SI231b: Matrix Computations

Lecture 11: Eigenvalue Problems

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Outline

- ► Eigenvalues and Eigenvectors
- ► Characteristic Polynomials
- Eigenspaces
- ► Algebraic and Geometric Multiplicity
- ► Similarity Transformation
- ► Defective Eigenvalues and Matrices
- ► Eigenvalue Decomposition



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Eigenvalues and Eigenvectors

Problem: given a $A \in \mathbb{R}^{n \times n}$ (or $\mathbb{C}^{n \times n}$), find a vector $v \in \mathbb{C}^n$ with $v \neq 0$ such that

$$\mathsf{Av} = \lambda \mathsf{v}, \qquad \mathsf{for some} \ \lambda \in \mathbb{C} \tag{*}$$

- (*) is called an eigenvalue problem or eigen-equation
- let (v, λ) be a solution to (*). We call
 - (v, λ) an eigen-pair of A
 - λ an eigenvalue of A
 - ullet v an eigenvector of A associated with λ
- ▶ if (v, λ) is an eigen-pair of A, $(\alpha v, \lambda)$ is also an eigen-pair for any $\alpha \in \mathbb{C}, \alpha \neq 0$
- unless specified, we will assume $\|\mathbf{v}\|_2 = 1$ in the sequel

Left/Right Eigenvector

Right Eigenvector

• $Ax = \lambda x$ for $x \neq 0$

Left Eigenvector

$$\triangleright$$
 $x^H A = \lambda x^H$ for $x \neq 0$

Unless specified, eigenvectors in our lecture are right eigenvectors.

Spectral Radius

$$\rho(\mathsf{A}) = \max |\lambda(\mathsf{A})|$$

Numerical Range

$$W(\mathsf{A}) = \left\{ \mathsf{x}^{\mathsf{H}} \mathsf{A} \mathsf{x} | \|\mathsf{x}\|_2 = 1 \right\}$$

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Characteristic Polynomial

Fact: Every $A \in \mathbb{R}^{n \times n}$ (or $\mathbb{C}^{n \times n}$) has n eigenvalues.

from the eigenvalue problem we see that

- ▶ let $p(\lambda) = \det(A \lambda I)$, called the characteristic polynomial of A
- ightharpoonup it can be shown that $p(\lambda)$ is a polynomial of degree n,

$$p(\lambda) = \alpha_0 + \alpha_1 \lambda + \alpha_2 \lambda^2 + \ldots + \alpha_n \lambda^n$$

where $\{\alpha_i\}_{i=1}^{n+1}$ depend on A

- ▶ as $p(\lambda)$ is a polynomial of degree n, it can be factored as $p(\lambda) = \prod_{i=1}^{n} (\lambda_i \lambda)$ where $\lambda_1, \dots, \lambda_n$ are the roots of $p(\lambda)$
- we have $det(A \lambda I) = 0 \iff \lambda \in \{\lambda_1, \dots, \lambda_n\}$



Eigenvalues and Eigenvectors

Fact: an eigenvalue can be complex even if A is real.

- ▶ a polynomial $p(\lambda) = \alpha_0 + \alpha_1 \lambda + \alpha_2 \lambda^2 + \ldots + \alpha_n \lambda^n$ with real coefficients α_i 's can have complex roots
- example: consider

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

• we have $p(\lambda) = \lambda^2 + 1$, so $\lambda_1 = \boldsymbol{j}$, $\lambda_2 = -\boldsymbol{j}$

Fact: if A is real and there exists a real eigenvalue λ of A, the associated eigenvector v can be taken as real.

- lacktriangle obviously, when $A \lambda I$ is real we can define $\mathcal{N}(A \lambda I)$ on \mathbb{R}^n
- ▶ or, if v is a complex eigenvector of a real A associated with a real λ , we can write $v = v_R + jv_I$, where $v_R, v_I \in \mathbb{R}^n$. It is easy to verify that v_R and v_I are eigenvectors associated with λ

Eigenvalues and Eigenvectors

For $A \in \mathbb{R}^{n \times n}$ (or $\mathbb{C}^{n \times n}$), we should be careful

- ▶ the meaning of *n* eigenvalues: they are defined as the *n* roots of the characteristic polynomial $p(\lambda) = \det(A \lambda I)$
- example: consider

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

- from the original definition $Av=\lambda v$, one can verify that $\lambda=1$ is the only eigenvalue of A
- from the characteristic polynomial, which is $p(\lambda) = (1 \lambda)^2$, we see two roots $\lambda_1 = \lambda_2 = 1$ as two eigenvalues

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Eigenspaces

Eigenspace

If A is an $n \times n$ square matrix and λ is an eigenvalue of A, then the union of the zero vector 0 and the set of all eigenvectors corresponding to eigenvalues λ is a subspace of \mathbb{R}^n known as the eigenspace of λ .

Subspace Interpretation

Denote \mathcal{E}_{λ} the eigenspace of A associated with λ , then

- $\forall x \in \mathcal{E}_{\lambda}, x \neq 0, x$ is an eigenvector of A associated with eigenvalue λ .
- \triangleright $\mathcal{E}_{\lambda} = \mathcal{N}(A \lambda I)$
- \triangleright \mathcal{E}_{λ} is an invariant subspace of A, i.e., $A\mathcal{E}_{\lambda} \subset \mathcal{E}_{\lambda}$



Algebraic Multiplicity and Geometric Multiplicity

Repeated Eigenvalues

- ▶ order $\lambda_1, \ldots, \lambda_n$ such that $\{\lambda_1, \ldots, \lambda_k\}$ $(k \le n)$ is the set of all distinct eigenvalues of A, i.e., $\lambda_i \ne \lambda_j$ for all $i, j \in \{1, \ldots, k\}$ with $i \ne j$
- denote μ_i as the number of repeated eigenvalues of λ_i , $i=1,\ldots,k$
 - μ_i is called the algebraic multiplicity of the eigenvalue λ_i

$$p(\lambda) = (\lambda - \lambda_1)^{\mu_1} (\lambda - \lambda_2)^{\mu_2} \cdots (\lambda - \lambda_k)^{\mu_k},$$

with $\mu_1 + \mu_2 + \cdots + \mu_k = n$.

- ightharpoonup every λ_i can have more than one eigenvector (scaling not counted)
 - if $\dim \mathcal{N}(A \lambda_i I) = r$, we can find r linearly independent v_i 's
 - denote $\gamma_i = \dim \mathcal{N}(\mathsf{A} \lambda_i \mathsf{I}), i = 1, \dots, k$
 - γ_i is the dimension of the eigenspace of λ_i
 - γ_i is called the geometric multiplicity of the eigenvalue λ_i

Similarity Transformation

For $A \in \mathbb{R}^{n \times n}$ (or $\mathbb{C}^{n \times n}$), if $T \in \mathbb{R}^{n \times n}$ (or $\mathbb{C}^{n \times n}$) is nonsingular, the map $A \mapsto T^{-1}AT$ is called a similarity transformation of A.

Theorem 1 If T is nonsingular, then A and $T^{-1}AT$ have the same

- characteristic polynomial
- eigenvalues
- ► algebraic multiplicity
- geometric multiplicity

Hint: using characteristic polynomial to show.

Defective Eigenvalues and Matrices

Lemma 1: the algebraic multiplicity of an eigenvalue λ_i is at least as great as its geometric multiplicity, i.e., $\mu_i \geq \gamma_i$.

You need to prove this.

Defective Eigenvalue

An eigenvalue whose algebraic multiplicity exceeds its geometric multiplicity is a defective eigenvalue.

Defective Matrix

A matrix that has one or more defective eigenvalues.

Examples: consider the following matrices

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

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Diagonalizability and Eigenvalue Decomposition

Theorem 2: An $n \times n$ matrix A is nondefective if and only if it has an eigenvalue decomposition

$$A = V\Lambda V^{-1}$$
,

with $\Lambda = \operatorname{diag}(\lambda_1, \ \lambda_2, \ \cdots, \ \lambda_n)$ and the k-th column of V being the eigenvector v_k associated with λ_k .

Hint: you need the following lemma to prove the theorem

Lemma 2: Let $A \in \mathbb{C}^{n \times n}$, and suppose that the eigenvalues $\lambda_1, \ldots, \lambda_n$ are ordered such that $\{\lambda_1, \ldots, \lambda_k\}$, $k \leq n$, is the set of all distinct eigenvalues of A. Also, let v_i be *any* eigenvector associated with λ_i . Then v_1, \ldots, v_k must be linearly independent.

From the theorem 2, another term for nondefective is diagonalizable.

Properties of Eigenvalue Decomposition

If A admits an eigenvalue decomposition, the following properties can be shown (easily):

- $\blacktriangleright \ \det(\mathsf{A}) = \prod_{i=1}^n \lambda_i$
- $\operatorname{tr}(\mathsf{A}) = \sum_{i=1}^n \lambda_i$
- ▶ the eigenvalues of A^k are $\lambda_1^k, \ldots, \lambda_n^k$
- A is nonsigular if and only if A does not have zero eigenvalues
- \blacktriangleright suppose that A is also nonsingular. Then, $\mathsf{A}^{-1} = \mathsf{V} \Lambda^{-1} \mathsf{V}^{-1}$

Note: the first three properties does not require the eigenvalue decomposition to prove.

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