

Section 5.3: Diagonalization

Definition: An $n \times n$ matrix A is called **diagonalizable** if it is similar to a diagonal matrix D . That is, provided there exists a nonsingular matrix P such that $D = P^{-1}AP$ —i.e. $A = PDP^{-1}$.

Theorem: The $n \times n$ matrix A is diagonalizable if and only if A has n linearly independent eigenvectors. In this case, the matrix P is the matrix whose columns are the n linearly independent eigenvectors of A .

Remark: The diagonal matrix D will have the eigenvalues of A on its main diagonal. The order will correspond to the order in which the eigenvectors are used to construct the matrix P .

Example

Diagonalize the matrix A if possible. $A = \begin{bmatrix} 1 & 3 & 3 \\ -3 & -5 & -3 \\ 3 & 3 & 1 \end{bmatrix}$

The eigenvalues were $\lambda_1 = 1$ and $\lambda_2 = -2$. We found three linearly independent eigenvectors, so A is diagonalizable. We found a P and D

$$P = \begin{bmatrix} 1 & -1 & -1 \\ -1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \quad \text{and} \quad D = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -2 & 0 \\ 0 & 0 & -2 \end{bmatrix}.$$

Example

Diagonalize the matrix A if possible. $A = \begin{bmatrix} 2 & 4 & 3 \\ -4 & -6 & -3 \\ 3 & 3 & 1 \end{bmatrix}$. (With a

little effort, it can be shown that the characteristic polynomial of A is $(1 - \lambda)(2 + \lambda)^2$.)

The characteristic equation is

$$(1 - \lambda)(2 + \lambda)^2 = 0$$

A has two eigenvalues $\lambda_1 = 1$ and $\lambda_2 = -2$.

Find eigenvectors:

For $\lambda_1 = 1$ $A - 1I = \begin{bmatrix} 1 & 4 & 3 \\ -4 & -7 & -3 \\ 3 & 3 & 0 \end{bmatrix} \xrightarrow{\text{ref}} \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix}$

$$\begin{aligned}x_1 &= x_3 \\x_2 &= -x_3 \\x_3 &\text{- free}\end{aligned}$$

Eigen vectors look like

$$\vec{x} = x_3 \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$$

$$\text{Let } \vec{v}_1 = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}.$$

For $\lambda_2 = -2$

$$A - (-2)I = \begin{bmatrix} 4 & 4 & 3 \\ -4 & -4 & -3 \\ 3 & 3 & 3 \end{bmatrix} \xrightarrow{\text{ref}} \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\begin{aligned}x_1 &= -x_2 \\x_2 &\text{- free} \\x_3 &= 0\end{aligned}$$

Eigen vectors:

$$\vec{x} = x_2 \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix}$$

The algebraic multiplicity of $\lambda_2 = -2$ is two, but the geometric multiplicity is only one.

A is not diagonalizable.

Theorem (a second on diagonalizability)

Recall: (sec. 5.1) If λ_1 and λ_2 are distinct eigenvalues of a matrix, the corresponding eigenvectors are linearly independent.

Theorem: If the $n \times n$ matrix A has n distinct eigenvalues, then A is diagonalizable.

Note: This is a *sufficiency* condition, not a *necessity* condition. We've already seen a matrix with a repeated eigenvalue that was diagonalizable.

Theorem (a third on diagonalizability)

Theorem: Let A be an $n \times n$ matrix with distinct eigenvalues $\lambda_1, \dots, \lambda_p$.

- (a) The geometric multiplicity (dimension of the eigenspace) of λ_k is less than or equal to the algebraic multiplicity of λ_k .
- (b) The matrix is diagonalizable if and only if the sum of the geometric multiplicities is n —i.e. the sum of dimensions of all eigenspaces is n so that there are n linearly independent eigenvectors.
- (c) If A is diagonalizable, and \mathcal{B}_k is a basis for the eigenspace for λ_k , then the collection (union) of bases $\mathcal{B}_1, \dots, \mathcal{B}_p$ is a basis for \mathbb{R}^n .

Remark: The union of the bases referred to in part (c) is called an **eigenvector basis** for \mathbb{R}^n . (Of course, one would need to reference the specific matrix.)

Example

Diagonalize the matrix if possible. $A = \begin{bmatrix} 5 & -6 \\ 4 & -5 \end{bmatrix}$.

① Find the eigenvalues.

$$\det(A - \lambda I) = \det \begin{bmatrix} 5 - \lambda & -6 \\ 4 & -5 - \lambda \end{bmatrix}$$

$$= (5 - \lambda)(-5 - \lambda) + 24$$

$$= \lambda^2 - 25 + 24 = \lambda^2 - 1$$

$$0 = \lambda^2 - 1 \Rightarrow \lambda_1 = 1 \text{ or } \lambda_2 = -1$$

② Find eigenvectors

$$\lambda_1 = 1 \quad A - 1I = \begin{bmatrix} 4 & -6 \\ 4 & -6 \end{bmatrix} \xrightarrow{\text{ref}} \begin{bmatrix} 1 & -3/2 \\ 0 & 0 \end{bmatrix} \quad \begin{array}{l} x_1 = \frac{3}{2}x_2 \\ x_2 \text{ - free} \end{array}$$

Eigenvectors

$$\vec{x} = x_2 \begin{bmatrix} 3/2 \\ 1 \end{bmatrix}$$

Let $\vec{v}_1 = \begin{bmatrix} 3 \\ 2 \end{bmatrix}$ (eigenvector w/ $x_2 = 2$)

For $\lambda_2 = -1$

$$A - (-1)I = \begin{bmatrix} 6 & -6 \\ 4 & -4 \end{bmatrix} \xrightarrow{\text{ref}} \begin{bmatrix} 1 & -1 \\ 0 & 0 \end{bmatrix} \quad \begin{array}{l} x_1 = x_2 \\ x_2 \text{ - free} \end{array}$$

Eigenvectors

$$\vec{x} = x_2 \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \text{set } \vec{v}_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

③ Form matrix P

$$P = [\vec{v}_1, \vec{v}_2] = \begin{bmatrix} 3 & 1 \\ 2 & 1 \end{bmatrix}$$

④ Find $D = P^{-1}AP$, $A = \begin{bmatrix} 5 & -6 \\ 4 & -5 \end{bmatrix}$ $\det(P) = 3 - 2 = 1$

$$P^{-1} = \begin{bmatrix} 1 & -1 \\ -2 & 3 \end{bmatrix}$$

$$\begin{aligned} D = P^{-1}AP &= \begin{bmatrix} 1 & -1 \\ -2 & 3 \end{bmatrix} \begin{bmatrix} 5 & -6 \\ 4 & -5 \end{bmatrix} \begin{bmatrix} 3 & 1 \\ 2 & 1 \end{bmatrix} \\ &= \begin{bmatrix} 1 & -1 \\ -2 & 3 \end{bmatrix} \begin{bmatrix} 3 & -1 \\ 2 & -1 \end{bmatrix} \end{aligned}$$

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

$$= \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

Example Continued...

Find A^8 where $A = \begin{bmatrix} 5 & -6 \\ 4 & -5 \end{bmatrix}$.

* Recall: If A and B are similar matrices, then A^k and B^k are similar w/ the same similarity transformation matrix P .

We can use that

$$D^8 = P^{-1} A^8 P \Rightarrow A^8 = P D^8 P^{-1}$$

$$D = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \quad D^8 = \begin{bmatrix} 1^8 & 0 \\ 0 & (-1)^8 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$A^8 = P^{-1} D^8 P = P^{-1} I P = P^{-1} P \\ = I$$

Turns out

$$A^{2k} = I \quad \text{for natural number } k$$

$$A^{2k+1} = A \quad \text{for " " " .}$$

Section 6.1: Inner Product, Length, and Orthogonality

Recall: A vector \mathbf{u} in \mathbb{R}^n can be considered an $n \times 1$ matrix. It follows that \mathbf{u}^T is a $1 \times n$ matrix.

$$\text{If } \mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix}, \text{ then } \mathbf{u}^T = [u_1 \ u_2 \ \cdots \ u_n].$$

Definition of an Inner Product

Definition: For vectors \mathbf{u} and \mathbf{v} in \mathbb{R}^n we define the **inner product** of \mathbf{u} and \mathbf{v} (also called the **dot product**) by the **matrix product**

$$\mathbf{u}^T \mathbf{v} = \begin{matrix} 1 \times n & n \times 1 \\ [u_1 & u_2 & \cdots & u_n] \end{matrix} \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} = u_1 v_1 + u_2 v_2 + \cdots + u_n v_n.$$

Remark: Note that this product produces a scalar. It is sometimes called a scalar product.

Theorem (Properties of the Inner Product)

We'll use the notations $\mathbf{u} \cdot \mathbf{v} = \mathbf{u}^T \mathbf{v}$ interchangeably.

Theorem: For \mathbf{u} , \mathbf{v} and \mathbf{w} in \mathbb{R}^n and real scalar c

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

(b) $(\mathbf{u} + \mathbf{v}) \cdot \mathbf{w} = \mathbf{u} \cdot \mathbf{w} + \mathbf{v} \cdot \mathbf{w}$

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

(d) $\mathbf{u} \cdot \mathbf{u} \geq 0$, with $\mathbf{u} \cdot \mathbf{u} = 0$ if and only if $\mathbf{u} = \mathbf{0}$.

The Norm

The property $\mathbf{u} \cdot \mathbf{u} \geq 0$ means that $\sqrt{\mathbf{u} \cdot \mathbf{u}}$ always exists as a real number.

Definition: The **norm** of the vector \mathbf{v} in \mathbb{R}^n is the nonnegative number, denoted $\|\mathbf{v}\|$, defined by

$$\|\mathbf{v}\| = \sqrt{\mathbf{v} \cdot \mathbf{v}} = \sqrt{v_1^2 + v_2^2 + \cdots + v_n^2}$$

where v_1, v_2, \dots, v_n are the components of \mathbf{v} .

Remark: As a directed line segment, the norm is the same as the length.

Norm and Length

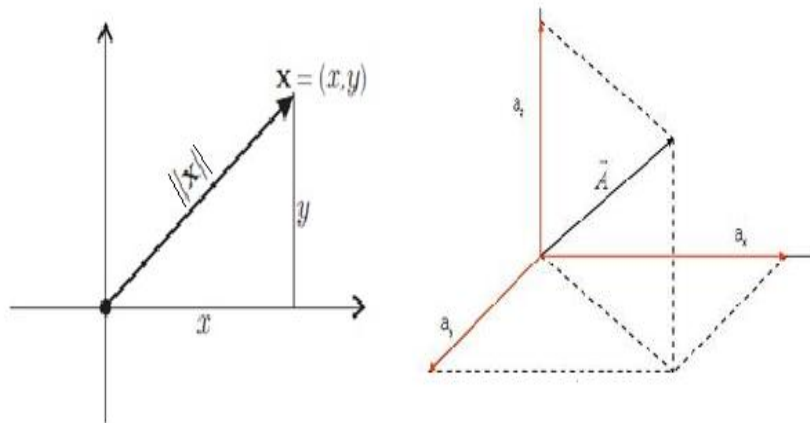


Figure: In \mathbb{R}^2 or \mathbb{R}^3 , the norm corresponds to the classic geometric property of length.

Unit Vectors and Normalizing

Theorem: For vector \mathbf{v} in \mathbb{R}^n and scalar c

$$\|c\mathbf{v}\| = |c|\|\mathbf{v}\|.$$

Example: If \mathbf{v} is a vector in \mathbb{R}^4 with norm $\|\mathbf{v}\| = 3$, then $-4\mathbf{v}$ is a vector in \mathbb{R}^4 with norm

$$\| -4\mathbf{v} \| = | -4 | \|\mathbf{v}\| = 4 \cdot 3 = 12.$$

Unit Vectors and Normalizing

Definition: A vector \mathbf{u} in \mathbb{R}^n for which $\|\mathbf{u}\| = 1$ is called a **unit vector**.

Remark: Given any nonzero vector \mathbf{v} in \mathbb{R}^n , we can obtain a unit vector \mathbf{u} in the same direction as \mathbf{v}

$$\mathbf{u} = \frac{\mathbf{v}}{\|\mathbf{v}\|}.$$

This process, of dividing out the norm, is called **normalizing** the vector \mathbf{v} .

Example

Show that $\mathbf{v}/\|\mathbf{v}\|$ is a unit vector.

$$\text{Note } \frac{\vec{v}}{\|\vec{v}\|} = \frac{1}{\|\vec{v}\|} \vec{v} \quad \text{and } \|\vec{v}\| > 0$$

$$\begin{aligned} \left\| \frac{\vec{v}}{\|\vec{v}\|} \right\| &= \left\| \frac{1}{\|\vec{v}\|} \vec{v} \right\| = \left| \frac{1}{\|\vec{v}\|} \right| \|\vec{v}\| \\ &= \frac{1}{\|\vec{v}\|} \|\vec{v}\| = 1 \end{aligned}$$

Example

Find a unit vector in the direction of $\mathbf{v} = (1, 3, 2)$.

$$\text{let } \vec{u} = \frac{\vec{v}}{\|\vec{v}\|}$$

$$\|\vec{v}\| = \sqrt{1^2 + 3^2 + 2^2} = \sqrt{14}$$

$$\vec{u} = \frac{1}{\sqrt{14}} \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{14}} \\ \frac{3}{\sqrt{14}} \\ \frac{2}{\sqrt{14}} \end{bmatrix}$$

Distance in \mathbb{R}^n

Definition: For vectors \mathbf{u} and \mathbf{v} in \mathbb{R}^n , the **distance between \mathbf{u} and \mathbf{v}** is denoted by

$$\text{dist}(\mathbf{u}, \mathbf{v}),$$

and is defined by

$$\text{dist}(\mathbf{u}, \mathbf{v}) = \|\mathbf{u} - \mathbf{v}\|.$$

Remark: This is the same as the traditional formula for distance used in \mathbb{R}^2 between points (x_0, y_0) and (x_1, y_1) ,

$$d = \sqrt{(y_1 - y_0)^2 + (x_1 - x_0)^2}.$$