

Singular Value Decomposition

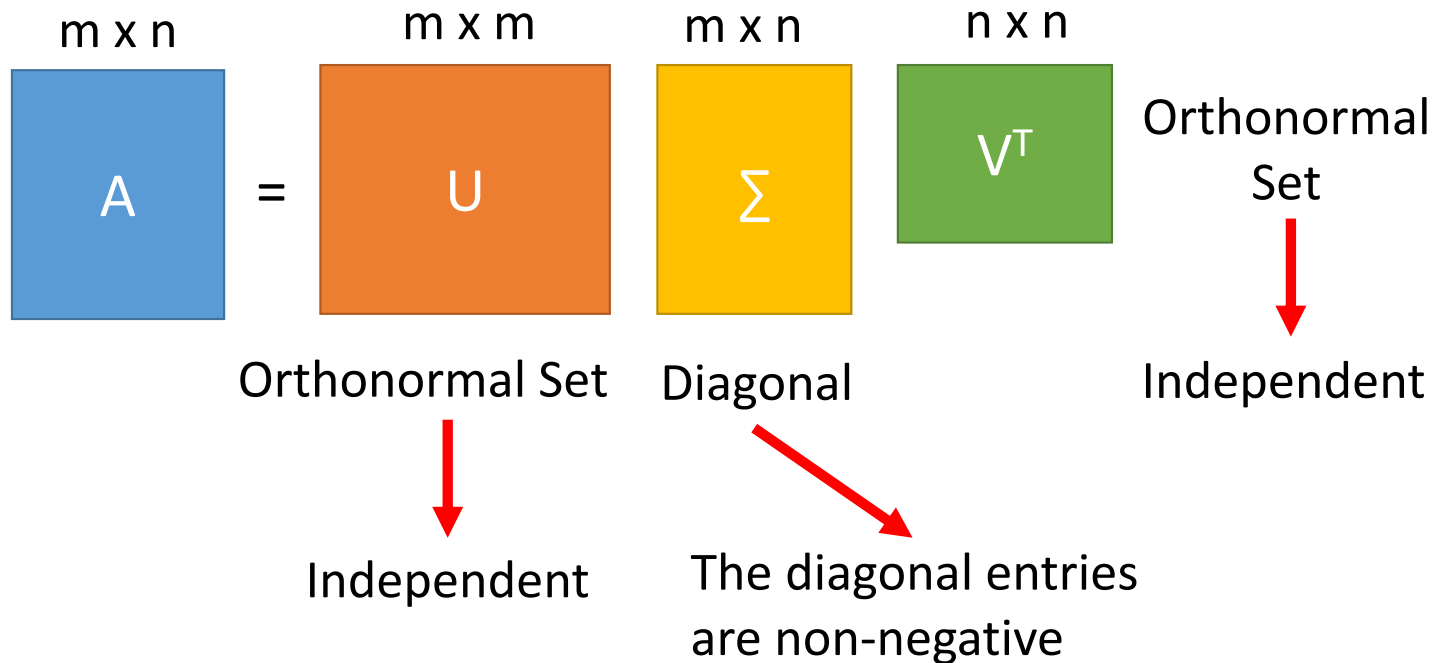
Hung-yi Lee

Outline

- Diagonalization can only apply on some square matrices.
- Singular value decomposition (SVD) can apply on any matrix.
- Reference: Chapter 7.7

SVD

- Any $m \times n$ matrix A



SVD

(We can exchange some rows and columns to achieve that)

$$\begin{bmatrix} \sigma_1 & 0 & \dots & 0 & | & 0 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 & | & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & | & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_k & | & 0 & 0 & \dots & 0 \\ \hline 0 & 0 & \dots & 0 & | & 0 & 0 & \dots & 0 \\ \vdots & \vdots & & \vdots & | & \vdots & \vdots & & \vdots \\ 0 & 0 & \dots & 0 & | & 0 & 0 & \dots & 0 \end{bmatrix}$$

- Any $m \times n$ matrix A

$$\begin{array}{ccccccc} m \times n & & m \times m & & m \times n & & n \times n \\ \boxed{A} & = & \boxed{U} & \boxed{\Sigma} & \boxed{V^T} & \text{Independent} \\ & & \text{Independent} & \text{Diagonal} & & = \text{rank}(\Sigma) \end{array}$$

What is the rank of A?

If A is a $m \times n$ matrix, and B is a $n \times k$ matrix.

$$\text{Rank}(AB) \leq \min(\text{Rank}(A), \text{Rank}(B))$$

If B is a matrix of rank n , then $\text{Rank}(AB) = \text{Rank}(A)$

If A is a matrix of rank n , then $\text{Rank}(AB) = \text{Rank}(B)$

SVD

- Any $m \times n$ matrix A

$$\begin{bmatrix} \sigma_1 & 0 & \dots & 0 & & \\ 0 & \sigma_2 & \dots & 0 & & \\ \vdots & \vdots & \ddots & \vdots & & \\ 0 & 0 & & \sigma_k & & \\ & & & & & \end{bmatrix}$$

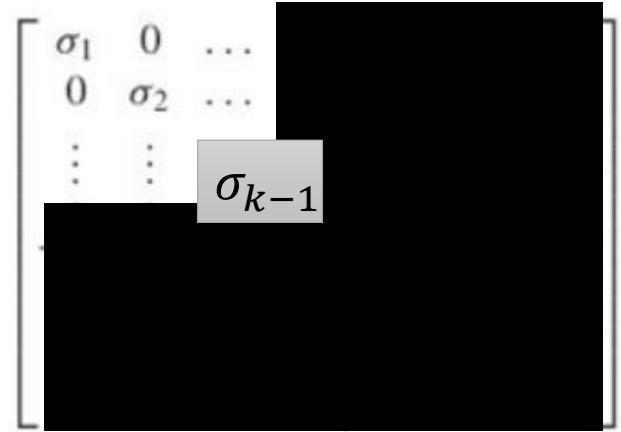
$$\begin{array}{c}
 \begin{array}{ccccc}
 m \times n & & m \times m & m \times n & n \times n \\
 \begin{array}{|c|} \hline A \\ \hline \end{array} & = & \begin{array}{|c|c|} \hline U & \\ \hline \end{array} & \begin{array}{|c|c|} \hline \Sigma & \\ \hline \end{array} & \begin{array}{|c|} \hline V^T \\ \hline \end{array} \\
 & & \text{Independent} & \text{Diagonal} & \\
 & & & k \times k & \\
 m \times n & & m \times k & k \times k & k \times n \\
 \begin{array}{|c|} \hline A \\ \hline \end{array} & = & \begin{array}{|c|} \hline U_1 \\ \hline \end{array} & \begin{array}{|c|} \hline \Sigma' \\ \hline \end{array} & \begin{array}{|c|} \hline V_1^T \\ \hline \end{array}
 \end{array}
 \end{array}$$

$[u_1, u_2] \cdot \begin{bmatrix} \Sigma' & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$
 $\swarrow \quad \searrow$
 $[u, \Sigma' \ 0]$
 $\swarrow \quad \searrow$
 $[u, \Sigma' v_1^T]$

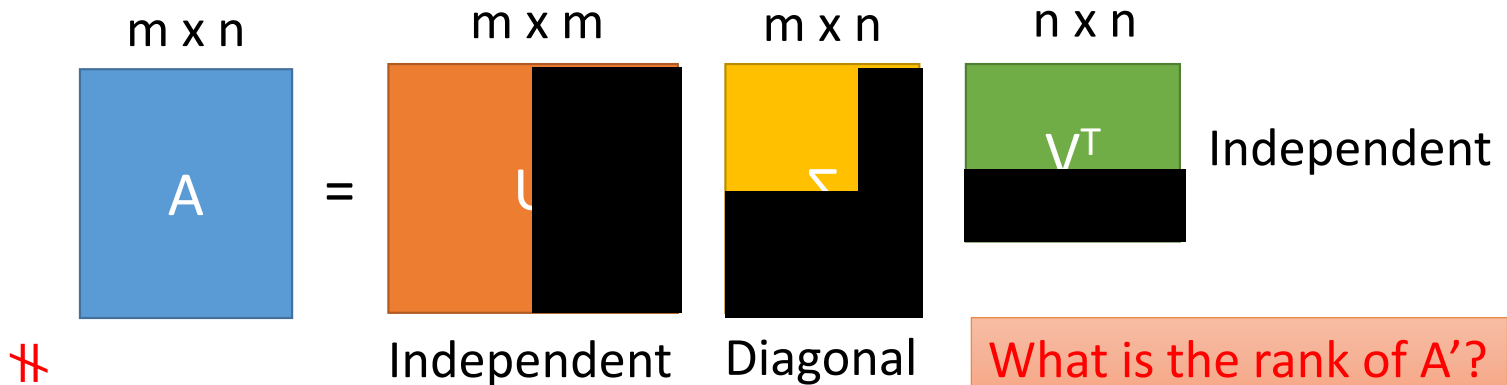
SVD

$$\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_k > 0$$

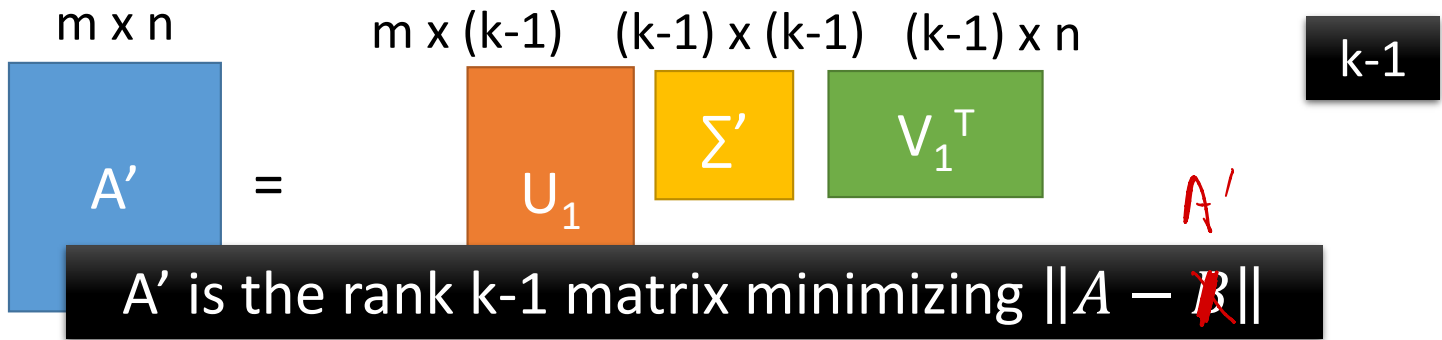
σ_k is deleted



- Any $m \times n$ matrix A

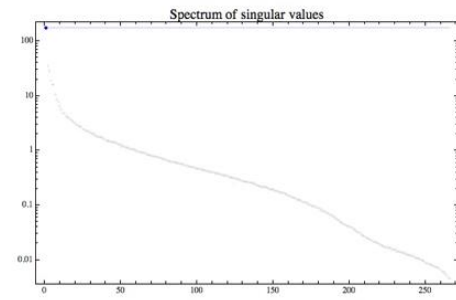
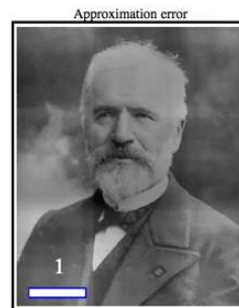
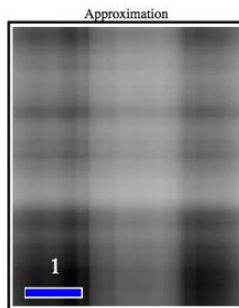
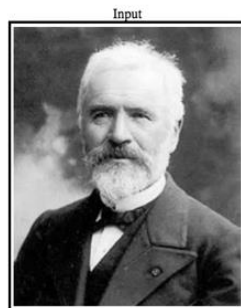


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A 是所有 rank 为 $k-1$ 的矩阵中最接近 A 的

Low rank approximation using the singular value decomposition



$k=1$

<https://www.youtube.com/watch?v=pAiVb7gWUrM>

<https://www.youtube.com/watch?v=fKVRsBFKnEw>

It Had To Be U

The Singular Value Decomposition
(SVD)

Thank You for Your Attention

<https://www.youtube.com/watch?v=R9UoFyqJca8>

