# Math 221: LINEAR ALGEBRA

# Chapter 5. Vector Space $\mathbb{R}^n$ §5-5. Similarity and Diagonalization

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**Diagonalization Revisited** 

Algebraic and Geometric Multiplicities

Characterizing Diagonalizable Matrices

**Complex Eigenvalues** 

Eigenvalues of Real Symmetric Matrices

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### Definition (Similar Matrices)

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Similarity is an equivalence relation, i.e., for  $n \times n$  matrices A, B and C

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- 3. if  $A \sim B$  and  $B \sim C$ , then  $A \sim C$  (transitive).

### Proof.

- 1. Since  $A = I_n A I_n$  and  $I_n^{-1} = I_n$ ,  $A = I_n^{-1} A I_n$ . Therefore,  $A \sim A$ .
- Suppose A ~ B. Then there exists an invertible n × n matrix P such that B = P<sup>-1</sup>AP. Multiplying both sides on the left by P, on the right by P<sup>-1</sup>, and simplifying gives us PBP<sup>-1</sup> = A. Therefore, A = (P<sup>-1</sup>)<sup>-1</sup>A(P<sup>-1</sup>), so A ~ B.

### Proof. (continued)

3. Since A  $\sim$  B and B  $\sim$  C, there exist invertible n  $\times$  n matrices P and Q such that

$$\mathbf{B} = \mathbf{P}^{-1}\mathbf{A}\mathbf{P} \quad \text{and} \quad \mathbf{C} = \mathbf{Q}^{-1}\mathbf{B}\mathbf{Q}.$$

Thus

$$C = Q^{-1}BQ = Q^{-1}(P^{-1}AP)Q = (Q^{-1}P^{-1})A(PQ) = (PQ)^{-1}A(PQ),$$

where PQ is invertible, and hence A  $\sim$  C.

## Definition

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### Lemma (Properties of trace)

For  $n \times n$  matrices A and B, and any  $k \in \mathbb{R}$ ,

1. 
$$tr(A + B) = tr(A) + tr(B);$$

2. 
$$tr(kA) = k \cdot tr(A);$$

3. tr(AB) = tr(BA).

The proofs of (1) and (2) are trivial. As for (3),  $\dots$ 

Recall that for any  $n \times n$  matrix A, the characteristic polynomial of A is

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and is a polynomial of degree n.

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### Theorem (Properties of Similar Matrices)

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

- 1. det(A) = det(B);
- 2. rank (A) = rank (B);
- 3. tr(A) = tr(B);
- ${\rm 4.} \ c_{\rm A}(x) = c_{\rm B}(x);$
- 5. A and B have the same eigenvalues.

Since  $A \sim B$ , there exists an  $n \times n$  invertible matrix P so that  $B = P^{-1}AP$ .

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1.  $det(B) = det(P^{-1}AP) = det(P^{-1}) \cdot det(A) \cdot det(P).$ Since P is invertible,  $det(P^{-1}) = \frac{1}{det(P)}$ , so

$$det(B) = \frac{1}{det(P)} \cdot det(A) \cdot det(P) = \frac{1}{det(P)} \cdot det(P) \cdot det(A) = det(A).$$

Therefore, det(B) = det(A).

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Therefore, det(B) = det(A).

2. rank (B) = rank (P<sup>-1</sup>AP).
Since P is invertible, rank (P<sup>-1</sup>AP) = rank (P<sup>-1</sup>A), since P<sup>-1</sup> is invertible, rank (P<sup>-1</sup>A) = rank (A).
Therefore, rank (B) = rank (A).

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$$\det(\mathbf{B}) = \frac{\mathbf{1}}{\det(\mathbf{P})} \cdot \det(\mathbf{A}) \cdot \det(\mathbf{P}) = \frac{\mathbf{1}}{\det(\mathbf{P})} \cdot \det(\mathbf{P}) \cdot \det(\mathbf{A}) = \det(\mathbf{A}).$$

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Therefore, rank (B) = rank (A).

3. 
$$tr(B) = tr[(P^{-1}A)P] = tr[P(P^{-1}A)] = tr[(PP^{-1})A] = tr(IA) = tr(A).$$

# Proof. (continued) 4.

Since P is invertible,  $det(P^{-1}) = \frac{1}{det(P)}$ , so

$$c_B(x) = \frac{1}{\det(P)} \cdot \det(P) \cdot \det(xI - A) = \det(xI - A) = c_A(x).$$

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$$c_B(x) = \frac{1}{\det(P)} \cdot \det(P) \cdot \det(xI - A) = \det(xI - A) = c_A(x).$$

5. Since the eigenvalues of a matrix are the roots of the characteristic polynomial,  $c_B(x) = c_A(x)$  implies that A and B have the same eigenvalues.

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Recall that if  $\lambda$  is an eigenvalue of A, then  $A\vec{x} = \lambda \vec{x}$  for some nonzero vector  $\vec{x}$  in  $\mathbb{R}^n$ . Such a vector  $\vec{x}$  is called a  $\lambda$ -eigenvector of A or an eigenvector of A corresponding to  $\lambda$ .

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### Definition (Diagonalizable – rephrased)

An n  $\times$  n matrix A is diagonalizable if A  $\sim$  D for some diagonal matrix D.

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### Remark (Diagonalizability)

Determining whether or not a square matrix A is diagonalizable is done by checking whether

the number of linearly independent eigenvectors – geometric multiplicity ||?

> the multiplicity of each eigenvalue – algebraic multiplicity

#### Example

Let  $A = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}$ . Then  $\lambda = -1$  is an eigenvalue of A, and  $\vec{x} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$  is a (-1)-eigenvector of A since

$$A\vec{x} = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} -1 \\ 0 \end{bmatrix} = (-1) \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

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#### Theorem

Suppose A is an  $n \times n$  matrix.

- 1. The eigenvalues of A are the roots of  $c_A(x)$ .
- 2. The  $\lambda$ -eigenvectors of A are all the nonzero solutions to  $(\lambda I A)\vec{x} = \vec{0}_n$ .

# $\operatorname{Problem}$

Determine all eigenvalues of  $\mathbf{A}=$ 

$$\left[\begin{array}{rrrrr} -2 & 0 & 0 & 0 \\ 3 & 6 & 0 & 0 \\ -1 & 0 & 6 & 0 \\ 4 & 2 & -1 & 1 \end{array}\right].$$

### Problem

Determine all eigenvalues of A =

$$\begin{bmatrix} -2 & 0 & 0 & 0 \\ 3 & 6 & 0 & 0 \\ -1 & 0 & 6 & 0 \\ 4 & 2 & -1 & 1 \end{bmatrix}.$$

### Solution

$$det(xI - A) = \begin{vmatrix} x + 2 & 0 & 0 & 0 \\ -3 & x - 6 & 0 & 0 \\ 1 & 0 & x - 6 & 0 \\ -4 & -2 & 1 & x - 1 \end{vmatrix} = (x + 2)(x - 6)(x - 6)(x - 1).$$

Thus, the eigenvalues of A are -2, 6, 6 and 1, precisely the elements on the main diagonal of A.

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#### Remark

In general, the eigenvalues of any triangular matrix are the entries on its main diagonal.

#### Theorem

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

- 1. A is diagonalizable if and only if  $\mathbb{R}^n$  has a basis  $\{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n\}$  of eigenvectors of A.
- 2. If  $\{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n\}$  are eigenvectors of A and form a basis of  $\mathbb{R}^n$ , then

$$\mathbf{P} = \left[ \begin{array}{ccc} \vec{x}_1 & \vec{x}_2 & \cdots & \vec{x}_n \end{array} \right]$$

is an invertible matrix such that

$$P^{-1}AP = diag(\lambda_1, \lambda_2, \dots, \lambda_n),$$

where  $\lambda_i$  is the eigenvalue of A corresponding to  $\vec{x}_i$ .

This result was covered earlier, but without the use of term basis.

### Theorem

Let A be an  $n \times n$  matrix, and suppose that A has distinct eigenvalues  $\lambda_1, \lambda_2, \ldots, \lambda_k$ . For each i, let  $\vec{x}_i$  be a  $\lambda_i$ -eigenvector of A. Then  $\{\vec{x}_1, \vec{x}_2, \ldots, \vec{x}_k\}$  is linearly independent.

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#### Proof.

We need to show that  $t_1\vec{x}_1 + t_2\vec{x}_2 + \cdots + t_k\vec{x}_k = \vec{0}$  only has trivial solution  $t_1 = \cdots = t_k = 0$ . Notice that

$$\begin{aligned} t_1 A \vec{x}_1 + t_2 A \vec{x}_2 + \cdots + t_k A \vec{x}_k &= t_1 \lambda_1 \vec{x}_1 + t_2 \lambda_2 \vec{x}_2 + \cdots + t_k \lambda_k \vec{x}_k = \vec{0} \\ t_1 A^2 \vec{x}_1 + t_2 A^2 \vec{x}_2 + \cdots + t_k A^2 \vec{x}_k &= t_1 \lambda_1^2 \vec{x}_1 + t_2 \lambda_2^2 \vec{x}_2 + \cdots + t_k \lambda_k^2 \vec{x}_k = \vec{0} \\ &: &: \end{aligned}$$

 $t_1A^{k-1}\vec{x}_1+\cdots\cdots+t_kA^{k-1}\vec{x}_k=t_1\lambda_1^{k-1}\vec{x}_1+\cdots\cdots+t_k\lambda_k^{k-1}\vec{x}_k=\vec{0}$ 

$$\begin{pmatrix} \vec{x}_1 & \vec{x}_2 & \cdots & \vec{x}_k \end{pmatrix} \begin{pmatrix} t_1 & 0 & 0 & 0 \\ 0 & t_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & t_k \end{pmatrix} \begin{pmatrix} \lambda_1^0 & \lambda_1^1 & \cdots & \lambda_1^{k-1} \\ \lambda_2^0 & \lambda_2^1 & \cdots & \lambda_2^{k-1} \\ \vdots & \vdots & \vdots & \vdots \\ \lambda_k^0 & \lambda_k^1 & \cdots & \lambda_k^{k-1} \end{pmatrix} = O_{k \times k}.$$

Since  $\lambda_i$  are distinct, the Vandermonde matrix is invertible, hence,

Only trivial solution is found. Hence,  $\{\vec{x}_1,\vec{x}_2,\ldots,\vec{x}_k\}$  is independent.

### Proof. ( Another proof left for you to study )

The proof is by induction on k, the number of distinct eigenvalues. Basis. If k = 1, then  $\{\vec{x}_1\}$  is an independent set because  $\vec{x}_1 \neq \vec{0}_n$ . Suppose that for some  $k \ge 1$ ,  $\{\vec{x}_1, \vec{x}_2, \ldots, \vec{x}_k\}$  is independent, where  $\vec{x}_i$  is an eigenvector of A corresponding to  $\lambda_i$ ,  $1 \le i \le k$ , and  $\lambda_1, \lambda_2, \ldots, \lambda_k$  are distinct. (This is the Inductive Hypothesis.) Now suppose  $\lambda_1, \lambda_2, \ldots, \lambda_{k+1}$  are distinct eigenvalues of A that have corresponding eigenvectors  $\vec{x}_1, \vec{x}_2, \ldots, \vec{x}_{k+1}$ , respectively. Consider

$$t_1 \vec{x}_1 + t_2 \vec{x}_2 + \dots + t_{k+1} \vec{x}_{k+1} = \vec{0}_n, \text{ for } t_1, t_2, \dots, t_{k+1} \in \mathbb{R}.$$
 (1)

Multiplying equation (1) by A (on the left) gives us

## Proof. (continued)

$$t_{1}A\vec{x}_{1} + t_{2}A\vec{x}_{2} + \dots + t_{k+1}A\vec{x}_{k+1} = \vec{0}_{n},$$

$$\downarrow$$

$$t_{1}\lambda_{1}\vec{x}_{1} + t_{2}\lambda_{2}\vec{x}_{2} + \dots + t_{k+1}\lambda_{k+1}\vec{x}_{k+1} = \vec{0}_{n}.$$
(2)

Also, multiplying (1) by  $\lambda_{k+1}$  gives us

$$t_1 \lambda_{k+1} \vec{x}_1 + t_2 \lambda_{k+1} \vec{x}_2 + \dots + t_{k+1} \lambda_{k+1} \vec{x}_{k+1} = \vec{0}_n,$$
(3)

and subtracting (3) from (2) results in

$$t_1(\lambda_1-\lambda_{k+1})\vec{x}_1+t_2(\lambda_2-\lambda_{k+1})\vec{x}_2+\cdots+t_k(\lambda_k-\lambda_{k+1})\vec{x}_k=\vec{0}_n.$$

### Proof. (continued)

By the inductive hypothesis,  $\{\vec{x}_1,\vec{x}_2,\ldots,\vec{x}_k\}$  is independent, so

$$t_i(\lambda_i - \lambda_{k+1}) = 0$$
 for  $i = 1, 2, ... k$ .

Since  $\lambda_1, \lambda_2, \ldots, \lambda_k$  are distinct,  $(\lambda_i - \lambda_{k+1}) \neq 0$  for  $i = 1, 2, \ldots, k$ , and thus  $t_i = 0$  for  $i = 1, 2, \ldots, k$ . Substituting these values into (1) yields

$$t_{k+1}\vec{x}_{k+1}=\vec{0}_n$$

implying that  $t_{k+1} = 0$ , since  $\vec{x}_{k+1} \neq \vec{0}_n$ . Therefore,  $\{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_{k+1}\}$  is an independent set, and the result follows by induction. The next result is an easy consequence of the previous Theorem.

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Theorem (Covered earlier, but now with a proof) If A is an  $n \times n$  matrix with n distinct eigenvalues, then A is diagonalizable.

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

## Proof.

Let  $\{\lambda_1, \lambda_2, \ldots, \lambda_n\}$  denote the n (distinct) eigenvalues of A, and let  $\vec{x}_i$  be an eigenvector of A corresponding to  $\lambda_i$ ,  $1 \le i \le n$ . By the previous Theorem,  $\{\vec{x}_1, \vec{x}_2, \ldots, \vec{x}_n\}$  is an independent set. A subset of n linearly independent vectors of  $\mathbb{R}^n$  also spans  $\mathbb{R}^n$ , and thus  $\{\vec{x}_1, \vec{x}_2, \ldots, \vec{x}_n\}$  is a basis of  $\mathbb{R}^n$ . Thus A is diagonalizable.

## Problem

Is the matrix

$$\mathbf{A} = \begin{bmatrix} 0 & -1 & 1\\ 8 & 6 & -2\\ 0 & 0 & -3 \end{bmatrix}$$

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### Solution

Because A has characteristic polynomial

$$c_A(x) = (x+3)(x-2)(x-4),$$

A has distinct eigenvalues -3, 2 and 4.

Since A has three distinct eigenvalues, A is diagonalizable.

## Problem (Covered earlier, but with different wording)

Is 
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 diagonalizable? Explain.

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### Solution

First,  $c_A(x) = (x - 2)(x + 1)^2$ , so the eigenvalues of A are  $\lambda_1 = 2, \lambda_2 = -1$ , and  $\lambda_3 = -1$ . Since the eigenvalues are not distinct, it isn't immediately obvious that A is diagonalizable. The general solution to  $(-I - A)\vec{x} = \vec{0}_3$ :

$$\begin{bmatrix} -1 & -1 & -1 & 0 \\ -1 & -1 & -1 & 0 \\ -1 & -1 & -1 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

is  $x_1 = -s - t, x_2 = s$ , and  $x_3 = t$  for  $s, t \in \mathbb{R}$ , leading to basic solutions

$$\left[\begin{array}{c} -1\\1\\0\end{array}\right] \quad \text{and} \quad \left[\begin{array}{c} -1\\0\\1\end{array}\right]$$

that are linearly independent. Therefore, there is a basis of  $\mathbb{R}^3$  consisting of eigenvectors of A, so A is diagonalizable.

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#### Lemma (Technical but useful)

Let A be an  $n \times n$  matrix, with independent eigenvectors  $\{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_k\}$ . Extend  $\{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_k\}$  to a basis  $\{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_k, \dots, \vec{x}_n\}$  of  $\mathbb{R}^n$ , and let  $P = \begin{bmatrix} \vec{x}_1 & \vec{x}_2 & \cdots & \vec{x}_n \end{bmatrix}$ . If  $\lambda_1, \lambda_2, \dots, \lambda_k$  are the (not necessarily distinct) eigenvalues corresponding to  $\vec{x}_1, \vec{x}_2, \dots, \vec{x}_k$ , then

$$\mathbf{P}^{-1}\mathbf{A}\mathbf{P} = \begin{bmatrix} \operatorname{diag}(\lambda_1, \dots, \lambda_k) & \mathbf{B} \\ \mathbf{0}_{(n-k) \times k} & \mathbf{A}_1 \end{bmatrix},$$

where B is an  $k \times (n-k)$  matrix and A<sub>1</sub> is an  $(n-k) \times (n-k)$  matrix.

$$\begin{bmatrix} \vec{x}_1 & \cdots & \vec{x}_k & \vec{x}_{k+1} & \cdots & \vec{x}_n \end{bmatrix} \begin{bmatrix} \lambda_1 & & a_{1,k+1} & \cdots & a_{1,k+1} \\ & \ddots & & \vdots & \vdots & \vdots \\ & & \lambda_k & a_{k,k+1} & \cdots & a_{k,k+1} \\ & & & a_{k+1,k+1} & \cdots & a_{k+1,k+1} \\ & & & & \vdots & & \vdots \\ & & & & a_{n,k+1} & \cdots & a_{n,k+1} \end{bmatrix}$$

$$\begin{bmatrix} \vec{x}_{1} & \cdots & \vec{x}_{k} & \vec{x}_{k+1} & \cdots & \vec{x}_{n} \end{bmatrix} \begin{bmatrix} \lambda_{1} & & a_{1,k+1} & \cdots & a_{1,k+1} \\ & \ddots & \vdots & \vdots & \vdots \\ & & \lambda_{k} & a_{k,k+1} & \cdots & a_{k,k+1} \\ & & & a_{k+1,k+1} & \cdots & a_{k+1,k+1} \\ & & & \vdots & \vdots & \vdots \\ & & & a_{n,k+1} & \cdots & a_{n,k+1} \end{bmatrix}$$

$$\uparrow & \cdots & \uparrow$$

$$P^{-1}A\vec{x}_{k+1} & \cdots & P^{-1}A\vec{x}_{m}$$

 $\begin{bmatrix} A\vec{x}_1 & \cdots & A\vec{x}_k & A\vec{x}_{k+1} & \cdots & A\vec{x}_n \end{bmatrix} = \begin{bmatrix} \lambda_1 \vec{x}_1 & \cdots & \lambda_k \vec{x}_k & A\vec{x}_{k+1} & \cdots & A\vec{x}_n \end{bmatrix}$   $= \begin{bmatrix} \lambda_1 \vec{x}_1 & \cdots & \lambda_k \vec{x}_k & A\vec{x}_{k+1} & \cdots & A\vec{x}_n \end{bmatrix}$   $= \begin{bmatrix} \lambda_1 \vec{x}_1 & \cdots & \lambda_k \vec{x}_k & A\vec{x}_{k+1} & \cdots & A\vec{x}_n \end{bmatrix}$ 

$$\begin{bmatrix} \vec{x}_{1} & \cdots & \vec{x}_{k} & \vec{x}_{k+1} & \cdots & \vec{x}_{n} \end{bmatrix} \begin{bmatrix} \lambda_{1} & & a_{1,k+1} & \cdots & a_{1,k+1} \\ & \ddots & & \vdots & \vdots & \vdots \\ & & \lambda_{k} & a_{k,k+1} & \cdots & a_{k,k+1} \\ & & & a_{k+1,k+1} & \cdots & a_{k+1,k+1} \\ & & & \vdots & \vdots & \vdots \\ & & & a_{n,k+1} & \cdots & a_{n,k+1} \end{bmatrix}$$

$$\uparrow & \cdots & \uparrow$$

$$P^{-1}A\vec{x}_{k+1} & \cdots & P^{-1}A\vec{x}_{n}$$

$$\uparrow$$

$$\mathbf{AP} = \mathbf{P} \begin{bmatrix} \operatorname{diag}(\lambda_1, \dots, \lambda_k) & B \\ 0_{(n-k) \times k} & A_1 \end{bmatrix}$$

 $\begin{bmatrix} A\vec{x}_1 & \cdots & A\vec{x}_k & A\vec{x}_{k+1} & \cdots & A\vec{x}_n \end{bmatrix} = \begin{bmatrix} \lambda_1 \vec{x}_1 & \cdots & \lambda_k \vec{x}_k & A\vec{x}_{k+1} & \cdots & A\vec{x}_n \end{bmatrix}$   $= \begin{bmatrix} \lambda_1 \vec{x}_1 & \cdots & \lambda_k \vec{x}_k & A\vec{x}_{k+1} & \cdots & A\vec{x}_n \end{bmatrix}$   $= \begin{bmatrix} \lambda_1 \vec{x}_1 & \cdots & \lambda_k \vec{x}_k & A\vec{x}_{k+1} & \cdots & A\vec{x}_n \end{bmatrix}$ 

$$\begin{bmatrix} \vec{x}_{1} & \cdots & \vec{x}_{k} & \vec{x}_{k+1} & \cdots & \vec{x}_{n} \end{bmatrix} \begin{bmatrix} \lambda_{1} & & a_{1,k+1} & \cdots & a_{1,k+1} \\ & \ddots & & \vdots & \vdots & \vdots \\ & & \lambda_{k} & a_{k,k+1} & \cdots & a_{k,k+1} \\ & & & a_{k+1,k+1} & \cdots & a_{k+1,k+1} \\ & & & & \vdots & \vdots & \vdots \\ & & & a_{n,k+1} & \cdots & a_{n,k+1} \end{bmatrix}$$

$$\uparrow & & & & \uparrow \\ P^{-1}A\vec{x}_{k+1} & \cdots & P^{-1}A\vec{x}_{n}$$

#### Proof. (Another proof)

Recall that  $\{\vec{e}_1, \vec{e}_2, \dots, \vec{e}_n\}$  is the standard basis of  $R_n$ . Since  $I_n = P^{-1}P$ ,

$$\begin{bmatrix} \vec{e}_1 & \vec{e}_2 & \cdots & \vec{e}_n \end{bmatrix} = P^{-1}P = P^{-1}\begin{bmatrix} \vec{x}_1 & \vec{x}_2 & \cdots & \vec{x}_n \end{bmatrix}$$
$$= \begin{bmatrix} P^{-1}\vec{x}_1 & P^{-1}\vec{x}_2 & \cdots & P^{-1}\vec{x}_n \end{bmatrix}$$

Thus for each j,  $1 \le j \le n$ ,  $P^{-1}\vec{x}_j = \vec{e}_j$ . Also,

$$\begin{array}{rcl} P^{-1}AP &=& P^{-1}A\left[\begin{array}{ccc} \vec{x}_1 & \vec{x}_2 & \cdots & \vec{x}_n \end{array}\right] \\ &=& \left[\begin{array}{ccc} P^{-1}A\vec{x}_1 & P^{-1}A\vec{x}_2 & \cdots & P^{-1}A\vec{x}_n \end{array}\right], \end{array}$$

so the j<sup>t</sup>h column of  $P^{-1}AP$ ,  $1 \le j \le k$ , is equal to

$$P^{-1}(A\vec{x}_j) = P^{-1}(\lambda_j \vec{x}_j) = \lambda_j (P^{-1} \vec{x}_j) = \lambda_j \vec{e}_j.$$

This gives us the first k columns of  $P^{-1}AP$ , and the result follows.

Let A be an n  $\times$  n matrix and  $\lambda \in \mathbb{R}.$  The eigenspace of A corresponding to  $\lambda$  is the set

 $E_{\lambda}(A) = \{ \vec{x} \in \mathbb{R}^n \mid A\vec{x} = \lambda \vec{x} \}.$ 

Let A be an  $n \times n$  matrix and  $\lambda \in \mathbb{R}$ . The eigenspace of A corresponding to  $\lambda$  is the set

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#### Remark

1. The eigenspace  $E_{\lambda}(A)$  is indeed a subspace of  $\mathbb{R}^n$  because

$$E_{\lambda}(A) = \{ \vec{x} \in \mathbb{R}^n \mid A\vec{x} = \lambda \vec{x} \} = \{ \vec{x} \in \mathbb{R}^n \mid (\lambda I - A)\vec{x} = \vec{0}_n \} = \text{null}(\lambda I - A).$$

2. If  $\lambda$  is not an eigenvalue of A, then  $E_{\lambda}(A) = \{0\}$ .

1. If A is an  $n \times n$  matrix and  $\lambda$  is an eigenvalue of A, then the (algebraic) multiplicity of  $\lambda$  is the largest value of m for which

$$c_A(x) = (x - \lambda)^m g(x)$$

for some polynomial g(x), i.e., the multiplicity of  $\lambda$  is the number of times that  $\lambda$  occurs as a root of  $c_A(x)$ .

2. dim( $E_{\lambda}(A)$ ) is called the geometric multiplicity of  $\lambda$ .

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#### Lemma

If A is an  $n \times n$  matrix, and  $\lambda$  is an eigenvalue of A of multiplicity m, then

 $\dim(\mathrm{E}_{\lambda}(\overline{\mathrm{A}})) \leq \mathbf{m},$ 

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#### Lemma

If A is an  $n \times n$  matrix, and  $\lambda$  is an eigenvalue of A of multiplicity m, then

 $\dim(\mathrm{E}_{\lambda}(A)) \leq m,$ 

that is,

Geometric multiplicity  $\leq$  Algebraic multiplicity.

Let  $d = \dim(E_{\lambda}(A))$ , and let  $\{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_d\}$  be a basis of  $E_{\lambda}(A)$ . As a consequence, we know that there exists an invertible  $n \times n$  matrix P so that

$$P^{-1}AP = \begin{bmatrix} \operatorname{diag}(\lambda, \dots, \lambda) & B\\ 0_{(n-d)\times d} & A_1 \end{bmatrix} = \begin{bmatrix} \lambda I_d & B\\ 0_{(n-d)\times d} & A_1 \end{bmatrix}$$

where B is  $d \times (n - d)$  and  $A_1$  is  $(n - d) \times (n - d)$ .

Define  $A' = P^{-1}AP$ . Then  $A \sim A'$ , so A and A' have the same characteristic polynomial. Thus

$$\begin{split} c_A(x) &= c_{A'}(x) = \det(xI - A') &= \det \begin{bmatrix} (x - \lambda)I_d & -B \\ 0_{(n-d)\times d} & xI_{n-d} - A_1 \end{bmatrix} \\ &= \det[(x - \lambda)I_d] \det(xI_{n-d} - A_1) \\ &= (x - \lambda)^d c_{A_1}(x) \\ &= (x - \lambda)^d g(x). \end{split}$$

Since  $\lambda$  has multiplicity m, d  $\leq$  m, and therefore dim(E<sub> $\lambda$ </sub>(A))  $\leq$  m as required.

Similar Matrices

**Diagonalization Revisited** 

Algebraic and Geometric Multiplicities

Characterizing Diagonalizable Matrices

**Complex Eigenvalues** 

Eigenvalues of Real Symmetric Matrices

The crucial consequence of this Lemma is the characterization of matrices that are diagonalizable.

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## Theorem (Covered earlier, here with new terminology)

For an  $n\times n$  matrix A, the following two conditions are equivalent.

- 1. A is diagonalizable.
- 2. For each eigenvalue  $\lambda$  of A, dim(E<sub> $\lambda$ </sub>(A)) is equal to the multiplicity of  $\lambda$ , i.e.,

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Diagonalizable

 $\Rightarrow$ 

Geometric multiplicity = Algebraic multiplicity, for all  $\lambda$ .

Problem (Covered earlier, here with new terminology)

If possible, diagonalize the matrix  $A = \begin{bmatrix} 3 & 1 & 6 \\ 2 & 1 & 0 \\ -1 & 0 & -3 \end{bmatrix}$ . Otherwise,

explain why A is not diagonalizable.

Problem (Covered earlier, here with new terminology)

If possible, diagonalize the matrix  $A = \begin{bmatrix} 3 & 1 & 6 \\ 2 & 1 & 0 \\ -1 & 0 & -3 \end{bmatrix}$ . Otherwise, explain why A is not diagonalizable.

#### Solution

 $c_A(x) = (x - 3)(x + 1)^2$ , so A has eigenvalues  $\lambda_1 = 3$ ,  $\lambda_2 = \lambda_3 = -1$ . Find the dimension of  $E_{-1}(A)$  by solving the linear system  $(-I - A)\vec{x} = \vec{0}_3$ .

$$\left[ \begin{array}{ccccc} 4 & -1 & -6 & 0 \\ -2 & -2 & 0 & 0 \\ 1 & 0 & 2 & 0 \end{array} \right] \rightarrow \left[ \begin{array}{cccccc} 1 & 0 & 2 & 0 \\ 0 & 1 & -2 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right].$$

From this, we see that  $\dim(E_{-1}(A)) = 1$ . Since -1 is an eigenvalue of multiplicity two, A is not diagonalizable.

Problem (Covered earlier, here with new terminology) Let

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} \quad \text{and} \quad \mathbf{B} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

Show that A is diagonalizable, and that B is not diagonalizable.

Problem (Covered earlier, here with new terminology) Let

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Show that A is diagonalizable, and that B is not diagonalizable.

#### Solution

Both A and B are triangular matrices, so we immediately see that A and B have the same eigenvalues:  $\lambda_1 = \lambda_2 = 1$  and  $\lambda_3 = 2$ . Thus for each matrix, 1 is an eigenvalue of multiplicity two.

Solving the system  $(I - A)\vec{x} = \vec{0}_3$ :

		1					
0	0	0	$\rightarrow$	0	0	0	Ι,
		-1					

we see that there are two parameters in the general solution, so  $\dim(E_1(A)) = 2$ . Therefore, A is diagonalizable.

## Solution (continued)

Solving the system  $(I - B)\vec{x} = \vec{0}_3$ :

$$\left[ \begin{array}{ccc} 0 & -1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -1 \end{array} \right] \rightarrow \left[ \begin{array}{ccc} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{array} \right],$$

we see that the general solution has only one parameter, so  $\dim(E_1(B)) = 1$ . However, the algebraic multiplicity of  $\lambda = 1$  is 2. Therefore, B is not diagonalizable.

Similar Matrices

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If a matrix has eigenvalues that have imaginary parts (and aren't simply real numbers), we can still find eigenvectors and possibly diagonalize the matrix.

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### Problem

Diagonalize, if possible, the matrix  $A = \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}$ .

If a matrix has eigenvalues that have imaginary parts (and aren't simply real numbers), we can still find eigenvectors and possibly diagonalize the matrix.

#### Problem

Diagonalize, if possible, the matrix 
$$A = \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}$$
.

### Solution

$$c_A(x) = det(xI - A) = \begin{vmatrix} x - 1 & -1 \\ 1 & x - 1 \end{vmatrix} = x^2 - 2x + 2.$$

The roots of  $c_A(x)$  are distinct complex numbers:  $\lambda_1 = 1 + i$  and  $\lambda_2 = 1 - i$ , so A is diagonalizable. Corresponding eigenvectors are

$$ec{\mathbf{x}}_1 = \left[ egin{array}{c} -\mathrm{i} \\ 1 \end{array} 
ight] \quad ext{and} \quad ec{\mathbf{x}}_2 = \left[ egin{array}{c} \mathrm{i} \\ 1 \end{array} 
ight],$$

respectively.

# Solution (continued)

A diagonalizing matrix for A is

$$\mathbf{P} = \left[ \begin{array}{cc} -\mathbf{i} & \mathbf{i} \\ 1 & 1 \end{array} \right],$$

and

$$\mathbf{P}^{-1}\mathbf{A}\mathbf{P} = \left[\begin{array}{cc} 1+\mathbf{i} & \mathbf{0} \\ \mathbf{0} & 1-\mathbf{i} \end{array}\right].$$

## Solution (continued)

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and

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#### Remark

Notice that A is a real matrix, but has complex eigenvalues (and eigenvectors).

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# Eigenvalues of Real Symmetric Matrices

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Theorem

The eigenvalues of any real symmetric matrix are real.

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The eigenvalues of any real symmetric matrix are real.

# Proof.

Let A be an  $n \times n$  real symmetric matrix, and let  $\lambda$  be an eigenvalue of A. To prove that  $\lambda$  is real, it is enough to prove that  $\overline{\lambda} = \lambda$ , i.e.,  $\lambda$  is equal to its (complex) conjugate.

We use  $\overline{A}$  to denote the matrix obtained from A by replacing each entry by its conjugate. Since A is real,  $\overline{A} = A$ .

Suppose

$$\vec{\mathbf{x}} = \begin{bmatrix} \mathbf{z}_1 \\ \mathbf{z}_2 \\ \vdots \\ \mathbf{z}_n \end{bmatrix}$$

is a  $\lambda$ -eigenvector of A. Then  $A\vec{x} = \lambda \vec{x}$ .

#### Proof. (continued)

Let 
$$\mathbf{c} = \vec{\mathbf{x}}^{\mathrm{T}} \overline{\vec{\mathbf{x}}} = \begin{bmatrix} \mathbf{z}_1 & \mathbf{z}_2 & \cdots & \mathbf{z}_n \end{bmatrix} \begin{bmatrix} \overline{\mathbf{z}}_1 \\ \overline{\mathbf{z}}_2 \\ \vdots \\ \overline{\mathbf{z}}_n \end{bmatrix}$$
.

Then  $c = z_1\overline{z}_1 + z_2\overline{z}_2 + \cdots + z_n\overline{z}_n = |z_1|^2 + |z_2|^2 + \cdots + |z_n|^2$ ; since  $\vec{x} \neq \vec{0}$ , c is a positive real number. Now

$$\begin{aligned} \lambda c &= \lambda (\vec{x}^{\mathrm{T}} \vec{\overline{x}}) = (\lambda \vec{x}^{\mathrm{T}}) \vec{\overline{x}} = (\lambda \vec{x})^{\mathrm{T}} \vec{\overline{x}} \\ &= (A \vec{x})^{\mathrm{T}} \vec{\overline{x}} = \vec{x}^{\mathrm{T}} A^{\mathrm{T}} \vec{\overline{x}} \\ &= \vec{x}^{\mathrm{T}} A \vec{\overline{x}} \quad (\text{since A is symmetric}) \\ &= \vec{x}^{\mathrm{T}} \overline{A} \vec{\overline{x}} \quad (\text{since A is real}) \\ &= \vec{x}^{\mathrm{T}} (\overline{A} \vec{\overline{x}}) = \vec{x}^{\mathrm{T}} (\overline{\lambda} \vec{\overline{x}}) = \vec{x}^{\mathrm{T}} \overline{\lambda} \vec{\overline{x}} \\ &= \overline{\lambda} (\vec{x}^{\mathrm{T}} \vec{\overline{x}}) \\ &= \overline{\lambda} c. \end{aligned}$$

Thus,  $\lambda c = \overline{\lambda}c$ . Since  $c \neq 0$ , it follows that  $\lambda = \overline{\lambda}$ , and therefore  $\lambda$  is real.