

MA1140: 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

- 1 A NON-ZERO vector $v \in V$ is called an **eigenvector** of T if $T(v) = \lambda v$ for SOME scalar λ .
 - 2 A scalar λ is called an **eigenvalue** of T if there EXISTS a non-zero vector $v \in V$ such that $T(v) = \lambda v$.
 - 3 If $T(v) = \lambda v$, then λ is called an eigenvalue of T corresponding to 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} .

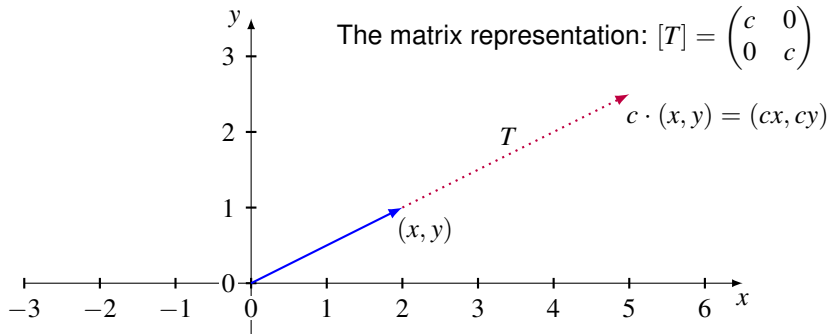
- 1 A NON-ZERO column vector $v \in \mathbb{R}^n$ is called an **eigenvector** of A if $Av = \lambda v$ for SOME $\lambda \in \mathbb{R}$.
- 2 A scalar λ is called an **eigenvalue** of A if there EXISTS a non-zero column vector $v \in \mathbb{R}^n$ such that $Av = \lambda v$.
- 3 If $Av = \lambda v$, then λ is called an eigenvalue of A corresponding to 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

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

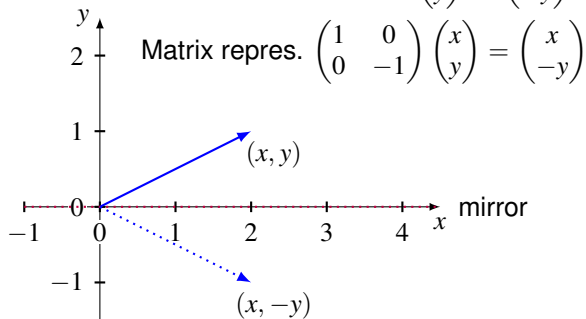
The matrix representation: $[T] = \begin{pmatrix} c & 0 \\ 0 & c \end{pmatrix}$



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.

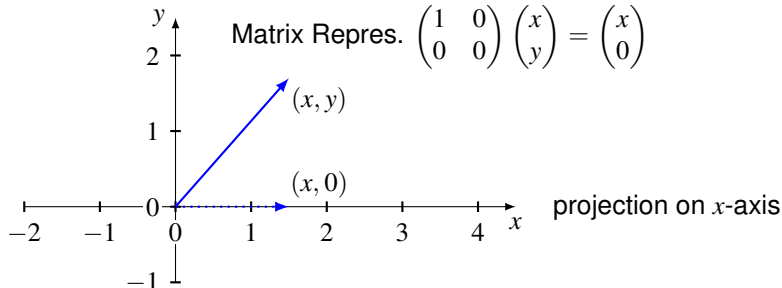
For $y \neq 0$, $\begin{pmatrix} 0 \\ y \end{pmatrix}$ is an eigenvector of T with eigenvalue -1 .

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

Example 3: eigenvalues and eigenvectors of projection

Define $T : \mathbb{R}^2 \longrightarrow \mathbb{R}^2$ 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 over a particular field

- 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 λ 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 matrix A has eigenvalues and eigenvectors over \mathbb{C} , but not over \mathbb{R} .

Characteristic polynomial of a matrix

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

Lemma

The following statements are equivalent:

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

Proof. Note that λ is an eigenvalue of $A \Leftrightarrow$ there is $v \neq 0$ in \mathbb{C}^n such that $Av = \lambda v$, i.e., $(A - \lambda I_n)v = 0 \Leftrightarrow (A - \lambda I_n)X = 0$ has a non-trivial solution $\Leftrightarrow \det(A - \lambda I_n) = 0 \Leftrightarrow \det(\lambda I_n - A) = 0$.

Definition

- 1 The **characteristic polynomial** of A , denoted by $p_A(x)$, is the polynomial defined by $p_A(x) := \det(xI_n - A)$.
- 2 Thus the eigenvalues of A are nothing but the roots of $p_A(x)$.
- 3 The **algebraic multiplicity** $\text{AM}_A(\lambda)$ of the eigenvalue λ of A is its multiplicity as a root of the characteristic polynomial $p_A(x)$, that is, the largest integer k such that $(x - \lambda)^k$ is a factor of $p_A(x)$.

Eigenspace associated with an eigenvalue

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

Lemma

The following statements are equivalent:

- 1 $v \in \mathbb{C}^n$ is an eigenvector of A with the corr. eigenvalue λ .
- 2 $v \in \mathbb{C}^n$ is a non-trivial solution of the system $(A - \lambda I_n)X = 0$, i.e., $v \in \mathbb{C}^n \setminus \{0\}$ lies in $\text{Null}(A - \lambda I_n)$.

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

Definition

- 1 Given a particular eigenvalue λ of A . The set of all eigenvectors of A corresponding to λ , together with the zero vector, is called the **eigenspace** of A associated with λ . It is denoted by E_λ . Note that $E_\lambda = \text{Null}(A - \lambda I_n)$.
- 2 The dimension of $E_\lambda = \text{Null}(A - \lambda I_n)$ is referred to as the **geometric multiplicity of λ** , denoted by $\text{GM}_A(\lambda)$.

Some inequalities on algebraic/geometric multiplicities

Theorem

Let A be an $n \times n$ matrix over \mathbb{C} . For every eigenvalue λ of A , we have

- 1 $1 \leq \text{AM}_A(\lambda) \leq n$ and $1 \leq \text{GM}_A(\lambda) \leq n$.
- 2 $\sum_{i=1}^r \text{AM}_A(\lambda_i) = n$, the sum varies over all the eigenvalues of A .
- 3 $1 \leq \text{GM}_A(\lambda) \leq \text{AM}_A(\lambda) \leq n$.

Proof.

- 1 Note that $\deg(p_A(x)) = n$ and $p_A(x) = (x - \lambda)^{\text{AM}_A(\lambda)} f(x)$ for some f . Since $\text{GM}_A(\lambda) = \dim(\text{Null}(A - \lambda I_n))$, we have $1 \leq \text{GM}_A(\lambda) \leq n$.
- 2 It follows from $p_A(x) = \prod_{i=1}^r (x - \lambda_i)^{\text{AM}_A(\lambda_i)}$ and $\deg(p_A(x)) = n$.
- 3 We will skip it.



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 $\frac{5 \pm \sqrt{33}}{2}$.
- The eigenvalues of A are $\lambda_1 = \frac{5 - \sqrt{33}}{2}$ and $\lambda_2 = \frac{5 + \sqrt{33}}{2}$.
- The algebraic multiplicities of both λ_1 and λ_2 are 1.

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 λ , solve the homogeneous system:

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

to get eigenspace of A associated with λ .

- 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.

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{C}). The following are equivalent:

- 1 A is diagonalizable.
- 2 The eigenvectors of A form a basis of \mathbb{R}^n , 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).
- 3 $GM_A(\lambda) = AG_A(\lambda)$ for every eigenvalue λ of A .
- 4 The minimal polynomial of A has distinct roots (equivalently, A satisfies a polynomial $p(x) \in \mathbb{C}[x]$ having distinct roots).

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

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

Hence multiply by P from the left side.

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

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

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

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

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

(1) \Leftrightarrow (3) \Leftrightarrow (4): We will skip it.



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
$$f(A) = a_r A^r + \cdots + a_2 A^2 + a_1 A + a_0 I_n \text{ is an } n \times n \text{ matrix/}\mathbb{R}.$$

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

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: $P^{-1}A^rP = (P^{-1}AP)(P^{-1}AP) \cdots (P^{-1}AP) = B^r$,
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. \square

Proof of the Cayley-Hamilton Theorem 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). □

Remark

It can be observed from the proof that if A is diagonalizable, then A satisfies a polynomial having distinct roots.

Applications of Eigenvalues and Eigenvectors

Some real life applications of the use of eigenvalues and eigenvectors in science, engineering and computer science can be found here:

[https://www.intmath.com/matrices-determinants/
8-applications-eigenvalues-eigenvectors.php](https://www.intmath.com/matrices-determinants/8-applications-eigenvalues-eigenvectors.php)

Thank You!