

2/12/2025

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→ Linear Algebra for Data Science, AI46  
Session 5, Mans.

→ Review

→ Diagonalization

→ Eigen decomposition

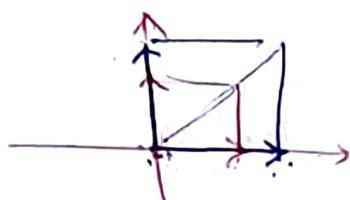
→ Singular Value Decomposition (SVD)

→ Principal Component Analysis (PCA)

→ Algebraic Multiplicity of an eigen-value ( $\lambda_i$ ): # of repeated values of an eigenvalue.

Ex:

$$A = \begin{bmatrix} 1.5 & 0 \\ 0 & 1.5 \end{bmatrix}$$



eig.:  $\det(\lambda I - A) = 0$

$$(\lambda - 1.5)(\lambda - 1.5) = 0$$

$$\Rightarrow \underline{\lambda_1 = 1.5}, \underline{\lambda_2 = 1.5}$$

matrix  $A$  has an eigenvalue 1.5 with algebraic multiplicity of 2

→ Geometric Multiplicity of an eigen vector. for  $\lambda = 1.5$  (2)

$$N(-) \rightarrow (\lambda I - A) \vec{v}_A = \vec{0}$$

Null space  $\begin{bmatrix} 1.5 & 0 \\ 0 & 1.5 \end{bmatrix} - \begin{bmatrix} 1.5 & 0 \\ 0 & 1.5 \end{bmatrix}$

$$\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_{A_1} \\ v_{A_2} \end{bmatrix} = 0$$

$v_1, v_2$  are both free variable.

ex  $v_1 = K_1$      $v_2 = K_2$

let  $K_1 = 1, K_2 = 0$   $\begin{bmatrix} K_1 \\ K_2 \end{bmatrix}$

$$\vec{v}_{A_1} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \leftarrow$$

let  $K_2 = 0, K_1 = 1$

$$\vec{v}_A = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \leftarrow$$

Geometric multiplicity of dimensionality of eigen vector space (# of eigen vectors) associated with a given  $\lambda$ .

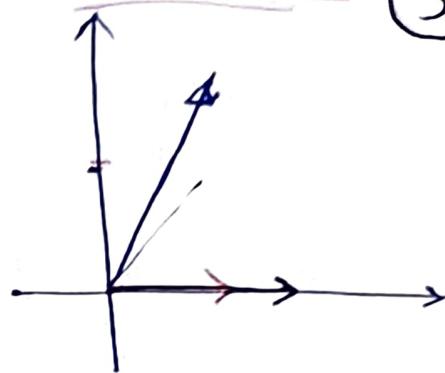
In this ex. Geometric Multiplicity = 2

# Defective Matrices

(not diagonalizable) ③

ex

$$A = \begin{bmatrix} 1.5 & 1 \\ 0 & 1.5 \end{bmatrix}$$



$$\lambda_i : \det(\lambda I - A) = 0$$

Characteristic equation  $\Rightarrow \begin{vmatrix} \lambda & \lambda - 1.5 & 1 \\ 0 & 0 & \lambda - 1.5 \end{vmatrix} = 0$

$$(\lambda - 1.5)(\lambda - 1.5) - 1 \times 0 = 0$$

$$(\lambda - 1.5)^2 = 0$$

$$\lambda_1 = 1.5, \lambda_2 = 1.5$$

$\lambda = 1.5$  with algebraic multiplicity  
~~= 2~~

## Eigenvectors

Geometric multiplicity  
= 1

$$\frac{\lambda I - A}{\lambda - 1.5}$$

$$\begin{bmatrix} 1.5 & 0 \\ 0 & 1.5 \end{bmatrix} - \begin{bmatrix} 1.5 & 1 \\ 0 & 1.5 \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_{A_1} \\ v_{A_2} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$v_{A_2} = 0$$

$v_{A_1}$  is a free variable

$$\Rightarrow \vec{v}_{A_1} = \begin{bmatrix} 1 \\ K \\ 0 \end{bmatrix}, \text{ let } K = 1$$

$$v_{A_1} = K$$

# Decomposition of A

$$A = BCD$$

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## I- Diagonalization

Review  $\underline{I}_{3 \times 3} = I_3 =$

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

diagonal

→ Identity Matrix

→ diagonal Matrix

$$D = \begin{bmatrix} d_{11} & 0 & 0 \\ 0 & d_{22} & 0 \\ 0 & 0 & d_{33} \end{bmatrix}$$

main diagonal

Scaling "scalar"

Matrix

$$= KI =$$

$$\begin{bmatrix} K & 0 & 0 \\ 0 & K & 0 \\ 0 & 0 & K \end{bmatrix}$$

main diagonal

## → Diagonalization

$$A_{n \times n} = B_{n \times n} D_{n \times n} C_{n \times n}$$

matrix

diagonal matrix

matrix

① is every square matrix diagonalizable? No.

② if so, how to find  $P, D$ ?

③ why?

$$A_{n \times n} = P_{n \times n} D_{n \times n} P^{-1}_{n \times n}$$

# eigen decomposition

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if  $A$  is diaagonalizable

$$\Rightarrow \text{square matrix} \quad A_{n \times n} = Q_{n \times n} \Delta_{n \times n} Q_{n \times n}^{-1}$$

-  $\Delta$ : matrix that has eigenvalues of  $A$  in its main diagonal

$$\Delta = \begin{bmatrix} \lambda_1 & 0 & 0 & \dots & 0 \\ 0 & \lambda_2 & & & 0 \\ \vdots & & \ddots & & \vdots \\ & & & \ddots & 0 \end{bmatrix}$$

$$Q = \begin{bmatrix} \uparrow & \uparrow & \uparrow \\ U_{A_1} & U_{A_2} & \dots & U_{A_n} \\ \downarrow & \downarrow & & \downarrow \end{bmatrix}$$

$$Q^{-1} = \text{inv}(Q)$$

$$A = Q \Delta Q^{-1} \Leftrightarrow \Delta = Q^{-1} A Q$$

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$$A = P D P^{-1} \Leftrightarrow D = P^{-1} A P$$


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given a matrix A

how to find  $A^K$  ?

$$A^K = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \cdots \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

if A is diagonalizable  $A = \underbrace{P D P^{-1}}$

$$\begin{aligned} \Rightarrow A^K &= (P D P^{-1})^K \\ &= (\cancel{P D P^{-1}}) \underset{I}{\cancel{(P D P^{-1})}} \cancel{(P D P^{-1})} \cdots \cancel{(P D P^{-1})} \\ &= P D^K P^{-1} \\ &= [P] \begin{bmatrix} d_{11} & 0 & \cdots & 0 \\ 0 & d_{22} & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & 0 & d_{nn} \end{bmatrix}^K P^{-1} \end{aligned}$$

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$$\begin{bmatrix} d_{11} & 0 & 0 & \cdots & 0 \\ 0 & d_{22} & & & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & \cdots & 0 & d_{nn} & \end{bmatrix}^K = \begin{bmatrix} d_{11}^K & 0 & 0 & \cdots & 0 \\ 0 & d_{22}^K & & & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & \cdots & 0 & d_{nn}^K & \end{bmatrix}$$


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# Dimensionality Reduction

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$\Rightarrow$  Rank Reduction (Reduced Rank Matrix)

ex

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

$$\approx \underbrace{\begin{bmatrix} \overset{\uparrow}{U_{A_1}} & \overset{\uparrow}{U_{A_2}} & \overset{\uparrow}{U_{A_3}} \\ \downarrow & \downarrow & \downarrow \\ U_{A_1} & U_{A_2} & U_{A_3} \end{bmatrix}}_Q \begin{bmatrix} 10 \\ 6 \\ 0 \end{bmatrix} \begin{bmatrix} \dots \\ \dots \\ \dots \end{bmatrix}$$

$$\hat{A} \approx \begin{bmatrix} \overset{\uparrow}{U_{A_1}} & \overset{\uparrow}{U_{A_2}} & \overset{\circ}{\dots} \\ \downarrow & \downarrow & \downarrow \\ U_{A_1} & U_{A_2} & \vdots \end{bmatrix} \begin{bmatrix} 10 & 0 & 0 \\ 0 & 6 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \dots \\ \dots \\ \dots \end{bmatrix}$$

Outer Product

vs. Inner "dot" Product

$$\vec{v}_1 \otimes \vec{v}_2$$

$$= \vec{v}_1 \vec{v}_2^T = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \begin{bmatrix} -1 \\ -2 \end{bmatrix}$$

$$\vec{v}_1 \otimes \vec{v}_2 = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \begin{bmatrix} 3 & 4 \end{bmatrix}$$

$$= \begin{bmatrix} 3 \\ -6 \end{bmatrix} \begin{bmatrix} 4 \\ 8 \end{bmatrix}$$

$$\left[ \begin{array}{c} \vec{v}_1 \\ \vdots \end{array} \right] \cdot \left[ \begin{array}{c} \vec{v}_2 \\ \vdots \end{array} \right] = \text{scalar}$$

$$\vec{v}_1^T \vec{v}_2 = \begin{bmatrix} \quad \end{bmatrix} \begin{bmatrix} \quad \end{bmatrix} = \vec{v}_1 \cdot \vec{v}_2$$

$$\vec{v}_1 = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \quad \vec{v}_2 = \begin{bmatrix} 3 \\ 4 \end{bmatrix}$$

$$\vec{v}_1 \cdot \vec{v}_2 = \begin{bmatrix} 1 & 2 \end{bmatrix} \begin{bmatrix} 3 \\ 4 \end{bmatrix} = 1 \times 3 + 2 \times 4 = 11$$

$$A = \begin{bmatrix} \uparrow \\ U_{A_1} \\ \downarrow \end{bmatrix} \quad \begin{bmatrix} \uparrow \\ U_{A_2} \\ \downarrow \end{bmatrix} \quad \begin{bmatrix} \uparrow \\ U_{A_3} \\ \downarrow \end{bmatrix} \quad \begin{bmatrix} \lambda_1 \\ 0 \\ 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ 0 \\ \lambda_3 \end{bmatrix} \quad \boxed{\begin{bmatrix} \leftarrow \vec{u}_{q_1} \rightarrow \\ \leftarrow \vec{u}_{q_2} \rightarrow \\ \leftarrow \vec{u}_{q_3} \rightarrow \end{bmatrix}}$$

$$= \lambda_1 \begin{bmatrix} \uparrow \\ U_{A_1} \\ \downarrow \end{bmatrix} \begin{bmatrix} \leftarrow \vec{u}_{q_1} \rightarrow \end{bmatrix} + \lambda_2 \begin{bmatrix} \uparrow \\ U_{A_2} \\ \downarrow \end{bmatrix} \begin{bmatrix} \leftarrow \vec{u}_{q_2} \rightarrow \end{bmatrix}$$

( A<sub>1</sub> )

$$\begin{bmatrix} \exists & \dots \\ \vdots & \ddots \end{bmatrix}$$

$$+ \cancel{\lambda_3 \begin{bmatrix} \uparrow \\ U_{A_3} \\ \downarrow \end{bmatrix} \begin{bmatrix} \uparrow \vec{u}_{q_3} \downarrow \end{bmatrix}} + \cancel{\lambda_3 \begin{bmatrix} \uparrow \\ U_A \\ \downarrow \end{bmatrix} \begin{bmatrix} \leftarrow \vec{u}_{q_1} \rightarrow \end{bmatrix}}$$

# $\Rightarrow$ Singular Value Decomposition (SVD) (9)

$$\underline{A_{m \times n}} = U \sum_{m \times m} \sum_{m \times n} V^T$$

$U$ : Orthogonal matrix

$V$ : "

Starting with  $\underbrace{(A^T A)}_{\text{square matrix}}_{n \times n}$

Square matrix

$\rightarrow$  eigen vectors  $(A^T A)$   $\rightarrow$  Right singular vectors

$\rightarrow$  eigen values  $(A^T A)$   $\rightarrow$   $\sigma(A)$  singular values

then

$$\underbrace{(A A^T)}_{\text{square matrix}}_{m \times m}$$

Square matrix

eigen vectors  $(A A^T)$   $\rightarrow$  left singular vectors

non-zero eigen values  $(A A^T)$  = non-zero eigen values  $(A^T A)$

$$\sum_{m \times n} = \begin{bmatrix} \tilde{\sigma_1} & & & \\ & \tilde{\sigma_2} & & \\ & & \tilde{\sigma_3} & \ddots \\ 0 & 0 & \dots & 0 \end{bmatrix} \text{ or } \begin{bmatrix} \tilde{\sigma_1} & & & \\ & \tilde{\sigma_2} & & \\ & & \ddots & \ddots \\ 0 & 0 & \dots & 0 \end{bmatrix}$$

$$V = \begin{bmatrix} \uparrow & \uparrow \\ \text{Right singular} & \text{vectors} \\ \downarrow & \downarrow \end{bmatrix}$$

$$U = \begin{bmatrix} \uparrow & \uparrow & \uparrow \\ \text{Left singular} & \text{vectors} \\ \downarrow & \downarrow & \downarrow \end{bmatrix}$$

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$$\text{ex } X = \begin{bmatrix} \hat{U}_1 & \hat{U}_2 \\ \downarrow & \downarrow \end{bmatrix} \quad \hat{U}_1 \perp \hat{U}_2$$

$$\hat{U}_1 \cdot \hat{U}_2 = 0$$

$$X^T = \begin{bmatrix} \leftarrow \hat{U}_1 \rightarrow \\ \leftarrow \hat{U}_2 \rightarrow \end{bmatrix}$$

$$X^T \cancel{\times} X = \begin{bmatrix} \hat{U}_1 & \hat{U}_2 \\ \downarrow & \downarrow \end{bmatrix} \begin{bmatrix} \leftarrow \hat{U}_1 \rightarrow \\ \leftarrow \hat{U}_2 \rightarrow \end{bmatrix} \begin{bmatrix} \hat{U}_1 & \hat{U}_2 \\ \downarrow & \downarrow \end{bmatrix}$$

$$= \begin{bmatrix} \hat{U}_1 \cdot \hat{U}_1 & \hat{U}_1 \cdot \hat{U}_2 \\ \hat{U}_2 \cdot \hat{U}_1 & \hat{U}_2 \cdot \hat{U}_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

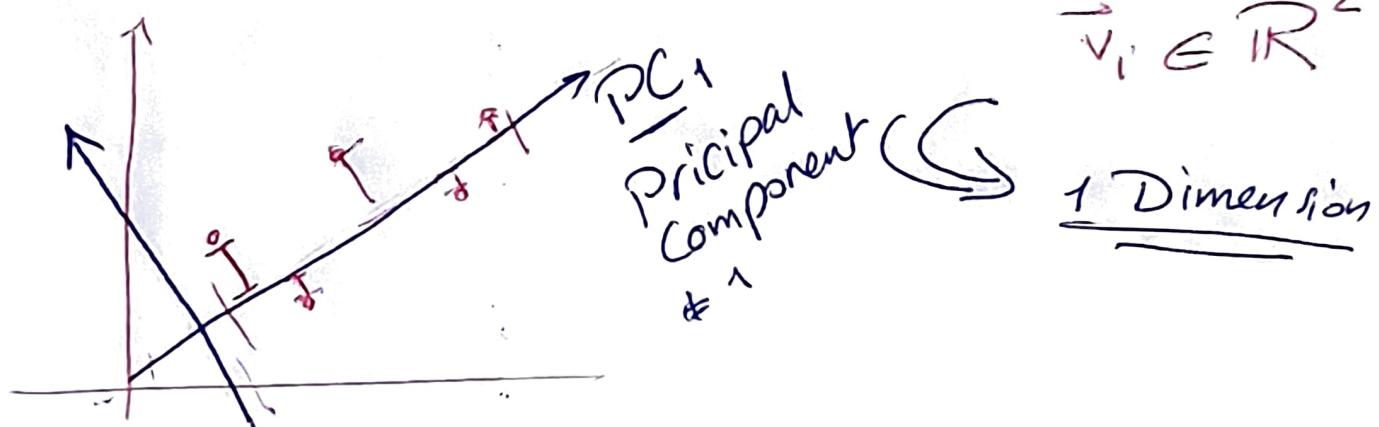
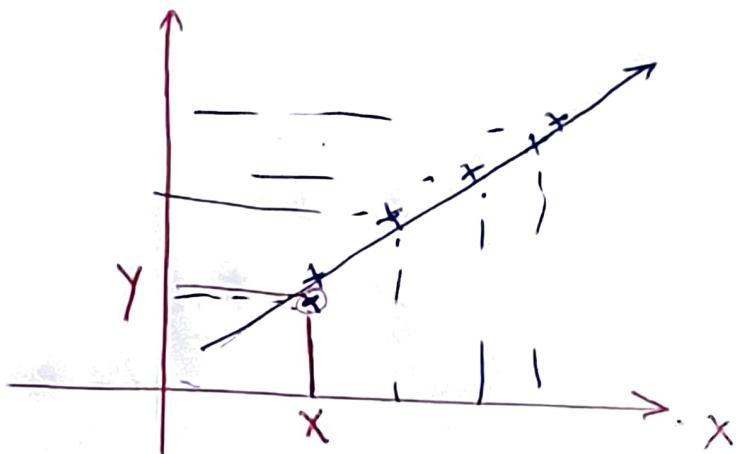
$$X^T X = I \Rightarrow X^T = X^{-1}$$

if ~~or~~  $X$  is orthogonal  
 Matrix  $\Rightarrow$  column vectors are  
 unit vectors & column vectors  
 are orthogonal to each other.  
 (Column vectors are orthonormal)

# Principal Component Analysis

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## Dimensionality Reduction



note      PCA      vs.      LS      solutions

