 114 linear transformations and, 202-203, 221-222, 235-245 LU factorization of, 69, 72-75 minors and cofactors of, 56 nullity of, 221-223 null space of, 152-153 orthogonal, 381-382 permutation, 76-77 positive definite, 354 positive semidefinite, 354 rank of, 222 scalar multiplication, 27 singular values of, 393-396 stochastic, 275, 311, 314

subspaces and, 362

that commute, 32, 33

transition, 177-182, 275, 276,

symmetric, 36

311-313

transpose of, 35-36 triangular, 15, 56-57, 283 vector spaces of, 130 Matrix addition, 27-29 Matrix algebra addition and scalar multiplication, 27 - 29explanation of, 26-27 facts about, 36-37 matrix multiplication, 29-35 symmetric matrix, 36 transpose of matrix, 35-36 Matrix equations, 48-51 Matrix form, of linear systems, 48 Matrix multiplication definition of, 32 explanation of, 29 35, 210 linear combinations and, 107 lin ar ton formations between finite dimensional vector spaces and, 236-237 properties of, 35 0 write linear systems in terms of matrices and vectors, 48-51 Members, of sets, 409 Minors, of matrices, 56 Multiplication. See Matrix multiplication; Scalar multiplication, Multiplicative identity, 39 Multivariate calculus, 322

Ν

Natural numbers. See also Mathematical induction, set of, 409 statements involving, 429-434 Network flow application, 79-81 Newton, Isaac, 61 Nilpotent, 299 Noninvertible matrix, 41 Normal equation, least squares solution to, 369-370 Nullity, of matrices, 221-223 Null sets, 410 Null space, of linear transformations, 214-221 of matrices, 152-153, 221 Nutrition application, 81-82

Index **487**

matrix representation relative to, 235-237 polynomials of, 163 Standard position, of vectors, 95 State vectors, Markov chains and, 311-312 Steady-state vectors explanation of, 276 Markov chain and, 313-314 Stochastic matrix, 275, 311, 314 Subsets, 410, 412 Subspaces closure criteria for, 144 definition of, 140 examples of, 142-143 explanation of, 140-142 facts about, 153 four fundamental, 401 of inner product spaces, 355-360, 362 null space and column space of matrix and, 152-153 span of set of vectors trivial, 142 Preview fra forward, **p**_sitica principle, 188–189 uve functions, 420 urjective mapping. See Onto mapping, Symmetric matrix diagonalization of, 377-383 explanation of, 36 Syndrome vectors, 128 Systems of linear differential equations diagonalization and, 302-309 explanation of, 300 to model concentration of salt in interconnected tanks, 307-309 phase plane and, 301-302 uncoupled, 300-301 Systems of linear equations. See

Linear systems

Т

Terminal point, vector, 95 Theorems converse of, 424–425 explanation of, 424 Tower of Hanoi puzzle, 429-430 Trace, of square matrices, 142 - 143Trajectories, 301-302 Transformation, 199-200. See also Linear transformations Transition matrix diagonalizing the, 312-313 example of, 275, 276 explanation of, 177-180 inverse of, 181-182 Markov chains and, 311-312 Translation, 262-264 Transpose, of matrices, 35-36 Triangular form of linear syst 4, 6-7, 10 maric sin, 15 hangular matrix determinant of, 57, 58 eigenvalues of, 283 explanation of, 56-57 Trigonometric polynomials, 373-374 Trivial solution, to homogeneous systems, 49,50 Trivial subspaces, 142

U

Uncoupled systems, 300–301 Uniform scaling, 257 Union, of sets, 410 Unit vectors, 325 Universal quantifiers, 427 Universal set, 410 Upper triangular matrix examples of, 57 explanation of, 56, 68, 74

V

Vector addition, 95–99, 129 Vector form of linear systems, 106–107 of solution to linear systems, 48–50 Vectors addition and scalar multiplication of, 95–99 algebraic properties of, 97–98 angle between, 327–330 applications for, 94