

11/30 Lecture

Thursday, November 30, 2023 1:55 PM

Singular-Value Decomposition

$$A \in M_{m \times n}(\mathbb{R})$$

$$A = U \Sigma^T V^T \quad \text{where } U \text{ and } V \text{ are orthogonal matrices}$$

$$U \in M_n(\mathbb{R})$$

$$\Sigma \in M_{mn}(\mathbb{R})$$

$$V \in M_n(\mathbb{R})$$

① $m < n$

$$\boxed{A} = \boxed{U} \boxed{\begin{matrix} \Sigma \\ \delta_1 \dots \delta_m \end{matrix}} \boxed{V^T}$$

② $m > n$

$$\boxed{A} = \boxed{U} \boxed{\begin{matrix} \Sigma \\ \delta_1 \dots \delta_n \\ 0 \end{matrix}} \boxed{V^T}$$

convenient to write $AV = U\Sigma$

$$\therefore AV_i = U_i \delta_i \quad \text{for } 1 \leq i \leq r$$

$$U_i = \frac{1}{\delta_i} AV_i$$

ex1

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

① form $A^T A$

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 2 & 2 \end{bmatrix}$$

② orthogonal ly diagonalize $A^T A = Q D Q^T$

$$\lambda_1 = 3 \quad \lambda_2 = 1 \quad \lambda_3 = 0$$

$$\delta_1 = \sqrt{3} \quad \delta_2 = 1 \quad \delta_3 = 0$$

$$E_{\lambda_1} = \text{span} \left\{ \frac{1}{\sqrt{6}} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \right\} \leftarrow v_1$$

$$E_{\lambda_2} = \text{span} \left\{ \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \\ -1 \end{pmatrix} \right\} \leftarrow v_2$$

$$E_{\lambda_3} = \text{span} \left\{ \frac{1}{\sqrt{3}} \begin{pmatrix} 1 \\ -1 \\ 1 \end{pmatrix} \right\} \leftarrow v_3$$

③ images of v_i under A

$$u_1 = \frac{Av_1}{\delta_1} = \frac{\frac{1}{\sqrt{6}} \begin{pmatrix} 3 \\ 2 \\ 2 \end{pmatrix}}{\sqrt{3}}$$

$$u_2 = \frac{\frac{1}{\sqrt{2}} \begin{pmatrix} -1 \\ 1 \\ 1 \end{pmatrix}}{1}$$

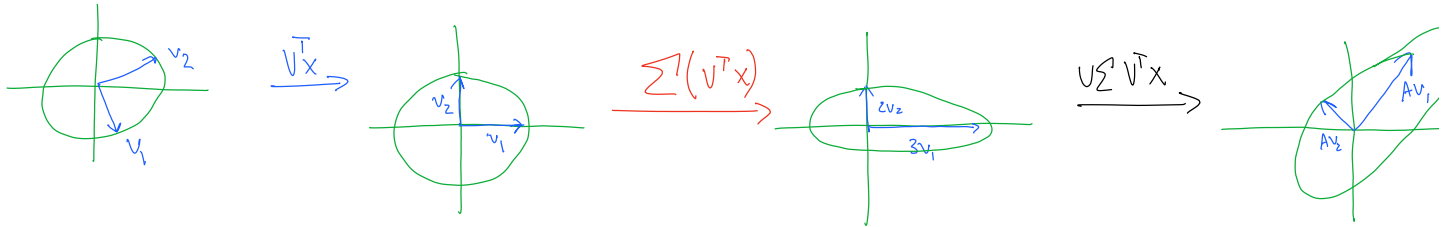
$$u_3 = NA \text{ since } \delta_3 = 0$$

$$\begin{matrix} \textcircled{4} & U \Sigma^T V^T \\ \downarrow & \downarrow \\ 2 \times 2 & 2 \times 3 \end{matrix}$$

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

ex1

$$A = \begin{pmatrix} 2 & -1 \\ 2 & 2 \end{pmatrix} \quad \text{SVD} \quad A = \begin{pmatrix} \frac{1}{\sqrt{5}} & -\frac{2}{\sqrt{5}} \\ \frac{2}{\sqrt{5}} & \frac{1}{\sqrt{5}} \end{pmatrix} \begin{pmatrix} 3 & 0 \\ 0 & 2 \end{pmatrix} \begin{pmatrix} \frac{2}{\sqrt{5}} & -\frac{1}{\sqrt{5}} \\ \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \end{pmatrix} \begin{matrix} v_1 \\ v_2 \end{matrix}$$



Prop let $\text{Rank}(A) = r$ then singular values of A

$\sigma_1, \dots, \sigma_r$ are non zero but $\sigma_{r+1}, \dots, \sigma_n$ are zero

Proof

$\{Av_1, \dots, Av_r\}$ span the $\text{Col}(A)$

The Rank of $A = \dim(\text{Col}(A)) = r$

- Relation of SVD to The 4 Fundamental Spaces

- from studio $\{Av_1, \dots, Av_r\}$ span $\text{Col}(A)$
 $\Rightarrow Av_i = \sigma_i u_i, v_i$
 $\{u_1, \dots, u_r\}$ span $\text{Col}(A)$

- $\{v_{r+1}, \dots, v_n\}$ span $\text{Null}(A)$

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

\Rightarrow Apply transpose

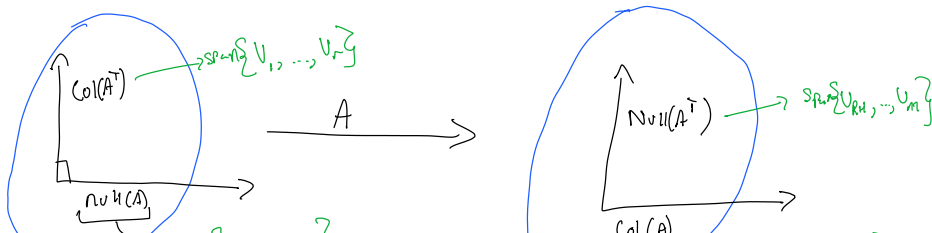
$$A^T = V^T \Sigma^T U^T \Rightarrow A^T U = V \Sigma^T$$

$$\Rightarrow A^T u_i = \sigma_i v_i$$

$$A v_i = \sigma_i u_i$$

$\{A^T u_1, \dots, A^T u_r\}$ spans $\text{Col}(A^T)$

$\{v_{r+1}, \dots, v_n\}$ spans $\text{Null}(A)$
 $\Rightarrow A^T v_i = \sigma_i v_i$
 $\Rightarrow \{v_1, \dots, v_r\}$ span $\text{Col}(A)$



$$\mathbb{R}^n \rightarrow \text{Span}\{v_1, \dots, v_n\}$$

$$\mathbb{R}^M \rightarrow \text{Span}\{u_1, \dots, u_n\}$$

$$\boxed{\begin{aligned} Av_i &= \sigma_i u_i \\ A^T u_i &= \sigma_i v_i \end{aligned} \quad 1 \leq i \leq r}$$

Best low Rank approximation

$$A = \begin{pmatrix} | & & | \\ u_1 & & u_n \\ | & & | \end{pmatrix} \begin{pmatrix} \sigma_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_r \end{pmatrix} \begin{pmatrix} -v_1^T \\ \vdots \\ -v_n^T \end{pmatrix}$$

$$\Rightarrow \sum_{i=1}^r \sigma_i \vec{u}_i \vec{v}_i^T \quad A \approx \sigma_1 u_1 v_1^T \rightarrow \text{Rank 1 appx}$$

$$A \approx \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T \rightarrow \text{Rank 2 appx}$$

$$A = \sum_{i=1}^r \sigma_i u_i v_i^T$$

Least Square Solution + SVD

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

Prop $\vec{x}^* = \frac{b \cdot u_1}{\sigma_1} v_1 + \dots + \frac{b \cdot u_r}{\sigma_r} v_r$

is a least square solution to $A\vec{x} = \vec{b}$

Proof NT $A\vec{x}^*$ is proj of \vec{b} onto $\text{Col}(A)$
 $A\vec{x}^* = \text{proj}_{\text{Col}(A)} \vec{b}$

Consider $A\vec{x}^* = A \sum_{i=1}^r \frac{b \cdot u_i}{\sigma_i} v_i$

$$\Rightarrow \sum_{i=1}^r \frac{b \cdot u_i}{\sigma_i} A v_i$$

$$\Rightarrow \sum_{i=1}^r \frac{b \cdot u_i}{\sigma_i} \sigma_i u_i$$

$$\Rightarrow \sum_{i=1}^r (b \cdot \vec{u}_i) \vec{u}_i \Rightarrow \sum_{i=1}^r \frac{b \cdot u_i}{\|u_i\|} u_i$$

$\Rightarrow \text{Proj}_{\text{Col}(A)}^v$ Since $\{v_1, \dots, v_r\}$ spans $\text{Col}(A)$

Back to diagonal matrix

$$\text{Let } D = \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix}$$

$$D^2 = \begin{pmatrix} \lambda_1^2 & & 0 \\ & \ddots & \\ 0 & & \lambda_n^2 \end{pmatrix}$$

$$D^2 + 3D + 2I_n = \begin{pmatrix} \lambda_1^2 + 3\lambda_1 + 2 & & 0 \\ & \ddots & \\ 0 & & \lambda_n^2 + 3\lambda_n + 2 \end{pmatrix}$$

$p(x)$ is a polynomial of finite degree

$$p(D) = \begin{pmatrix} p(\lambda_1) & & 0 \\ & \ddots & \\ 0 & & p(\lambda_n) \end{pmatrix}$$

$$e^x = 1 + x + \frac{x^2}{2} + \frac{x^3}{3!} + \dots + \frac{x^n}{n!}$$

$$e^D = 1 + D + \frac{D^2}{2} + \frac{D^3}{3!} + \dots + \frac{D^n}{n!}$$

$$\Rightarrow \begin{pmatrix} 1 + \lambda_1 + \frac{\lambda_1^2}{2} + \dots & & 0 \\ & \ddots & \\ 0 & & 1 + \lambda_n + \frac{\lambda_n^2}{2} + \dots \end{pmatrix}$$

$$\text{Let } A = XDX^{-1}$$

$$e^A = X e^D X^{-1}$$

$$y = y(t), \quad t \geq 0$$

$$\text{Solve IVP } \frac{dy}{dt} = ky, \quad y(0) = y_0$$

$$\text{Solution is } y = y_0 e^{kt}$$

