

FODA LZ1

# Principal Component Analysis (PCA) & MultiDimensional Scaling (MDS)

Nov 8, 2022

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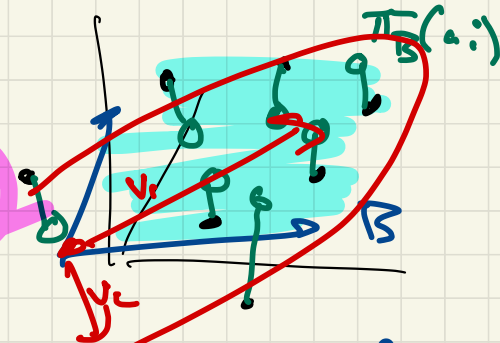
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Input  $A = \{a_1, \dots, a_n\} \subset \mathbb{R}^d$

Goal

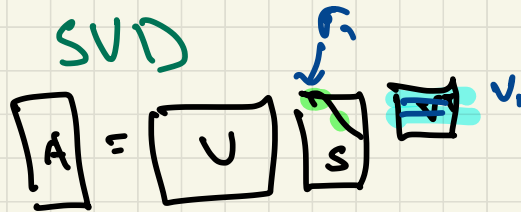
optimize  $\sum_{i=1}^n \|a_i - \pi_B(a_i)\|^2$   
 $B$  rank  $k$   
 $B$  contains  $0$



$B: V_B = \{v_1, v_2, \dots, v_k\} \subset \mathbb{R}^d$   $\|v_i\|=1$   $v_i \in \mathbb{R}^d$   
 $\langle v_j, v_i \rangle = 0$

Solve for  $V_B$  through SVD

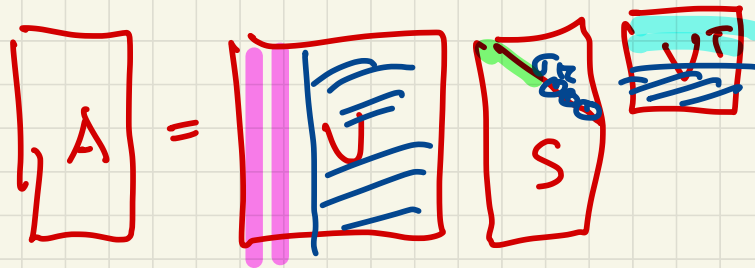
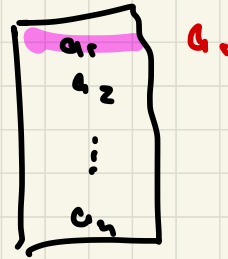
$$A = USV^T$$



how much info  $\rightarrow$   
 $u_1$   $v_1$   $\leftarrow$  orthogonal basis  
 $u_2$   $v_2$   $\leftarrow$   
 $u_3$   $v_3$   $\leftarrow$

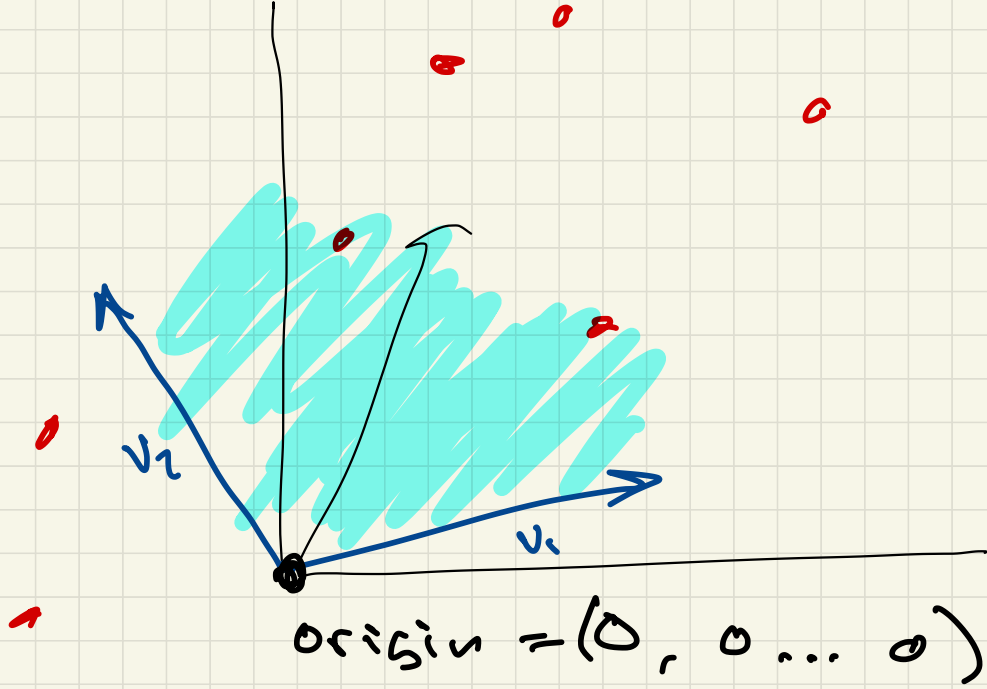
$$A = \{a_1 \dots a_n\} \in \mathbb{R}^d$$

$$A \in \mathbb{R}^{n \times d}$$

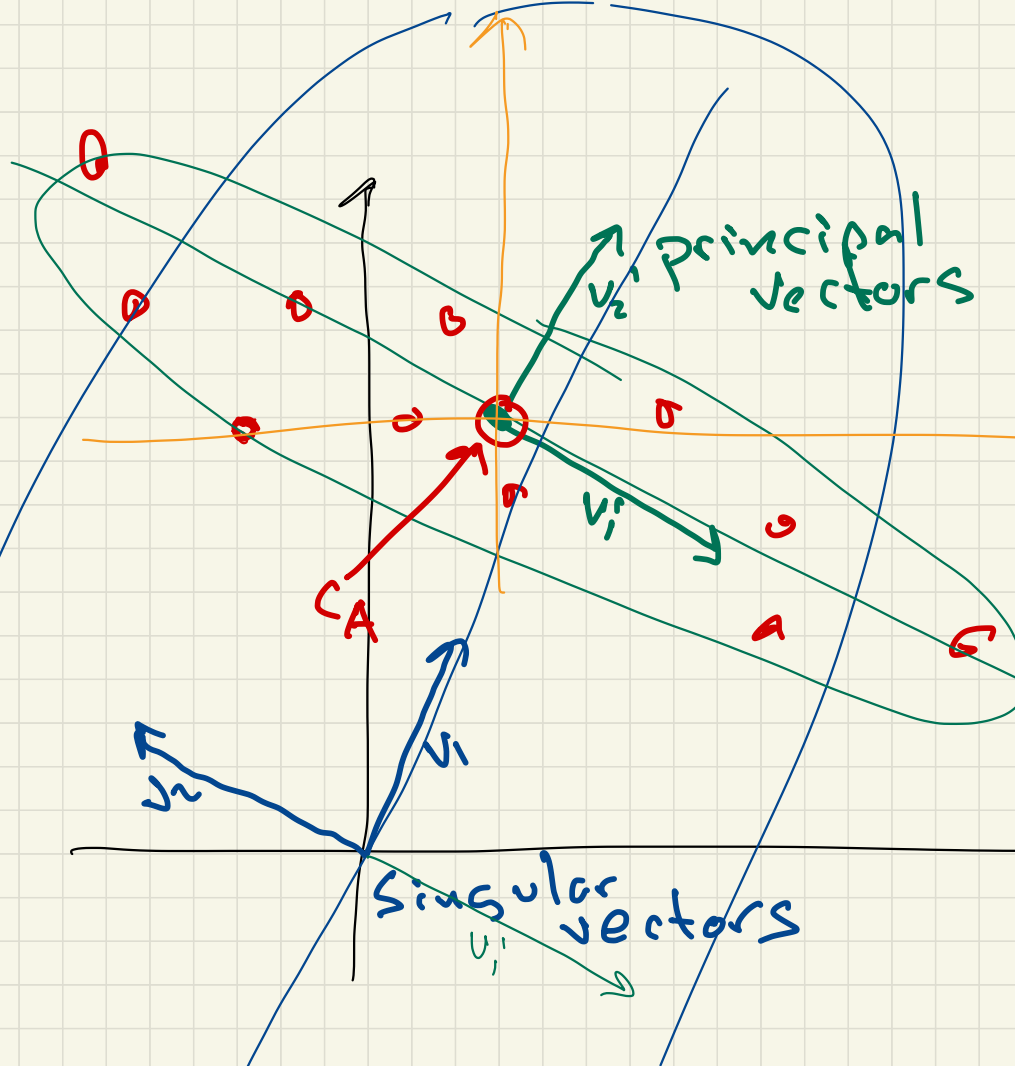


$$A_k = \sum_{j=1}^k \sigma_j u_j v_j^T \in \mathbb{R}^{n \times d}$$

$$\|A - A_k\|_{\text{F}}$$



# Principal Component Analysis (PCA)



$$c = (\bar{a}_1, \dots, \bar{a}_d)$$

$$\bar{a}_j = \frac{1}{n} \sum_{i=1}^n A_{ij}$$

average of row  $j$

Singular vectors  
 $v_1'$

principal vectors  
 $v_2'$

$CA$

$v_2$

$v_1$

$v_1'$

$v_2'$

# PCA

0. Input  $A = \{a_1, \dots, a_n\} \in \mathbb{R}^d$

1. Find center  $c_A = (\bar{a}_1, \dots, \bar{a}_d) = \frac{1}{n} \sum_{i=1}^n a_i$

2. For all  $a_i \in A$  } centering w.r.t  $c_A = 0$

$$\vec{a}_i = a_i - c_A$$

$$\vec{A} = \{\vec{a}_1, \dots, \vec{a}_n\}$$

3.  $U, S, V^T = \text{svd}(\vec{A})$

①  $a_i \rightarrow b_i \in \mathbb{R}^k$

$$b_i = (\langle v_1, a_i \rangle, \dots, \langle v_k, a_i \rangle)$$

4. Principal component:  $v_1, \dots, v_k$  ← right sing. vectors of  $\vec{A}$

also report  $c_A$

$$\textcircled{2} \vec{a}_i = c_A + \sum_{j=1}^k v_j \langle v_j, a_i \rangle \in \mathbb{R}^d$$

# Centering Matrix

$$C_n = I_n - \frac{1}{n} \mathbf{1}\mathbf{1}^T$$

$$\begin{bmatrix} 1 & & & \\ & \ddots & & \\ & & \ddots & \\ & & & 1 \end{bmatrix} \begin{matrix} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{matrix}$$

$n \times n$

$$\frac{1}{n} \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & 1 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & 1 \end{bmatrix}$$

$n \times n$

$$= \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & 1 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & 1 \end{bmatrix}$$

$n \times n$

$$\tilde{A} = C_n A = \left( I - \frac{1}{n} \mathbf{1}\mathbf{1}^T \right) A = A - \frac{1}{n} \mathbf{1}\mathbf{1}^T A$$

$$\begin{aligned} \text{PCA} &= \text{SVD}(\text{centered}(A)) \\ &= \text{SVD}(C_n A) \end{aligned}$$

# Multi Dimensional Scaling (MDS)

Input  $n = |\Omega|$  objects  $x_1, \dots, x_n$   
distance function  $d: \Omega \times \Omega \rightarrow \mathbb{R}_{\geq 0}$

Goal: Find  $a_1, \dots, a_n \in \mathbb{R}^k$   $k \ll n$   
 $d(x_i, x_j) \approx \|a_i - a_j\|$

Input distance matrix  $D \in \mathbb{R}^{n \times n}$

$$D^{(2)} = \{P_{ij}^{(2)} = d(x_i, x_j)^2\}$$

$$D_{ij} = d(x_i, x_j)$$



# classical MDS

Input  $D \in \mathbb{R}^{n \times n}$  distance matrix

1. Double centering  $M = -\frac{1}{2} C_n D^{(2)} C_n$

2. eigendecomposition

$$[L, V] = \text{eig}(M)$$

$$M = V L V^T$$

3. Return  $Q = V_{12} L_{12}^{1/2}$

sing.  
values

$$\|g_i - g_j\| \approx D_{ij}$$

$$Q = \{g_1, g_2, \dots, g_n\} \in \mathbb{R}^{12}$$

Why does cMDS work?  $A = \{a_1, \dots, a_n\}$

$D_{ij}$  think comes from  $\|a_i - a_j\|$

$a_i, a_j \in \mathbb{R}^d$

$$(a-b)^2 = a^2 + b^2 - 2ab$$

$$\|a_i - a_j\|^2 = \|a_i\|^2 + \|a_j\|^2 - 2 \langle a_i, a_j \rangle$$

$$\langle a_i, a_j \rangle = \frac{1}{2} (\|a_i\|^2 + \|a_j\|^2 - \|a_i - a_j\|^2)$$

assump  
 $a_i = 0 \in \mathbb{R}^d$   
 $\|a_i\| = \|a_i - a_i\|$   
 $\|a_i\| = D_{ii}$

$$(AA^T)_{ij} = \langle a_i, a_j \rangle$$

$$A \in \mathbb{R}^{n \times d} = U \Sigma^{1/2}$$

$$\text{eigs}(AA^T) = [L, U]$$

$\uparrow$  left sing. val. of  $X$   
 $\uparrow$  sg. sing. values  $A$