

# **Lecture 24: Similarity Transformations; Singular Value Decompositions (Sections 5.6-6.3)**

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## Similar transformations

- ▶ **Definition.** Two  $n \times n$  matrices  $A$  and  $B$  are called **similar** if  $B = M^{-1}AM$  for some invertible  $n \times n$  matrix  $M$ .
- ▶ **Example.** If  $A$  can be diagonalized,  $\Lambda$  and  $A$  are similar.
- ▶ **Property.** If  $A$  and  $B$  are similar, they have the same eigenvalues. Every eigenvector  $x$  of  $A$  corresponds to an eigenvector  $M^{-1}x$  of  $B$ .  
 $A - \lambda I$  and  $B - \lambda I$  have the same determinant.

## Triangular forms with a unitary $M$

**Theorem.** (Schur's Theorem) There is a unitary matrix  $U$  such that  $U^{-1}AU = T$  is triangular. The eigenvalues of  $A$  appear along the diagonal of this similar matrix  $T$ .

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► **Example.**  $A = \begin{bmatrix} 2 & -1 \\ 1 & 0 \end{bmatrix}$  has the eigenvalue  $\lambda = 1$  (twice).

$$U^{-1}AU = \begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ 1/\sqrt{2} & -1/\sqrt{2} \end{bmatrix} \begin{bmatrix} 2 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ 1/\sqrt{2} & -1/\sqrt{2} \end{bmatrix} = \begin{bmatrix} 1 & 2 \\ 0 & 1 \end{bmatrix} = T.$$

## Diagonalize symmetric and Hermitian matrices

**Theorem.** (Spectral Theorem) Every real symmetric  $A$  can be diagonalized by an orthogonal matrix  $Q$ . Every Hermitian matrix can be diagonalized by a unitary  $U$ :

**(real)**  $Q^{-1}AQ = \Lambda$  or  $A = Q\Lambda Q^T$

**(complex)**  $U^{-1}AU = \Lambda$  or  $A = U\Lambda U^H$

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- For  $\lambda_1 = \lambda_2 = 1$ , eigenvectors  $\mathbf{x}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$  and  $\mathbf{x}_2 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
- For  $\lambda_3 = -1$ , eigenvector  $\mathbf{x}_3 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}$ .

These are the columns of  $Q$ .



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► **Example.**

- Symmetric and Hermitian matrices are normal.
- Orthogonal and unitary matrices are also normal.

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- ▶ **Property.** A triangular  $T$  that is normal must be diagonal.  
(Why?)

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How if  $A$  cannot be diagonalized?



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If  $A$  has  $s$  independent eigenvectors, it is similar to a matrix with  $s$  blocks:

Jordan form

$$J = M^{-1}AM = \begin{bmatrix} J_1 & & \\ & \ddots & \\ & & J_s \end{bmatrix}.$$

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Each  $J_i$  has only a single eigenvalue  $\lambda_i$  and one eigenvector:

Jordan block  $J_i = \begin{bmatrix} \lambda_i & 1 & & \\ & \lambda_i & \cdot & \\ & & \cdot & 1 \\ & & & \lambda_i \end{bmatrix}.$

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## The Jordan form

► **Example.**  $T = \begin{bmatrix} 1 & 2 \\ 0 & 1 \end{bmatrix}$ ,  $A = \begin{bmatrix} 2 & -1 \\ 1 & 0 \end{bmatrix}$ , and  $B = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$  all lead to  $J = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$ .

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► **Definition.** If  $A$  is an  $n \times n$  matrix, a **generalized eigenvector** of  $A$  corresponding to the eigenvalue  $\lambda$  is a nonzero vector  $\mathbf{x}$  satisfying

$$(A - \lambda I)^p \mathbf{x} = 0$$

for some positive integer  $p$ .

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$$M^{-1}TM = \begin{bmatrix} 0 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} = J.$$

## The Jordan form

► **Example.** For  $A = \begin{bmatrix} 0 & 1 & 2 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}$  and  $B = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$ . Which of the following matrices are the Jordan forms of  $A$  and  $B$ ?

$$J_1 = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \quad J_2 = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad J_3 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

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- columns of  $U$  ( $m$  by  $m$ ) are eigenvectors of  $AA^T$
- columns of  $V$  ( $n$  by  $n$ ) are eigenvectors of  $A^TA$
- The  $r$  singular values on the diagonal of  $\Sigma$  ( $m$  by  $n$ ) are the square roots of the nonzero eigenvalues of both  $AA^T$  and  $A^TA$ .

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$$A = U\Sigma V^T = \frac{1}{\sqrt{2}} \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \sqrt{3} & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1/\sqrt{6} & -2/\sqrt{6} & 1/\sqrt{6} \\ -1/\sqrt{2} & 0 & 1/\sqrt{2} \\ 1/\sqrt{3} & 1/\sqrt{3} & 1/\sqrt{3} \end{bmatrix}.$$