

## 7.1 Orthogonal Matrices

**DEFINITION 1** A square matrix  $A$  is said to be *orthogonal* if its transpose is the same as its inverse, that is, if

$$A^{-1} = A^T$$

or, equivalently, if

$$AA^T = A^T A = I \quad (1)$$

**THEOREM 7.1.1** *The following are equivalent for an  $n \times n$  matrix  $A$ .*

- (a)  $A$  is orthogonal.
- (b) The row vectors of  $A$  form an orthonormal set in  $R^n$  with the Euclidean inner product.
- (c) The column vectors of  $A$  form an orthonormal set in  $R^n$  with the Euclidean inner product.

**THEOREM 7.1.2**

- (a) The transpose of an orthogonal matrix is orthogonal.
- (b) The inverse of an orthogonal matrix is orthogonal.
- (c) A product of orthogonal matrices is orthogonal.
- (d) If  $A$  is orthogonal, then  $\det(A) = 1$  or  $\det(A) = -1$ .

**THEOREM 7.1.3** *If  $A$  is an  $n \times n$  matrix, then the following are equivalent.*

- (a)  $A$  is orthogonal.
- (b)  $\|A\mathbf{x}\| = \|\mathbf{x}\|$  for all  $\mathbf{x}$  in  $R^n$ .
- (c)  $A\mathbf{x} \cdot A\mathbf{y} = \mathbf{x} \cdot \mathbf{y}$  for all  $\mathbf{x}$  and  $\mathbf{y}$  in  $R^n$ .

If  $A$  is an orthogonal matrix and  $T_A: R^n \rightarrow R^n$  is multiplication by  $A$ , then we will call  $T_A$  an *orthogonal operator* on  $R^n$ . It follows from parts (a) and (b) of Theorem 7.1.3 that the orthogonal operators on  $R^n$  are precisely those operators that leave the lengths (norms) of vectors unchanged. However, this implies that orthogonal operators also leave angles and distances between vectors in  $R^n$  unchanged since these can be expressed in terms of norms

**THEOREM 7.1.4** If  $S$  is an orthonormal basis for an  $n$ -dimensional inner product space  $V$ , and if

$$(\mathbf{u})_S = (u_1, u_2, \dots, u_n) \quad \text{and} \quad (\mathbf{v})_S = (v_1, v_2, \dots, v_n)$$

then:

$$(a) \quad \|\mathbf{u}\| = \sqrt{u_1^2 + u_2^2 + \dots + u_n^2}$$

$$(b) \quad d(\mathbf{u}, \mathbf{v}) = \sqrt{(u_1 - v_1)^2 + (u_2 - v_2)^2 + \dots + (u_n - v_n)^2}$$

$$(c) \quad \langle \mathbf{u}, \mathbf{v} \rangle = u_1 v_1 + u_2 v_2 + \dots + u_n v_n$$

**THEOREM 7.1.5** Let  $V$  be a finite-dimensional inner product space. If  $P$  is the transition matrix from one orthonormal basis for  $V$  to another orthonormal basis for  $V$ , then  $P$  is an orthogonal matrix.

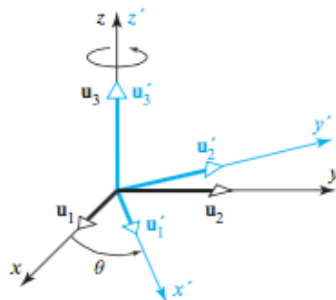
$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

or, equivalently,

$$\begin{aligned} x' &= x \cos \theta + y \sin \theta \\ y' &= -x \sin \theta + y \cos \theta \end{aligned}$$

These are sometimes called the **rotation equations** for  $R^2$ .

### Application to Rotation of Axes in 3-Space



$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta & 0 \\ -\sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

A linear operator on  $R^2$  is called **rigid** if it does not change the lengths of vectors, and it is called **angle preserving** if it does not change the angle between nonzero vectors.

## 7.2 Orthogonal Diagonalization

In this section we will be concerned with the problem of diagonalizing a symmetric matrix  $A$ . As we will see, this problem is closely related to that of finding an orthonormal basis for  $\mathbb{R}^n$  that consists of eigenvectors of  $A$ . Problems of this type are important because many of the matrices that arise in applications are symmetric.

**DEFINITION 1** If  $A$  and  $B$  are square matrices, then we say that  $B$  is *orthogonally similar* to  $A$  if there is an orthogonal matrix  $P$  such that  $B = P^TAP$ .

If  $A$  is orthogonally similar to some diagonal matrix, say  $P^TAP = D$ , then we say that  $A$  is orthogonally diagonalizable and that  $P$  orthogonally diagonalizes  $A$ .

$A^T = (PDP^T)^T = (P^T)^TD^TP^T = PDP^T = A$  so  $A$  must be symmetric if it is orthogonally diagonalizable.

**THEOREM 7.2.1** If  $A$  is an  $n \times n$  matrix with real entries, then the following are equivalent.

- (a)  $A$  is orthogonally diagonalizable.
- (b)  $A$  has an orthonormal set of  $n$  eigenvectors.
- (c)  $A$  is symmetric.

**THEOREM 7.2.2** If  $A$  is a symmetric matrix with real entries, then:

- (a) The eigenvalues of  $A$  are all real numbers.
- (b) Eigenvectors from different eigenspaces are orthogonal.

### Orthogonally Diagonalizing an $n \times n$ Symmetric Matrix

**Step 1.** Find a basis for each eigenspace of  $A$ .

**Step 2.** Apply the Gram–Schmidt process to each of these bases to obtain an orthonormal basis for each eigenspace.

**Step 3.** Form the matrix  $P$  whose columns are the vectors constructed in Step 2. This matrix will orthogonally diagonalize  $A$ , and the eigenvalues on the diagonal of  $D = P^TAP$  will be in the same order as their corresponding eigenvectors in  $P$ .

***Spectral Decomposition***

If  $A$  is a symmetric matrix that is orthogonally diagonalized by  $P = [\mathbf{u}_1 \mathbf{u}_2 \cdots \mathbf{u}_n]$  and if  $\lambda_1, \lambda_2, \dots, \lambda_n$  are the eigenvalues of  $A$  corresponding to the unit eigenvectors  $\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n$ , then we know that  $D = P^T A P$ , where  $D$  is a diagonal matrix with the eigenvalues in the diagonal positions.  $\mathbf{u}\mathbf{u}^T$  is the standard matrix for the orthogonal projection of  $\mathbb{R}^n$  on the subspace spanned by the vector  $\mathbf{u}$ .

$$A = \lambda_1 \mathbf{u}_1 \mathbf{u}_1^T + \lambda_2 \mathbf{u}_2 \mathbf{u}_2^T + \cdots + \lambda_n \mathbf{u}_n \mathbf{u}_n^T$$

The spectral decomposition of  $A$  tells that the image of a vector  $\mathbf{x}$  under multiplication by a symmetric matrix  $A$  can be obtained by projecting  $\mathbf{x}$  orthogonally on the lines (one-dimensional subspaces) determined by the eigenvectors of  $A$ , then scaling those projections by the eigenvalues, and then adding the scaled projections.

**Schur decomposition of  $A$** **THEOREM 7.2.3 Schur's Theorem**

*If  $A$  is an  $n \times n$  matrix with real entries and real eigenvalues, then there is an orthogonal matrix  $P$  such that  $P^T A P$  is an upper triangular matrix of the form*

$$P^T A P = \begin{bmatrix} \lambda_1 & \times & \times & \cdots & \times \\ 0 & \lambda_2 & \times & \cdots & \times \\ 0 & 0 & \lambda_3 & \cdots & \times \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \lambda_n \end{bmatrix} \quad (11)$$

*in which  $\lambda_1, \lambda_2, \dots, \lambda_n$  are the eigenvalues of  $A$  repeated according to multiplicity.*

That is every square matrix  $A$  is orthogonally similar to an upper triangular matrix that has the eigenvalues of  $A$  on the main diagonal.

$A = P S P^T$  which is called a **Schur decomposition of  $A$**

## Upper Hessenberg decomposition

### THEOREM 7.2.4 Hessenberg's Theorem

If  $A$  is an  $n \times n$  matrix with real entries, then there is an orthogonal matrix  $P$  such that  $P^T A P$  is a matrix of the form

$$P^T A P = \begin{bmatrix} \times & \times & \cdots & \times & \times & \times \\ \times & \times & \cdots & \times & \times & \times \\ 0 & \times & \ddots & \times & \times & \times \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \times & \times & \times \\ 0 & 0 & \cdots & 0 & \times & \times \end{bmatrix} \quad (13)$$

Every square matrix with real entries is orthogonally similar to a matrix in which each entry below the first *subdiagonal* is zero

$A = P H P^T$  which is called an *upper Hessenberg decomposition* of  $A$ .