

# Preclass 09: Singular Value Decomposition

[SCS4049] Machine Learning and Data Science

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# Singular value decomposition

Singular value decomposition (SVD) of a given matrix  $\mathbf{A}$

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T \quad (1)$$

$$= \begin{bmatrix} | & | & \cdots & | \\ \mathbf{u}_1 & \mathbf{u}_2 & \cdots & \mathbf{u}_r \\ | & | & \cdots & | \end{bmatrix} \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_k \end{bmatrix} \begin{bmatrix} \text{---} & \mathbf{v}_1^T & \text{---} \\ \text{---} & \mathbf{v}_2^T & \text{---} \\ & \vdots & \\ \text{---} & \mathbf{v}_r^T & \text{---} \end{bmatrix} \quad (2)$$

where

- $\mathbf{A} \in \mathbb{R}^{m \times n}$ ,  $\text{rank}(\mathbf{A}) = r$
- $\mathbf{U} \in \mathbb{R}^{m \times r}$ ,  $\mathbf{U}^T \mathbf{U} = \mathbf{I}$
- $\mathbf{V} \in \mathbb{R}^{n \times r}$ ,  $\mathbf{V}^T \mathbf{V} = \mathbf{I}$
- $\mathbf{\Sigma} = \text{diag}(\sigma_1, \dots, \sigma_r)$  where  $\sigma_1 \geq \dots \geq \sigma_r > 0$

# Singular value decomposition

$$\text{with } \mathbf{U} = \begin{bmatrix} | & | & \cdots & | \\ \mathbf{u}_1 & \mathbf{u}_2 & \cdots & \mathbf{u}_r \\ | & | & \cdots & | \end{bmatrix} \text{ and } \mathbf{V} = \begin{bmatrix} | & | & \cdots & | \\ \mathbf{v}_1 & \mathbf{v}_2 & \cdots & \mathbf{v}_r \\ | & | & \cdots & | \end{bmatrix},$$

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T = \sum_{k=1}^r \sigma_k \mathbf{u}_k \mathbf{v}_k^T \quad (3)$$

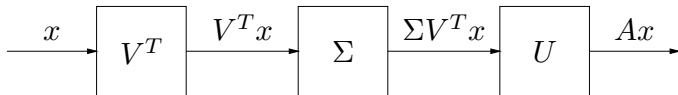
where

- $\sigma_i$  are the nonzero *singular values* of  $\mathbf{A}$
- $\mathbf{v}_i$  are the *right* or *input singular vectors* of  $\mathbf{A}$
- $\mathbf{u}_i$  are the *left* or *output singular vectors* of  $\mathbf{A}$

# Interpretations

SVD:

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T = \sum_{k=1}^r \sigma_k \mathbf{u}_k \mathbf{v}_k^T \quad (4)$$



Linear mapping  $\mathbf{y} = \mathbf{A}\mathbf{x}$  can be decomposed as

- compute coefficients of  $\mathbf{x}$  along input directions  $\mathbf{v}_1, \dots, \mathbf{v}_r$
- scale coefficients by  $\sigma_i$
- reconstitute along output directions  $\mathbf{u}_1, \dots, \mathbf{u}_r$

difference with eigenvalue decomposition for symmetric  $\mathbf{A}$ : input and output directions are *different*

# Geometric interpretation

