

L20: Principal Component Analysis & Multi-Dimensional Scaling

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FoDA

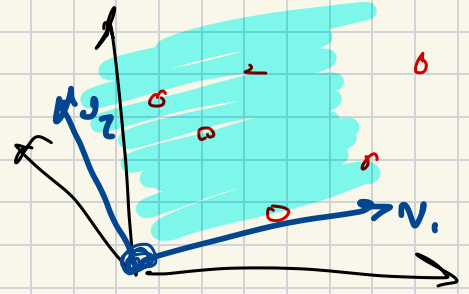
Jeff M. Phillips



Input $A = \{a_1, \dots, a_n\} \subset \mathbb{R}^d$ \iff all roads have same units & meanings

Goal

arg min $\sum_{i=1}^n \|a_i - \pi_F(a_i)\|^2$
 F rank k
 (contain 0) \iff remove constraint.



$F : V_F = \{v_1, v_2, \dots, v_k\}$

$\|v_j\| = 1$
 $\langle v_j, v_i \rangle = 0$

Solve for V_F using SVD

$A = USV^T$

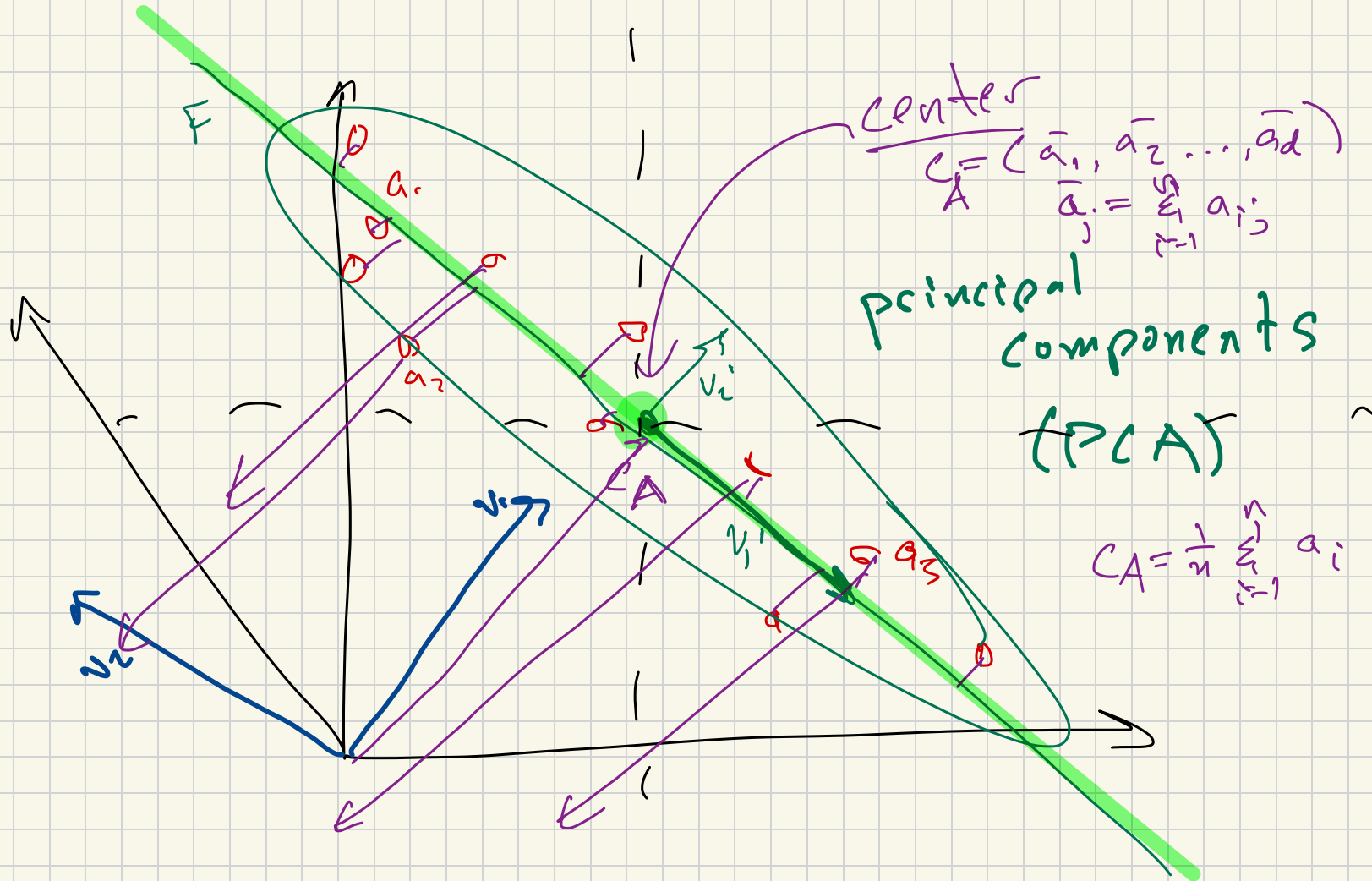
$A = U S V^T$

best rank k

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

\implies or
 Project to k -dim

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



center
 $c_A = (\bar{a}_1, \bar{a}_2, \dots, \bar{a}_d)$
 $\bar{a}_j = \frac{1}{n} \sum_{i=1}^n a_{ij}$

principal components
 (PCA)

$$c_A = \frac{1}{n} \sum_{i=1}^n a_i$$

PCA

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

1. Find center $C_A = \{\bar{a}_1, \bar{a}_2, \dots, \bar{a}_d\} = \frac{1}{n} \sum_{i=1}^n a_i$

2. For all $a_i \in A$

$$\tilde{a}_i = a_i - C_A$$

$$\hat{A} = \{\tilde{a}_1, \dots, \tilde{a}_n\}$$

centering

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

4. Principal components: v_1, v_2, \dots, v_k

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

$$b_i = (\langle a_i, v_1 \rangle, \langle a_i, v_2 \rangle, \dots, \langle a_i, v_k \rangle)$$

② $a_i \rightarrow \hat{a}_i \in \mathbb{R}^d$

$$\hat{a}_i = C_A + \sum_{j=1}^k v_j \langle v_j, a_i \rangle \in \mathbb{R}^d$$

Centering Matrix

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

$$\mathbb{1} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$$

$$I_n = \begin{bmatrix} 1 & & 0 \\ & \ddots & \\ 0 & & 1 \end{bmatrix}$$

$$\frac{1}{n} \mathbb{1} \mathbb{1}^T = \begin{bmatrix} \frac{1}{n} & \dots & \frac{1}{n} \\ \vdots & \ddots & \vdots \\ \frac{1}{n} & \dots & \frac{1}{n} \end{bmatrix}$$

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

centering

$$\tilde{A} = C_n A$$

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

MultiDimensional Scaling (MDS)

Input n objects $x_1, x_2, \dots, x_n \in \Omega$

distance function $d: \Omega \times \Omega \Rightarrow \mathbb{R}_{\geq 0}$

Goal Find $a_1, a_2, \dots, a_n \in \mathbb{R}^k$ $k \ll n$

so $d(x_i, x_j) \approx \|a_i - a_j\|$

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

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

classical MDS

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

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

2. eigen decomposition

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

$$M = V L V^T$$

3. Rotation $Q = V_k L_k^{1/2} \in \mathbb{R}^{n \times k}$

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

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

why does cMDS work

$D_{ij} \approx \|a_i - a_j\|$ for some $\{a_1, a_2, \dots, a_n\} \in \mathbb{R}^d$

$$D_{i,j}^2 \quad (a-b)^2 = a^2 + b^2 - 2ab$$

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

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

(cancel w/ confusions)

$$M_2 = (A A^T)_{i,j} = \langle a_i, a_j \rangle$$