

# MA 1140: Lecture 8

## Eigenvalues and eigenvectors

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# Eigenvalues and eigenvectors (of linear operators)

Let  $T : V \rightarrow V$  be a linear map, which we call linear operator.

## Definition

A non-zero vector  $v \in V$  is called an **eigenvector** of  $T$  if  $T(v) = \lambda v$  for some  $\lambda \in \mathbb{R}$ . This  $\lambda$  is called the **eigenvalue** of  $T$  associated with the eigenvector  $v$ .

- Geometrically, an eigenvector, corresponding to an eigenvalue, points in a direction that is stretched by the transformation, and the eigenvalue is the factor by which it is stretched. If the eigenvalue is negative, the direction is reversed.
- An eigenvalue can be positive, negative or zero.

# Eigenvalues and eigenvectors (of square matrices)

Since there is a one to one correspondence between the set of all linear operators from  $V (\cong \mathbb{R}^n)$  to itself and the collection of all  $n \times n$  matrices over  $\mathbb{R}$ , it is equivalent to define eigenvalues and eigenvectors of  $n \times n$  matrices.

## Definition

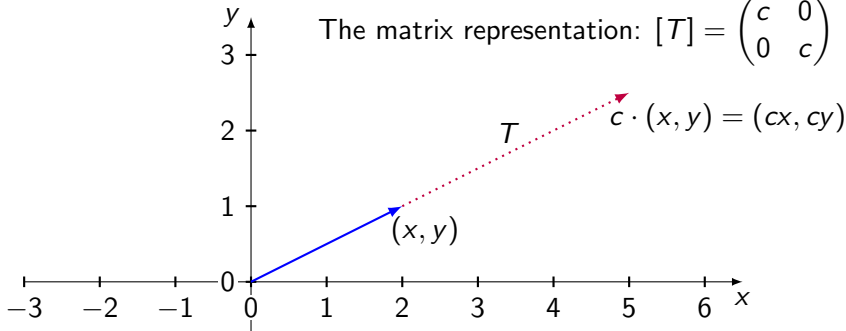
Let  $A$  be an  $n \times n$  matrix over  $\mathbb{R}$ . A non-zero column vector  $v \in \mathbb{R}^n$  is called an **eigenvector** of  $A$  if  $Av = \lambda v$  for some  $\lambda \in \mathbb{R}$ . This  $\lambda$  is called the **eigenvalue** of  $A$  associated with the eigenvector  $v$ .

# Example 1: eigenvalues and eigenvectors of stretching

Let  $c \in \mathbb{R}$ . Define  $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  by

$$T \begin{pmatrix} x \\ y \end{pmatrix} = c \begin{pmatrix} x \\ y \end{pmatrix} \text{ for every } \begin{pmatrix} x \\ y \end{pmatrix} \in \mathbb{R}^2.$$

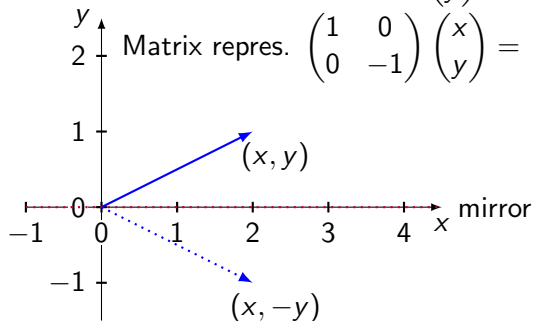
The matrix representation:  $[T] = \begin{pmatrix} c & 0 \\ 0 & c \end{pmatrix}$



Every  $v (\neq 0) \in \mathbb{R}^2$  is an eigenvector of  $T$  with the eigenvalue  $c$ .

## Example 2: eigenvalues and eigenvectors of reflection

$T : \mathbb{R}^2 \longrightarrow \mathbb{R}^2$  is defined by  $T \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x \\ -y \end{pmatrix}$ .



For  $x \neq 0$ ,  $\begin{pmatrix} x \\ 0 \end{pmatrix}$  is an eigenvector of  $T$  with eigenvalue 1.

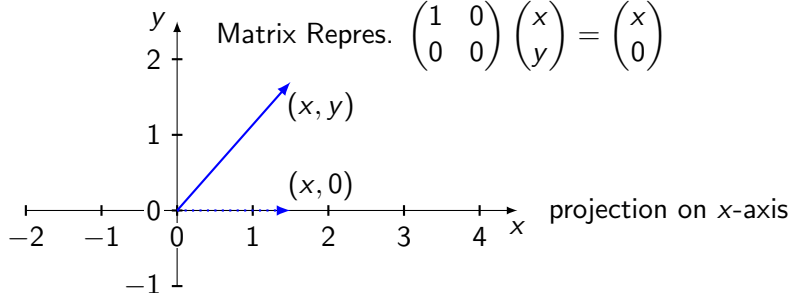
For  $y \neq 0$ ,  $\begin{pmatrix} 0 \\ y \end{pmatrix}$  is an eigenvector of  $T$  with eigenvalue  $-1$ .

These are ALL the eigenvectors of  $T$ . (Verify it!)

## Example 3: eigenvalues and eigenvectors of projection

Define  $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  by  $T \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x \\ 0 \end{pmatrix}$

Matrix Repres.  $\begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x \\ 0 \end{pmatrix}$



For  $x \neq 0$ ,  $\begin{pmatrix} x \\ 0 \end{pmatrix}$  is an eigenvector of  $T$  with eigenvalue 1.

For  $y \neq 0$ ,  $\begin{pmatrix} 0 \\ y \end{pmatrix}$  is an eigenvector of  $T$  with eigenvalue 0.

These are ALL the eigenvectors of  $T$ . (Verify it!)

## Example 4: $A$ may not have eigenvalues and eigenvectors

- Consider the matrix  $A = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix}$  over  $\mathbb{R}$ .
- Does  $A$  have eigenvalues and eigenvectors over  $\mathbb{R}$ ?
- If yes, then there are  $\begin{pmatrix} x \\ y \end{pmatrix} \in \mathbb{R}^2 \setminus \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix} \right\}$  and  $\lambda \in \mathbb{R}$  such that

$$\begin{aligned} & \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \lambda \begin{pmatrix} x \\ y \end{pmatrix} \\ \Rightarrow & \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \\ \Rightarrow & \begin{pmatrix} -\lambda & 1 \\ -1 & -\lambda \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \end{aligned}$$

Since  $\begin{pmatrix} x \\ y \end{pmatrix} \neq \begin{pmatrix} 0 \\ 0 \end{pmatrix}$ ,  $\det \begin{pmatrix} -\lambda & 1 \\ -1 & -\lambda \end{pmatrix} = 0$ . Hence  $\lambda^2 + 1 = 0$ .

But no such  $\lambda$  exists in  $\mathbb{R}$ .

- So  $A$  does not have eigenvalues and eigenvectors over  $\mathbb{R}$ .

# The existence of eigenvalues and eigenvectors

- Consider the matrix  $A = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix}$  over  $\mathbb{C}$ , the set of complex numbers.
- Does  $A$  have eigenvalues and eigenvectors over  $\mathbb{C}$ ? **Ans. Yes.**
- Note that  $\lambda^2 + 1$  has solutions:  $\pm i \in \mathbb{C}$ .
- Then, for each  $\lambda = \pm i$ , in view of the previous slide, one should solve the system

$$\begin{pmatrix} -\lambda & 1 \\ -1 & -\lambda \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}.$$

to get

$$\begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} \begin{pmatrix} i \\ -1 \end{pmatrix} = i \begin{pmatrix} i \\ -1 \end{pmatrix} \text{ and } \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} \begin{pmatrix} i \\ 1 \end{pmatrix} = -i \begin{pmatrix} i \\ 1 \end{pmatrix}$$

- Conclusion:** The existence of eigenvalues and eigenvectors of a given matrix depends on the base field.



# Similarity of matrices

## Definition

Two  $n \times n$  matrices  $A$  and  $B$  are called **similar** if there exists an invertible  $n \times n$  matrix  $P$  such that  $B = P^{-1}AP$ .

*Some statements (without proof) about importance of similarity of matrices:*

- Two matrices are similar if and only if they represent the same linear operator with respect to (possibly) different bases.
- Two similar matrices  $A$  and  $B$  share many properties:
  - $\text{rank}(A) = \text{rank}(B)$  as operators from  $\mathbb{R}^n$  to itself.
  - $\det(A) = \det(B)$ ;  $\text{tr}(A) = \text{tr}(B)$  (sum of all diagonal entries).
  - $A$  and  $B$  have same characteristic polynomial,  $\det(xI_n - A)$ .
  - Minimal polynomials of  $A$  and  $B$  are same. A monic polynomial  $p(X) \in \mathbb{R}[X]$  is said to be a minimal polynomial of  $A$  if  $p(A) = 0$  (zero matrix) and  $p$  has minimal possible degree.
  - Jordan canonical forms of  $A$  and  $B$  are same.

# Diagonalizable matrices

**Motivation:** For a matrix, eigenvalues and eigenvectors can be used to decompose the matrix, for example by diagonalizing it.

## Definition

A matrix  $A$  is said to be **diagonalizable** if  $A$  is similar to a diagonal matrix  $D$ , i.e., if there is an invertible matrix  $P$  such that

$$P^{-1}AP = \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix} \quad (\text{a diagonal matrix}).$$

The set of eigenvectors helps us to test whether a matrix is diagonalizable or not.

# The use of eigenvalues and eigenvectors on diagonalization

## Theorem

Let  $A$  be an  $n \times n$  matrix over  $\mathbb{R}$ . The following are equivalent:

- 1  $A$  is diagonalizable.
- 2 The eigenvectors of  $A$  form a basis, or equivalently,  $A$  has  $n$  linearly independent eigenvectors  $v_1, \dots, v_n$  with associated eigenvalues  $\lambda_1, \dots, \lambda_n$  (which need not be distinct).

**Proof.** (1)  $\Rightarrow$  (2): There is an  $n \times n$  invertible matrix  $P$  such that

$$P^{-1}AP = \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix} \quad \text{for some } \lambda_1, \dots, \lambda_n \in \mathbb{R}.$$

$$\text{Hence } AP = P \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \end{pmatrix}.$$

# Proof of the theorem contd...

**Proof.** (1)  $\Rightarrow$  (2): ... Thus  $AP = P \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix}$ .

Write  $P = [v_1 \ v_2 \ \cdots \ v_n]$  for some  $v_1, \dots, v_n \in \mathbb{R}^n$ .

Then  $AP = [Av_1 \ Av_2 \ \cdots \ Av_n]$  and

$$P \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix} = \left[ P \begin{pmatrix} \lambda_1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \ P \begin{pmatrix} 0 \\ \lambda_2 \\ \vdots \\ 0 \end{pmatrix} \ \cdots \ P \begin{pmatrix} 0 \\ 0 \\ \vdots \\ \lambda_n \end{pmatrix} \right]$$

$$= [\lambda_1 v_1 \ \lambda_2 v_2 \ \cdots \ \lambda_n v_n].$$

Therefore  $Av_i = \lambda_i v_i$  for every  $1 \leq i \leq n$ .

Note that  $v_1, \dots, v_n$  are linearly independent, since  $P$  is invertible.

# Proof of the theorem contd...

**Proof.** (2)  $\Rightarrow$  (1):  $A$  has  $n$  linearly independent eigenvectors  $v_1, \dots, v_n \in \mathbb{R}^n$  with associated eigenvalues  $\lambda_1, \dots, \lambda_n \in \mathbb{R}$ . Set  $P := [v_1 \ v_2 \ \cdots \ v_n]$ . Clearly  $P$  is an  $n \times n$  matrix. Since  $v_1, \dots, v_n$  are linearly independent,  $P$  is invertible.

Moreover

$$\begin{aligned} AP &= [Av_1 \ Av_2 \ \cdots \ Av_n] = [\lambda_1 v_1 \ \lambda_2 v_2 \ \cdots \ \lambda_n v_n] \\ &= P \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix}. \end{aligned}$$

Therefore

$$P^{-1}AP = \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix}.$$

# Eigenspace associated with an eigenvalue

Let  $A$  be an  $n \times n$  matrix over  $\mathbb{R}$ . Denote the identity matrix by  $I_n$ .

- The following are equivalent:
  - $v \in \mathbb{R}^n$  is an eigenvector of  $A$  with the corr. eigenvalue  $\lambda$ .
  - $v \in \mathbb{R}^n$  is a non-trivial solution of the system  $(A - \lambda I_n)X = 0$ , i.e.,  $v \in \mathbb{R}^n \setminus \{0\}$  lies in  $\text{Null}(A - \lambda I_n)$ .

**Proof.** Note that  $Av = \lambda v$  if and only if  $(A - \lambda I_n)v = 0$ .

- The set of all eigenvectors of  $A$  corresponding to an eigenvalue  $\lambda$ , together with the zero vector, is called the **eigenspace** of  $A$  associated with  $\lambda$ .  
It is nothing but  $\text{Null}(A - \lambda I_n)$ .

# Characteristic polynomial of a matrix

Let  $A$  be an  $n \times n$  matrix over  $\mathbb{R}$ . Denote the identity matrix by  $I_n$ .

- The following are equivalent:
  - $\lambda \in \mathbb{R}$  is an eigenvalue of  $A$ .
  - $\det(\lambda I_n - A) = 0$ .

**Proof.** Note that  $\lambda$  is an eigenvalue of  $A$  if and only if there is  $v \neq 0$  in  $\mathbb{R}^n$  such that  $Av = \lambda v$  if and only if  $(A - \lambda I_n)v = 0$  for some  $v \neq 0$  in  $\mathbb{R}^n$  if and only if  $(A - \lambda I_n)X = 0$  has a non-trivial solution if and only if  $\det(A - \lambda I_n) = 0$  if and only if  $\det(\lambda I_n - A) = 0$ .

## Definition

The characteristic polynomial of  $A$ , denoted by  $p_A(x)$ , is the polynomial over  $\mathbb{R}$  defined by  $p_A(x) := \det(xI_n - A)$ .

Therefore the set of all eigenvalues of  $A$  in  $\mathbb{R}$  is given by all the real roots of the characteristic polynomial  $p_A(x)$ .

## Example: Characteristic polynomial and eigenvalues

- Consider  $A = \begin{pmatrix} 1 & 2 \\ 3 & 4 \end{pmatrix}$ .
- The characteristic polynomial of  $A$  is given by

$$\begin{aligned} p_A(x) &= \det(xI_2 - A) = \det \begin{pmatrix} x-1 & -2 \\ -3 & x-4 \end{pmatrix} \\ &= (x-1)(x-4) - 6 = x^2 - 5x - 2. \end{aligned}$$

- The roots of  $p_A(x)$  are  $\frac{5 \pm \sqrt{33}}{2}$ .
- Therefore the eigenvalues of  $A$  are  $\frac{5 \pm \sqrt{33}}{2}$ .



# How to compute eigenvalues and eigenvectors

- First compute the characteristic polynomial  $p_A(x) = \det(xI_n - A)$  of  $A$ .
- Next compute the roots of  $p_A(x)$  by factorizing it into linear factors. Which gives the eigenvalues.
- Then, for each eigenvalue  $\lambda$ , solve the homogeneous system:

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

to get eigenspace of  $A$  associated with  $\lambda$ .

- Recall that in order to solve a linear system, you may apply elementary row operations to make it into a system with row reduced echelon coefficient matrix.

# Cayley-Hamilton Theorem

- Let  $A$  be an  $n \times n$  matrix over  $\mathbb{R}$ .
- Write  $A^r$  for the matrix multiplication of  $r$  many copies of  $A$ .
- For  $c \in \mathbb{R}$ ,  $cA$  is just component wise scalar multiplication.
- If  $f(x) = a_r x^r + \cdots + a_2 x^2 + a_1 x + a_0 \in \mathbb{R}[x]$ , then  $f(A) = a_r A^r + \cdots + a_2 A^2 + a_1 A + a_0 I_n$  is an  $n \times n$  matrix/ $\mathbb{R}$ .

## Theorem (Cayley-Hamilton)

Consider the characteristic polynomial  $p_A(x) := \det(xI_n - A)$ .  
Then  $p_A(A) = 0$  (zero matrix of order  $n \times n$ ).

**Warning:**  $p_A(A) \neq \det(AI_n - A)$ . LHS is a matrix; RHS is a scalar.

## Example

If  $A = \begin{pmatrix} 1 & 2 \\ 3 & 4 \end{pmatrix}$ , then  $p_A(x) = x^2 - 5x - 2$ . The Cayley-Hamilton

Theorem says that  $A^2 - 5A - 2I_2 = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$ .

# Similar matrices have same characteristic polynomial

## Theorem

Let  $A$  and  $B$  be similar, i.e.,  $B = P^{-1}AP$  for some invertible matrix  $P$ . Then  $\det(xI_n - A) = \det(xI_n - B)$ .

**Proof.**  $\det(xI_n - B) = \det(xP^{-1}I_nP - P^{-1}AP)$   
 $= \det(P^{-1}(xI_n - A)P) = (1/\det(P)) \det(xI_n - A) \det(P)$   
 $= \det(xI_n - A).$  □

## Theorem

Let  $A$  and  $B$  be similar, i.e.,  $B = P^{-1}AP$ . For a polynomial  $f(x) \in \mathbb{R}[x]$ ,  $f(A) = 0$  if and only if  $f(B) = 0$  (zero matrix).

**Proof.** Note:  $P^{-1}A^rP = (P^{-1}AP)(P^{-1}AP)\dots(P^{-1}AP) = B^r$ ,  
and  $P^{-1}(c_1D_1 + c_2D_2)P = c_1(P^{-1}D_1P) + c_2(P^{-1}D_2P)$ .  
Verify that  $P^{-1}f(A)P = f(B)$  and  $Pf(B)P^{-1} = f(A)$ .  
Hence the theorem follows. □

# Proof of Cayley-Hamilton Thm for diagonalizable matrix

Let  $A$  be a diagonalizable matrix, i.e., there is  $P$  such that

$$P^{-1}AP = \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix} = B \text{ (say).}$$

Note that  $\det(xI_n - A) = \det(xI_n - B) = (x - \lambda_1) \cdots (x - \lambda_n)$ .

By induction on  $n$ , one can verify that

$$(B - \lambda_1 I_n)(B - \lambda_2 I_n) \cdots (B - \lambda_n I_n) = 0.$$

Hence, multiplying  $P$  on left and  $P^{-1}$  on right, we get

$$(A - \lambda_1 I_n)(A - \lambda_2 I_n) \cdots (A - \lambda_n I_n) = 0$$

i.e.,  $p_A(A) = 0$  (zero matrix).



# Thank You!