

Singular Value Decomposition

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Singular Value Decomposition

- Generalize diagonalization to arbitrary (non-square) matrix

$$- A^k = S D^k S^{-1}, k \geq 0$$

$$- \|A\|_{\text{Fro}} = \sqrt{\sum |\lambda_j|^2}$$

Formula

$A = U \Sigma V^*$
max unitary max unitary max diagonal

ex. $\begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} \sqrt{2} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

U Σ V^*

How to find U, Σ, V given A ?

(P1) Let $A^* A v = \lambda v$ for $v \neq 0$
 $\therefore v^* A^* A v = v^* \lambda v = \lambda v^* v$
 $\|A v\|^2 = \lambda \|v\|^2 \rightarrow \lambda = 0$

(P2) $\therefore A^* A$ & $A A^*$ = same eigen values,
 $A A^* (A v) = A (A^* A v) = A \lambda v = \lambda A v$
 $\therefore \lambda, A v = \text{eigen pair for } A A^*$

(P3) $A^* A$ & $A A^*$ = Hermitian & Unitarily Diagonalizable

$A^* A = U \Sigma_1^2 U^*, \quad A A^* = V \Sigma_2^2 V^*$
 - non-zero entries of Σ_1^2 & Σ_2^2 = same
 $\Sigma_1^2 = \begin{bmatrix} \sigma_1^2 & & 0 \\ & \ddots & \\ 0 & & \sigma_n^2 \end{bmatrix}, \quad \Sigma_2^2 = \begin{bmatrix} \sigma_1^2 & & 0 \\ & \ddots & \\ 0 & & \sigma_n^2 \end{bmatrix}$
 let $\sigma_j = \sqrt{\sigma_j^2}$ & let $\Sigma = \begin{bmatrix} \sigma_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_n \end{bmatrix}$

Singular Value Decomposition (SVD)

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

ex. let $A = \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix}$ Find SVD of A

$$A^* A = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \rightarrow \lambda_1 = 2, \lambda_2 = 2, v_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, v_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$V = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \Sigma = \begin{bmatrix} \sqrt{2} & 0 \\ 0 & \sqrt{2} \end{bmatrix}$$

$\lambda_1 = 2, v_1 = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 0 & 0 \end{bmatrix}^T$

$$V = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \Sigma = \begin{bmatrix} \sqrt{2} & 0 \\ 0 & \sqrt{3} \end{bmatrix}$$

- $E_1 \perp U$: $AA^* = \begin{bmatrix} 2 & 0 & -1 \\ 0 & 2 & -1 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow \begin{matrix} \lambda_1=2, \\ \lambda_2=3, \\ \lambda_3=0, \end{matrix} \begin{matrix} u_1 = \begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} & 0 \end{bmatrix}^T \\ u_2 = \begin{bmatrix} 1/\sqrt{3} & -1/\sqrt{3} & 1/\sqrt{3} \end{bmatrix}^T \\ u_3 = \begin{bmatrix} 1/\sqrt{6} & 1/\sqrt{6} & 2/\sqrt{6} \end{bmatrix}^T \end{matrix}$

$$\therefore U = \begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{3} & -1/\sqrt{6} \\ 1/\sqrt{2} & -1/\sqrt{3} & 1/\sqrt{6} \\ 0 & 1/\sqrt{3} & 2/\sqrt{6} \end{bmatrix} = [u_1 \ u_2 \ u_3]$$

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

1. Nullspace of A

As in the example we obtain:

$$x \in N(A) \Leftrightarrow x \perp v_1^*, \dots, v_r^* \Leftrightarrow x \perp \text{span}\{v_1^*, \dots, v_r^*\}$$

Since $\{v_1, \dots, v_n\}$ is ONB:

$$x \in N(A) \Leftrightarrow x \in \text{span}\{v_{r+1}^*, \dots, v_n^*\}$$

Example:

$$A = \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 0 & 1 \end{bmatrix} = U \begin{bmatrix} \sqrt{2} & 0 \\ 0 & \sqrt{3} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \text{ so } N(A) = \{\vec{0}\}$$

$$A^* = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \sqrt{2} & 0 & 0 \\ 0 & \sqrt{3} & 0 \end{bmatrix} \begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} & 0 \\ 1/\sqrt{3} & -1/\sqrt{3} & 1/\sqrt{3} \\ -1/\sqrt{6} & 1/\sqrt{6} & 2/\sqrt{6} \end{bmatrix}, \text{ so } N(A^*) = \text{span} \left\{ \begin{bmatrix} 1/\sqrt{6} \\ 1/\sqrt{6} \\ 2/\sqrt{6} \end{bmatrix} \right\}$$

SVD of A^*

2. Range of A

$$R(A) = \{Ax : x \in \mathbb{R}^n\} = \{U \Sigma \underbrace{V^* x}_{=y} : x \in \mathbb{R}^n\}$$

$$= \{U \Sigma y : y \in \mathbb{R}^n\}$$

$$= \left\{ [u_1 \ u_2 \ \dots \ u_m] \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_r & & \\ & & & 0 & \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} : y \in \mathbb{R}^n \right\}$$

$$= \left\{ [u_1 \ u_2 \ \dots \ u_m] \begin{bmatrix} \sigma_1 y_1 \\ \sigma_2 y_2 \\ \vdots \\ \sigma_r y_r \\ 0 \\ \vdots \\ 0 \end{bmatrix} : y \in \mathbb{R}^n \right\}$$

$$= \left\{ \sum_{j=1}^r \underbrace{\sigma_j y_j}_{\text{scalar}} \underbrace{u_j}_{\text{vector}} : y \in \mathbb{R}^n \right\}$$

$$\Rightarrow R(A) = \text{span}\{u_1, \dots, u_r\}$$