

# Eigenvalues and Eigenvectors

Math 1410 Linear Algebra

# Matrix transformations

Let  $A$  be an  $m \times n$  matrix. If  $X$  is a vector in  $\mathbb{R}^n$  (an  $n \times 1$  matrix) then we know that  $AX = Y$  defines a vector in  $\mathbb{R}^m$  (an  $m \times 1$  matrix).

For any such matrix  $A$ , we get a **function**  $f_A : \mathbb{R}^n \rightarrow \mathbb{R}^m$ , called a **matrix transformation**, or **linear transformation**.

If  $A$  is a **square**  $n \times n$  matrix, we get a function  $f_A$  that transforms each vector in  $\mathbb{R}^n$  to another vector in  $\mathbb{R}^n$ .

For example, for  $A = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}$ , the function  $f_A$  rotates a each vector  $X = \begin{bmatrix} x & y \end{bmatrix}^T$  by an angle of  $\theta$ .

# Multiplication operators

For any scalar  $\lambda$ , we can consider the function  $f_\lambda : \mathbb{R}^n \rightarrow \mathbb{R}^n$  given by  $f_\lambda(X) = \lambda X$ .

This is the operator of scalar multiplication: if  $X = [x_1 \ x_2 \ \cdots \ x_n]^T$ , then

$$f_\lambda(X) = [\lambda x_1 \ \lambda x_2 \ \cdots \ \lambda x_n]^T.$$

We note that  $f_\lambda$  is also a matrix transformation:  $f_\lambda = f_A$ , where

$$A = \begin{bmatrix} \lambda & 0 & \cdots & 0 \\ 0 & \lambda & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda \end{bmatrix} = \lambda I_n,$$

where  $I_n$  is the  $n \times n$  identity matrix.

# Invariant directions for matrix transformations

For the matrix  $A = \lambda I_n$ , we note that for every vector  $X$  in  $\mathbb{R}^n$ ,  $AX$  is parallel to  $X$ . For other matrices, it's possible that there are **no** vectors with this property: for example, if  $A$  is the rotation matrix in  $\mathbb{R}^2$  (unless  $\theta$  is a multiple of  $2\pi$ ).

We'll be interested in the case where there are **some** vectors such that  $AX$  is parallel to  $X$ . For example, the function  $f : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  given by  $f(x, y) = (x + y, y)$  is an example of a **shear transformation**. It can be represented as the matrix transformation

$$f_A \left( \begin{bmatrix} x \\ y \end{bmatrix} \right) = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}.$$

# Eigenvalues and eigenvectors

## Definition

For any  $n \times n$  matrix  $A$ , we say that a scalar  $\lambda$  is an **eigenvalue** for  $A$  if there exists a non-zero vector  $X$ , called an **eigenvector**, such that

$$AX = \lambda X$$

## Example

Let  $A = \begin{bmatrix} 2 & -4 \\ -1 & 5 \end{bmatrix}$ . Then we have

$$\begin{bmatrix} 2 & -4 \\ -1 & 5 \end{bmatrix} \begin{bmatrix} 4 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 1 \end{bmatrix} \text{ and } \begin{bmatrix} 2 & -4 \\ -1 & 5 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 6 \\ -6 \end{bmatrix} = 6 \begin{bmatrix} 1 \\ -1 \end{bmatrix},$$

so  $\lambda = 1$  and  $\lambda = 6$  are eigenvalues of  $A$ , with corresponding eigenvectors  $\begin{bmatrix} 4 \\ 1 \end{bmatrix}$  and  $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$ , respectively.

# Eigenvectors and characteristic directions

## Theorem

*Suppose  $X$  is an eigenvector of an  $n \times n$  matrix  $A$ , with eigenvalue  $\lambda$ . Then for any scalar  $k \neq 0$ ,  $kX$  is also an eigenvector of  $A$ , corresponding to the same eigenvalue.*

# Finding eigenvalues and eigenvectors

Let  $A$  be an  $n \times n$  matrix, and suppose  $\lambda$  is an eigenvalue of  $A$ . Then there exists a **non-zero** vector  $X$  such that  $AX = \lambda X$ . That is,  $X \neq 0$  and

$$AX - \lambda X = (A - \lambda I_n)X = 0.$$

We note that  $A - \lambda I_n$  is an  $n \times n$  matrix, and that  $X$  is a **non-trivial** solution to the homogeneous system  $(A - \lambda I_n)X = 0$ . This means that  **$A - \lambda I_n$  cannot be invertible**. Since a matrix is invertible if and only if its determinant is non-zero, we arrive at:

## Theorem

*A scalar  $\lambda \in \mathbb{C}$  is an eigenvalue of  $A$  if and only if  $\det(A - \lambda I_n) = 0$*

# The characteristic polynomial

## Definition

For any  $n \times n$  matrix  $A$ , we define its **characteristic polynomial** by

$$c_A(x) = \det(xI_n - A).$$

**Note:** The eigenvalues of  $A$  are precisely the zeros of the characteristic polynomial of  $A$ .

## Example

Find the characteristic polynomial of  $A = \begin{bmatrix} 2 & 3 & -1 \\ 0 & 3 & 2 \\ 1 & 2 & 0 \end{bmatrix}$ .



## Example

Find the eigenvalues and eigenvectors of  $A = \begin{bmatrix} 1 & -5 \\ -5 & 1 \end{bmatrix}$ .

## Example

Find the eigenvalues and eigenvectors of  $A = \begin{bmatrix} 3 & 0 & 0 \\ 1 & 1 & -1 \\ 5 & 1 & 3 \end{bmatrix}$ .

# Similar matrices

## Definition

We say that two matrices  $A$  and  $B$  are **similar** if there exists an invertible matrix  $P$  such that  $B = P^{-1}AP$ .

## Theorem

*If  $A$  and  $B$  are similar matrices, then they have the same eigenvalues.*

# Diagonal and upper-triangular matrices

## Theorem

*If  $A$  is a triangular matrix, then the eigenvalues of  $A$  are given by the entries on the main diagonal of  $A$ .*

**Note:** In particular, this is true if  $A$  is diagonal, in which case the standard unit basis vectors are eigenvectors for  $A$ .

## Examples

Find the eigenvalues and eigenvectors of the following matrices:

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

# Diagonalization

## Definition

We say that an  $n \times n$  matrix  $A$  is **diagonalizable** if  $A$  is similar to a diagonal matrix; that is, if there exists an invertible matrix  $P$  such that  $D = P^{-1}AP$  is diagonal.

Note: since similar matrices have the same eigenvalues, we must have

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

## Theorem

*An  $n \times n$  matrix  $A$  is diagonalizable if and only if there exists a basis of  $\mathbb{R}^n$  consisting of eigenvectors of  $A$ .*

## Example

Determine whether or not the matrix  $A = \begin{bmatrix} 2 & 0 & 2 \\ 0 & 2 & -1 \\ 1 & -1 & 4 \end{bmatrix}$  can be diagonalized.

# Case of distinct eigenvalues

## Theorem

*If  $\lambda_1, \dots, \lambda_m$  are **distinct** eigenvalues of a matrix  $A$ , then the corresponding eigenvectors  $X_1, \dots, X_m$  are linearly independent.*

**Fact:** Any set of  $n$  linearly independent vectors forms a basis of  $\mathbb{R}^n$ .



# Repeated eigenvalues

In general a matrix  $A$  will have characteristic polynomial

$$c_A(x) = (x - \lambda_1)^{k_1} (x - \lambda_2)^{k_2} \cdots (x - \lambda_m)^{k_m},$$

where  $\lambda_1, \dots, \lambda_m$  are the eigenvalues and  $k_1, \dots, k_m$  are the **multiplicities** of the eigenvalues.

## Definition

Given an eigenvalue  $\lambda$  of a matrix  $A$ , we define the **eigenspace**  $E(\lambda, A)$  of  $A$  with respect to  $\lambda$  by

$$E(\lambda, A) = \{X \mid (A - \lambda I_n)X = 0\}.$$

Note: we always have  $1 \leq \dim E(\lambda_j, A) \leq k_j$  for each  $j$ .

A matrix  $A$  is diagonalizable if and only if  $\dim E(\lambda_j, A) = k_j$  for each  $j = 1, 2, \dots, k$ .

## Example

Determine whether or not the matrix  $A = \begin{bmatrix} 1 & 2 & 0 \\ -3 & 2 & 3 \\ -1 & 2 & 2 \end{bmatrix}$  is diagonalizable.

## Example

Determine whether or not the matrix  $A = \begin{bmatrix} 2 & 0 & 0 \\ -2 & -2 & 2 \\ -5 & -10 & 7 \end{bmatrix}$  is diagonalizable.

## Powers of matrices

Suppose we wanted to find  $A^7$ , where  $A$  was the matrix from the last slide. Finding this by hand would take a very long time. (For large matrices and high powers, even a computer will take a long time.)

However, we know that  $A = PDP^{-1}$ , where  $P = \begin{bmatrix} -2 & 1 & 0 \\ 1 & 0 & 2 \\ 0 & 1 & 5 \end{bmatrix}$ .

# Polynomials of matrices

Suppose  $p(x) = a_n x^n + \cdots + a_1 x + a_0$  is a polynomial and we want to compute  $p(A)$ , where  $A$  is diagonalizable.

# Symmetric matrices

Recall: an  $n \times n$  matrix  $A$  is **symmetric** if  $A^T = A$ .

## Theorem

*Suppose  $A$  is a symmetric matrix. If  $X_1$  and  $X_2$  are eigenvectors of  $A$  corresponding to eigenvalues  $\lambda_1 \neq \lambda_2$ , then  $X_1 \cdot X_2 = 0$ .*

## Theorem

*If  $A$  is an  $n \times n$  symmetric matrix, then there exists an **orthonormal basis** of  $\mathbb{R}^n$  consisting of eigenvectors of  $A$ .*

## Example

Given  $A = \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix}$ , find an orthogonal matrix  $P$  such that  $P^T A P$  is diagonal.

## Example

Sketch the curve defined by the equation  $3x^2 + 2xy + 3y^2 = 1$ .