## Linear Algebra

### Chapter 4: Eigenvalues and Eigenvectors

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## Dynamical System

- For  $A \in \mathbb{R}^{n \times n}$ ,  $\lim_{k \to \infty} A^k = ?$
- ▶ Try the Octave demos your selves!
- 1. Complete graphs (K4.m)
- Petersen graph (Petersen.m)
- 3. Cyclic graphs
  - 3.1 Odd number of nodes (C5.m)
  - 3.2 Even number of nodes (C6.m)
- 4. Complete bipartite graphs (K3\_3.m)
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## Eigenvalue Problem

- For a matrix  $A \in \mathbb{R}^{n \times n}$ , which vectors keep (or reverse) their directions after transformed by A? In other words, who satisfy  $Ax = \lambda x$ ?  $\rightarrow$  "Eigenvalue problem"
- ▶ eigen- [áigən]: "own" or "charateristic of"

### Definition

Let A be an  $n \times n$  matrix. A scalar  $\lambda$  is called an **eigenvalue** of A if there is a nonzero x such that  $Ax = \lambda x$ . Such a vector x is called an **eigenvector** of A corresponding to  $\lambda$ .

- ▶ Why are they important?
- ▶ Do they exist for any matrix?
- ▶ Is there only one eigenvector for an eigenvalue?
- Is there only one eigenvalue for an eigenvector?
- ► Given an eigenvalue, how can we find the corresponding eigenvectors? → Example 4.2
- ► How can we find eigenvalues?

## Eigenspace

- ► Example 4.2
  - $\rightarrow$  "The set of all eigenvectors corresponding to an eigenvalue  $\lambda$  of an  $n \times n$  matrix A is just the set of *nonzero* vectors in the null space of  $A \lambda I$ ."

#### Definition

Let A be an  $n \times n$  matrix and let  $\lambda$  be an eigenvalue of A. The collection of all eigenvectors corresponding to  $\lambda$ , together with the zero vector, is called the **eigenspace** of  $\lambda$  and is denoted by  $E_{\lambda}$ .

## Geometric Interpretation of Eigenvectors

- ▶ Ax and  $\lambda x$  are parallel, i.e., x is an eigenvector of A iff A transforms x into a parallel vector.
- ► Examples: Scaling, reflection (Ex 4.4), rotation
- ▶ Only the direction of an eigenvector matters.
  - → Only unit vectors need to be considered.

# Finding Eigenvalues

- ▶ For  $A \in \mathbb{R}^{n \times n}$ , the eigenvectors of  $\lambda$  are the nonzero vectors satisfying  $Ax = \lambda x$ .
  - $\rightarrow Ax \lambda Ix = 0 \rightarrow (A \lambda I)x = 0$
  - $\rightarrow$  The eigenspace  $E_{\lambda}$  is the non-trivial null space of  $A \lambda I$ .
- ▶ For  $2 \times 2$  matrices,
  - $\rightarrow$  a matrix has a non-trivial null space iff it is non-invertible.
  - $\rightarrow$  a matrix is non-invertible iff its determinant is zero.
  - $\rightarrow \lambda$  is an eigenvalue of A iff  $\det(A \lambda I) = 0$  (Example 4.5)
- Can be generalized to any square matrices.
  - $\rightarrow$  What are the determinants for  $n \times n$  matrices?

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### **Determinants**

- ▶ Notation:  $\det A = |A|$
- ▶  $1 \times 1$  matrices

$$\det A = |a| = a$$
 (Not the absolute value)

 $\triangleright$  2 × 2 matrices

$$\begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix} = a_{11}a_{22} - a_{12}a_{21}$$

ightharpoonup 3 imes 3 matrices

$$\left| \begin{array}{ccc} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{array} \right| = ?$$

## Determinant of a $3 \times 3$ Matrix

### Definition

Let 
$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$
 . Then the **determinant** of  $A$  is the

scalar

$$\det A = |A| = a_{11} \begin{vmatrix} a_{22} & a_{23} \\ a_{32} & a_{33} \end{vmatrix} - a_{12} \begin{vmatrix} a_{21} & a_{23} \\ a_{31} & a_{33} \end{vmatrix} + a_{13} \begin{vmatrix} a_{21} & a_{22} \\ a_{31} & a_{32} \end{vmatrix}$$

$$\begin{bmatrix}
a_{11} & a_{12} & a_{13} \\
a_{21} & a_{22} & a_{23} \\
a_{31} & a_{32} & a_{33}
\end{bmatrix} \rightarrow a_{12} \begin{vmatrix} a_{21} & a_{23} \\
a_{31} & a_{33} \end{vmatrix}$$

# Determinant of a $3 \times 3$ Matrix (cont'd)

▶ With  $A_{ij}$  defined as the submatrix of A obtained by deleting row i and column j,

$$\det A = a_{11} \det A_{11} - a_{12} \det A_{12} + a_{13} \det A_{13}$$
$$= \sum_{j=1}^{3} (-1)^{1+j} a_{1j} \det A_{1j}$$

- $\det A_{ij}$  is called the (i,j)-minor of A.
- Computed with respect to the first row.
  - → Why row not column? Why the first row?
  - ightarrow Can be generalized to columns or other rows (The Laplace Expansion Theorem)
- ► Another method (See (2) on p.264)

$$|A| = a_{11}a_{22}a_{33} + a_{12}a_{23}a_{31} + a_{13}a_{21}a_{32} - a_{31}a_{22}a_{13} - a_{32}a_{23}a_{11} - a_{33}a_{21}a_{12}$$

## Determinants of $n \times n$ Matrices

### Definition

Let  $A = [a_{ij}]$  be an  $n \times n$  matrix, where  $n \geq 2$ . Then the **determinant** of A is the scalar

$$\det A = |A| = a_{11} \det A_{11} - a_{12} \det A_{12} + \dots + (-1)^{1+n} a_{1n} \det A_{1n}$$
$$= \sum_{j=1}^{n} (-1)^{1+j} a_{1j} \det A_{1j}$$

► Cofactor expansion along the first row: With (i, j)-cofactor of A defined as

$$C_{ij} = (-1)^{i+j} \det A_{ij},$$

the definition becomes

$$\det A = \sum_{j=1}^{n} a_{1j} C_{1j}.$$

## The Laplace Expansion Theorem

### Theorem 4.1: The Laplace Expansion Theorem

The determinant of an  $n \times n$  matrix  $A = [a_{ij}]$ , where  $n \geq 2$ , can be computed as

$$\det A = a_{i1}C_{i1} + a_{i2}C_{i2} + \dots + a_{in}C_{in} = \sum_{j=1}^{n} a_{ij}C_{ij}$$

(which is the cofactor expansion along the ith row) and also as

$$\det A = a_{1j}C_{1j} + a_{2j}C_{2j} + \dots + a_{nj}C_{nj} = \sum_{i=1}^{n} a_{ij}C_{ij}$$

(the cofactor expansion along the jth column)

- ▶ Recursive computation → Not efficient (Note on p.268)
- ▶ Most useful when the matrix contains a row or column with lots of zeros. Why? (Example 4.11)

## Determinants of Triangular Matrices

► The Laplace expansion theorem is particularly useful when the matrix is (upper or lower) triangular.

#### Theorem 4.2

The determinant of a triangular matrix is the product of the entries on its main diagonal. Specifically, if  $A=[a_{ij}]$  is an  $n\times n$  triangular matrix then

$$\det A = a_{11}a_{22}\cdots a_{nn}$$

▶ Why? (Example 4.12)

## Properties of Determinants

#### Theorem 4.3

Let  $A = [a_{ij}]$  be a square matrix.

- a. If A has a zero row (column), then  $\det A = 0$ .
- b. If B is obtained by interchanging two rows (columns) of A, then  $\det B = -\det A$ .
- c. If A has two identical rows (columns), then  $\det A = 0$ .
- d. If B is obtained by multiplying a row (column) of A by k, then  $\det B = k \det A$ .
- e. If A, B, and C are identical except that the ith row (column) of C is the sum of the ith rows (columns) of A and B, then  $\det C = \det A + \det B$ .
- f. If B is obtained by adding a multiple of one row (column) of A to another row (column), then  $\det B = \det A$ .

## Determinants of Elementary Matrices

- ▶ (b), (d) and (f) of the properties are related to elementary row operations.
- ▶ What are the determinatns of elementary matrices?

#### Theorem 4.4

Let E be an  $n \times n$  elementary matrix.

- a. If E results from interchanging two rows of  $I_n$ , then  $\det E = -1$ .
- b. If E results from multiplying one row of  $I_n$  by k, then  $\det E = k$ .
- c. If E results from adding a multiple of one row of  $I_n$  to another row, then  $\det E = 1$ .
  - ▶ Determinants of all the elementary matrices are nonzero.

# Determinants of Elementary Matrices (cont'd)

 $\blacktriangleright$  If B = EA,  $\det B = ?$ 

### Lemma 4.5

Let B be an  $n\times n$  matrix and let E be an  $n\times n$  elementary matrix. Then

$$\det(EB) = (\det E)(\det B)$$

▶ How about  $\det(AB)$  when A is NOT an elementary matrix? → Theorem 4.8 (p.272)

#### Theorem 4.6

A square matrix A is invertible if and only if  $\det A \neq 0$ .

## Determinants and Matrix Operations

How can we write the followings in terms of  $\det A$  and  $\det B$ ?

- $ightharpoonup \det(kA) = ?$
- $ightharpoonup \det (A+B)=?$
- $ightharpoonup \det(AB) = ?$
- $ightharpoonup \det (A^{-1}) = ?$
- $ightharpoonup \det (A^T) = ?$

$$\det(kA)$$
 and  $\det(A+B)$ 

- $ightharpoonup \det(kA)$ 
  - Theorem 4.7

If A is an  $n \times n$  matrix, then

$$\det\left(kA\right) = k^n \det A$$

- ► See Theorem 4.3(d).
- $ightharpoonup \det (A+B)$ 
  - $det (A + B) = det A + det B? \rightarrow No!$
  - No general forumla.

# $\det(AB)$ , $\det(A^{-1})$ and $\det(A^{T})$

 $ightharpoonup \det (AB)$ 

Theorem 4.8

If A and B are  $n \times n$  matrices, then

$$\det(AB) = (\det A)(\det B)$$

 $ightharpoonup \det (A^{-1})$ Theorem 4.9

If A is invertible, then

$$\det\left(A^{-1}\right) = \frac{1}{\det A}$$

 $ightharpoonup \det (A^T)$ Theorem 4.10

For any square matrix A,

 $\det A = \det A^T$ 

### Cramer's Rule

▶ What is the relation between the solution of a linear system and its determinant?

### Theorem 4.11: Cramer's Rule

Let A be an invertible  $n \times n$  matrix and let  ${\boldsymbol b}$  be a vector in  $\mathbb{R}^n$ . Then the unique solution  ${\boldsymbol x}$  os the system  $A{\boldsymbol x}={\boldsymbol b}$  is given by

$$x_i = \frac{\det(A_i(\boldsymbol{b}))}{\det A}$$
 for  $i = 1, \dots, n$ 

▶  $A_i(b)$ : the matrix obtained by replacing the ith column of A by b

$$A_i(\boldsymbol{b}) = \begin{bmatrix} \boldsymbol{a}_1 & \cdots & \boldsymbol{b} & \cdots & \boldsymbol{a}_n \end{bmatrix}$$

- ▶ Requires to compute determinants
  - ightarrow Computationally inefficient except small systems.

## Adjoint

- What is the formula of the inverse of a matrix in terms of determinants?
- ▶ What is the solution of the equation AX = I?

$$A\boldsymbol{x}_1 = \boldsymbol{e}_1 \quad A\boldsymbol{x}_2 = \boldsymbol{e}_2 \quad \cdots \quad A\boldsymbol{x}_n = \boldsymbol{e}_n$$

### Theorem 4.12

Let A be an invertible  $n \times n$  matrix. Then

$$A^{-1} = \frac{1}{\det A} \operatorname{adj} A$$

ightharpoonup  $\operatorname{adj} A := [C_{ji}] = [C_{ij}]^T$ : the **adjoint** (or **adjugate**) of A

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# Finding Eigenvalues

- How to compute eigenvalues of a matrix?
- How many eigenvalues does a matrix have?
- lacksquare  $\lambda$  is an eigenvalue of A iff  $\det(A \lambda I) = 0$ .

The eigenvalues of a square matrix  ${\cal A}$  are precisely the solutions  $\lambda$  of the equation

$$\det\left(A - \lambda I\right) = 0$$

- ▶ What does  $\det(A \lambda I)$  look like?
  - $\rightarrow$  Polynomial in  $\lambda$  of degree n

### (Characteristic polynomial of A)

 $\rightarrow$  At most n distinct eigenvalues

## Finding Eigenvalues and Eigenvectors

#### Procedure

Let A be an  $n \times n$  matrix.

- 1. Compute the characteristic polynomial  $\det (A \lambda I)$  of A.
- 2. Find the eigenvalues of A by solving the characteristic equation  $\det{(A-\lambda I)}=0$  for  $\lambda$ .
- 3. For each eigenvalue  $\lambda$ , find the null spacec of the matrix  $A \lambda I$ . This is the eigenspace  $E_{\lambda}$ , the nonzero vectors of which are the eigenvectors of A corresponding to  $\lambda$ .
- 4. Find a basis for each eigenspace.
- ► **Algebraic multiplicity** of an eigenvalue: multiplicity as a root of the characteristic equation.
- ▶ **Geometric multiplicity** of an eigenvalue  $\lambda$ : dim  $E_{\lambda}$
- ▶ Geometric multiplicity ≤ Algebraic multiplicity (Lemma 4.26 on p.303)

# Eigenvalues of Triangular Matrices

### Theorem 4.15

The eigenvalues of a triangular matrix are the entries on its main diagonal.

▶ Why? (See Theorem 4.2 on p.268)

## Fundamental Theorem of Invertible Matrices: Ver. 3

#### Theorem 3.27

Let A be an  $n \times n$  matrix. The following statements are equivalent:

- a. A is invertible.
- b. Ax = b has a unique solution for every b in  $\mathbb{R}^n$ .
- c. Ax = 0 has only the trivial solution.
- d. The reduced row echelon form of A is  $I_n$ .
- e. A is a product of elementary matrices.
- f. rank(A) = n
- g.  $\operatorname{nullity}(A) = 0$
- h. The column vectors of A are linearly independent.
- i. The column vectors of A span  $\mathbb{R}^n$ .
- j. The column vectors of A form a basis for  $\mathbb{R}^n$ .
- k. The row vectors of A are linearly independent.
- I. The row vectors of A span  $\mathbb{R}^n$ .
- m. The row vectors of A form a basis for  $\mathbb{R}^n$ .
- n.  $\det A \neq 0$
- o. 0 is not an eigenvalue of A.

# Eigenvalue of $A^k$ and $A^{-1}$

#### Theorem 4.18

Let A be a square matrix with eigenvalue  $\lambda$  and corresponding eigenvector  $\boldsymbol{x}$ .

- a. For any positive integer k,  $\lambda^k$  is an eigenvalue of  $A^k$  with corresponding eigenvector  $\boldsymbol{x}$ .
- b. If A is invertible, then  $1/\lambda$  is an eigenvalue of  $A^{-1}$  with corresponding eigenvector x.
- c. For any integer k,  $\lambda^k$  is an eigenvalue of  $A^k$  with corresponding eigenvector  $\boldsymbol{x}$ .

# Computing $A^k x$

▶ How to compute  $A^k x$ , where x is not an eigenvector of A? (Example 4.21)

### Theorem 4.19

Suppose the  $n \times n$  matrix A has eigenvectors  $v_1, v_2, \cdots, v_m$  with corresponding eigenvalues  $\lambda_1, \lambda_2, \cdots, \lambda_m$ . If x is a vector in  $\mathbb{R}^n$  that can be expressed as a linear combination of these eigenvectors—say,

$$\boldsymbol{x} = c_1 \boldsymbol{v}_1 + c_2 \boldsymbol{v}_2 + \dots + c_m \boldsymbol{v}_m$$

then, for any integer k,

$$A^k \mathbf{x} = c_1 \lambda_1^k \mathbf{v}_1 + c_2 \lambda_2^k \mathbf{v}_2 + \dots + c_m \lambda_m^k \mathbf{v}_m$$

### Theorem 4.20

Let A be an  $n \times n$  matrix and let  $\lambda_1, \lambda_2, \cdots, \lambda_m$  be distinct eigenvalues of A with corresponding eigenvectors  $v_1, v_2, \cdots, v_m$ . Then  $v_1, v_2, \cdots, v_m$  are linearly independent.

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# Why Diagonalize Matrices?

- ► Triangular and diagonal matrices are good.
  - $\rightarrow$  How can we relate a square matrix to a triangular or diagonal one keeping the eigenvalues?
- Gaussian elimination?
  - → Eigenvalues are not preserved.
- Diagonalization

### Similar Matrices

#### Definition

Let A and B be  $n \times n$  matrices. We say that A is similar to B if there is an invertible  $n \times n$  matrix P such that  $P^{-1}AP = B$ . If A is similar to B, we write  $A \sim B$ .

- ▶ Equivalent to " $A = PBP^{-1}$ " or "AP = PB."
- " $A \sim B$ " does not necessarily mean " $B \sim A$ ."
- ▶ P depends on A and B. Is it unique?

#### Theorem 4.21

Let A, B and C be  $n \times n$  matrices.

- a.  $A \sim A$ . (Reflexivity)
- b. If  $A \sim B$ , then  $B \sim A$ . (Symmetry)
- c. If  $A \sim B$  and  $B \sim C$ , then  $A \sim C$ . (Transitivity)
  - Equivalent relation

# Similar Matrices (cont'd)

#### Theorem 4.22

Let A and B be  $n \times n$  matrices with  $A \sim B$ . Then

- a.  $\det A = \det B$ .
- b. A is invertible if and only if B is invertible.
- c. A and B have the same rank.
- ${\sf d}.$  A and B have the same characteristic polynomial.
- e. A and B have the same eigenvalues.
  - ▶ The converse is not necessarily true. (See Remark on p.300.)

## Diagonalization

- ▶ Good if a square matrix is similar to a diagonal matrix.
- Is it always possible?

#### Definition

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

# Diagonalization (cont'd)

▶ How can we find *D* and *P*?

### Theorem 4.23

Let A be an  $n \times n$  matrix. Then A is diagonalizable if and only if A has n linearly independent eigenvectors.

More precisely, there exist an invertible matrix P and a diagonal matrix D such that  $P^{-1}AP=D$  if and only if the columns of P are n linearly independent eigenvectors of A and the diagonal entries of D are eigenvalues of A corresponding to the eigenvectors in P in the same order.

▶ Is a non-invertible matrix diagonalizable? (Example 4.26)

# Diagonalization (cont'd)

► How can we check if the eigenvectors are linearly independent? (Example 4.26)

### Theorem 4.24

Let A be an  $n \times n$  matrix and let  $\lambda_1, \lambda_2, \cdots, \lambda_k$  be distinct eigenvalues of A. If  $\mathcal{B}_i$  is a basis for the eigenspace  $E_{\lambda_i}$ , then  $\mathcal{B} = \mathcal{B}_1 \cup \mathcal{B}_2 \cup \cdots \cup \mathcal{B}_k$  (i.e., the total collection of basis vectors for all the eigenspaces) is linearly independent.

### Theorem 4.25

If A is an  $n \times n$  matrix with n distinct eigenvalues, then A is diagonalizable.

## The Diagonalization Theorem

#### Lemma 4.26

If A is an  $n \times n$  matrix, then the geometric multiplicity of each eigenvalue is less than or equal to its algebraic multiplicity.

#### Theorem 4.27

Let A be an  $n \times n$  matrix whose distinct eigenvalues are  $\lambda_1, \lambda_2, \dots, \lambda_k$ . The following statements are equivalent:

- $\mathbf{a}$ . A is diagonalizable.
- b. The union  $\mathcal B$  of the bases of the eigenspaces of A (as in Theorem 4.24) contains n vectors.
- c. The algebraic multiplicity of each eigenvalue equals its geometric multiplicity.
  - Computing  $A^k$  (Example 4.29)  $A^k = PD^kP^{-1}$  for all  $k \ge 1$ .

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