

Lecture 28

Thursday, December 10, 2020 4:00 PM

A ... symmetric matrix

$$A = \begin{bmatrix} y & x & ? \\ + & ' & ? \\ + & x & ! \end{bmatrix}$$

$$A = \begin{bmatrix} \times & \times \\ \times & \times \\ \times & \times \end{bmatrix}$$

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

$\neq 0$

$A = A^T$
 — real eigenvalues
 — diagonalisable
 — P can be chosen to be orthogonal.

$$A = PDP^{-1}$$

Spectral decomposition → special case of S.V.D.

$$A = \begin{bmatrix} \square \\ \square \\ \dots \\ \square \end{bmatrix} + \begin{bmatrix} \square \\ \square \\ \dots \\ \square \end{bmatrix} + \dots + \begin{bmatrix} \square \\ \square \\ \dots \\ \square \end{bmatrix}$$

↑ ↑ ↑
rank 1 rank 1 rank 1

$$\begin{bmatrix} \square \\ \square \\ \square \\ \square \end{bmatrix}$$

rank 1

$$A = \begin{bmatrix} | & | & \dots & | \\ v_1 & v_2 & \dots & v_n \\ | & | & & | \end{bmatrix}$$

If $\text{rank}(A) = 1$ then $Av = cw$

$$\text{col}(A) = \left\{ c_1 v_1 + c_2 v_2 + \dots + c_n v_n : c_1, \dots, c_n \in \mathbb{R} \right\}$$

$$A \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix}$$

→ $\text{col}(A) = \{ Av : v \in \mathbb{R}^n \}$

$$A = P D P^{-1} = P D P^T = \begin{bmatrix} \underbrace{a_{11}}_{\lambda_1} & & \\ a_{21} & a_{22} & \\ \vdots & \vdots & \vdots \\ a_{n1} & & \underbrace{a_{nn}}_{\lambda_n} \end{bmatrix} \begin{bmatrix} \lambda_1 & & \\ 0 & \ddots & \\ & & \lambda_n \end{bmatrix} \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_n^T \end{bmatrix}$$

$$= \begin{bmatrix} \lambda_1 v_1 & & \\ & \lambda_2 v_2 & \\ & & \ddots \\ & & & \lambda_n v_n \end{bmatrix} \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_n^T \end{bmatrix}$$

$$A = \lambda_1 \underbrace{v_1 v_1^T}_{\text{number}} + \lambda_2 \underbrace{v_2 v_2^T}_{\text{number}} + \dots + \lambda_n \underbrace{v_n v_n^T}_{\text{number}} \leftarrow \text{Spectral decomposition}$$

$$\underbrace{v_1}_{n \times 1} \underbrace{v_1^T}_{1 \times n} \underbrace{a}_{n \times 1} = \text{number} \times \underbrace{v_1}_{n \times 1}$$

E_n :

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \leftarrow$$

$$0, 0, 3$$

$$E(0) = \text{span} \left\{ \underbrace{\begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}}_{u_1}, \underbrace{\begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix}}_{u_2} \right\}$$

$$A = \cancel{\lambda_1 v_1 v_1^T} + \cancel{\lambda_2 v_2 v_2^T}$$

$$+ \lambda_3 v_3 v_3^T$$

$$A = 3 \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{bmatrix}$$

$$E(3) = \text{span} \left\{ \underbrace{\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}}_{u_3} \right\}$$

$$A = \begin{bmatrix} | & | & | \\ u_1 & u_2 & u_3 \\ | & | & | \end{bmatrix} \begin{bmatrix} 0 & & \\ & 0 & \\ & & 3 \end{bmatrix} \begin{bmatrix} | & | & | \\ u_1 & u_2 & u_3 \\ | & | & | \end{bmatrix}^{-1}$$

$$\begin{pmatrix} v_1 \\ u_1 \end{pmatrix}, \begin{pmatrix} v_2 \\ u_2 \end{pmatrix}, \begin{pmatrix} v_3 \\ u_3 \end{pmatrix}$$

$$v_1 = \frac{u_1}{\|u_1\|} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}$$

$$v_2 = \frac{1}{\ell} (u_2 - \text{proj}_{u_1} u_2) = \frac{1}{\ell} \left(\begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix} - \frac{1}{2} \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \right)$$

$$v_3 = \frac{u_3}{\|u_3\|} = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \frac{1}{\ell} \begin{bmatrix} -1/2 \\ 1 \\ -1/2 \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} -1/2 \\ 1 \\ -1/2 \end{bmatrix}$$

A \longrightarrow spectral decm.
 Symmetric

$$A = P D P^T$$

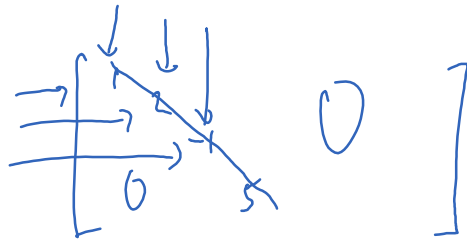
$\uparrow \quad \uparrow \quad \uparrow$

A $m \times n$ singular value decomposition.

$$A = U \Sigma V^T$$

$\underbrace{m \times m} \quad \underbrace{m \times n} \quad \underbrace{n \times n}$
 $\uparrow \quad \quad \quad \uparrow$
 orthogonal diagonal matrix orthogonal

What about U, Σ, V ?

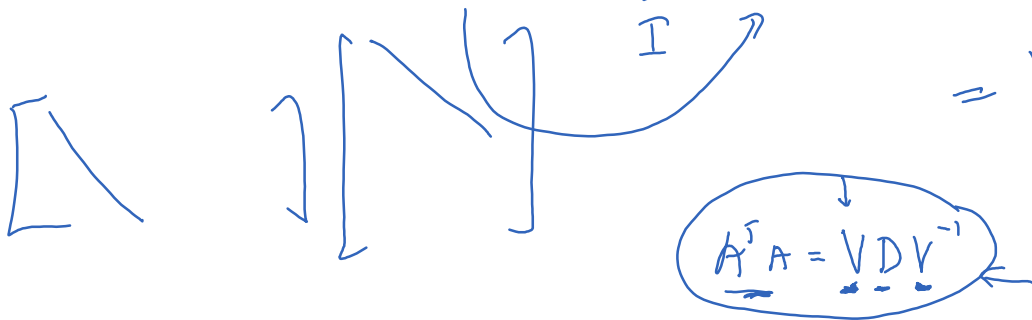


$$A = U \Sigma V^T$$

$$A^T = V \Sigma^T U^T$$

$$A^T A = V \Sigma^T \underbrace{U^T U}_I \Sigma V^T = V \Sigma^T \Sigma V^T$$

$$= V \underbrace{\Sigma^T \Sigma}_{\substack{n \times n \\ D}} V^{-1}$$



$A^T A$ \rightarrow orthogonally by

$$A^T A = V D V^T$$

$$\Sigma^T \Sigma = D$$

$$D = \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \end{bmatrix}$$

$$\Sigma = \begin{bmatrix} \sqrt{\sigma_1} & & & 0 \\ & \sqrt{\sigma_2} & & \\ & & \ddots & \\ 0 & & & \sqrt{\sigma_n} & & \\ & & & & & 0 \end{bmatrix}$$

$$A = U \Sigma V^T$$

How to get U ?

$$\begin{aligned} \underline{A}V &= U \Sigma \underbrace{V^T V}_I = U \Sigma = \begin{bmatrix} | & | & | \\ u_1 & u_2 & \dots u_m \\ | & | & | \end{bmatrix} \begin{bmatrix} \sqrt{\sigma_1} & & 0 \\ & \sqrt{\sigma_2} & \\ 0 & & \sqrt{\sigma_n} \dots \end{bmatrix} \\ &= \begin{bmatrix} | & | & \\ \sqrt{\sigma_1} u_1 & \sqrt{\sigma_2} u_2 & \dots \\ | & | & \end{bmatrix} \end{aligned}$$

$\sqrt{\sigma_1} u_1 =$ first col. of AV $\rightarrow u_1$
 u_2, \dots