## Lec6: Singular Value Decomposition (SVD)

Singular Value Decomposition

compare with  $S=Q \wedge Q^T$ , now  $A=U \sum_{i=1}^{N} V^T$  right singular vectors.

orth 
$$\lambda_i \geqslant 0$$

$$A^{\mathsf{T}} A = \mathbf{V}^{\mathsf{T}} \wedge \mathbf{V}^{\mathsf{T}} \qquad AA^{\mathsf{T}} = \mathbf{U} \wedge \mathbf{U}^{\mathsf{T}} \qquad A = \begin{bmatrix} 3 & 4 \\ 0 & 5 \end{bmatrix} \quad \sigma_{1} \cdot \sigma_{2} = 15 = \lambda_{1} \cdot \lambda_{2}$$

$$(n \times m) \begin{bmatrix} n \times m \end{bmatrix} = (n \times n) \qquad (m \times m)$$

Looking for 
$$AV_1 = \sigma_1 U_1$$
 $(r = rank)$ .  $AV_7 = \sigma_7 U_7$ 
 $AV_{TH} = 0$ 
 $AV_{N} = 0$ 
 $AV_{N} = 0$ 

multiply by  $AV_{N} = 0$ 

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$$A \cdot \begin{bmatrix} 1 & 1 \\ v_1 & \cdots & v_r \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ w_1 & \cdots & w_r \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \sigma_1 & \cdots & \sigma_r \\ \vdots & \ddots & \vdots \\ & & \sigma_r \end{bmatrix}$$

$$AV = U\Sigma$$
  $\Rightarrow$   $A = U\Sigma V^T$   $\sigma^2$ : eigenvalues of  $A^TA$   $\Rightarrow$   $A^TA = V\Sigma^TU^TU\Sigma V^T = V(\Sigma^T\Sigma)V^T$ 

v: eigenvectors of ATA

$$\Rightarrow AA^{T} = u \Sigma V^{T} V \Sigma^{T} u^{T} = u (\Sigma \Sigma^{T}) u^{T}$$

u's are orthognal eigenvectors of ATA

$$\big(\frac{A v_1}{\sigma_1}\big)^T \big(\frac{A v_2}{\sigma_2}\big) = \frac{v_1^T A^T A v_2}{\sigma_1 \cdot \sigma_2} = \frac{v_1^T \sigma_2^2 \, v_2}{\sigma_1 \cdot \sigma_2} = \frac{\sigma_2}{\sigma_1} \, v_1^T \, v_2 = \, 0.$$

