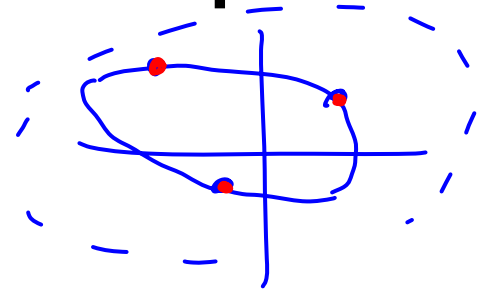


# Ex: minimum volume ellipsoid



- Given points  $x_1, x_2, \dots, x_k$

- $\min_{A, x_c} \text{vol}(A)$  s.t.

$$(\underline{x_i} - \underline{x_c})^T \underline{A} (\underline{x_i} - \underline{x_c}) \leq 1 \quad i = 1, \dots, k$$

$$\underline{A} \in \underline{S^{n \times n}}$$

$$\underline{A} \succcurlyeq 0$$

$$\min \underline{-\ln |A|} \text{ s.t. } \{\text{constraints}\}$$

$$\text{vol}(A) \propto \frac{1}{\sqrt{|A|}}$$

$$\ln \text{vol}(A) = -\frac{1}{2} \ln |A| + \text{const}$$

# Schur complement

- Symmetric block matrix  $\underline{M} = \begin{pmatrix} \underline{A} & \underline{B} \\ \underline{B}^T & \underline{C} \end{pmatrix}$
- Schur complement is  $\underline{S} =$
- $\underline{M} \succ 0$  iff  $\underline{A} \succ 0$  and  $\underline{S} \succ 0$   $\underline{S} = \underline{C} - \underline{B}^T \underline{A}^{-1} \underline{B}$

# Back to min-volume ellipsoid

$\bullet \max_{A, x_c} \log |A| \text{ s.t.}$ 
 $y_i = \begin{pmatrix} x_i \\ 1 \end{pmatrix}$

$\rightarrow \underline{(x_i - x_c)^T A (x_i - x_c) \leq 1 \quad i = 1, \dots, k}$

$\underline{A = A^T, A \succcurlyeq 0}$

$\bullet \max_{A, B, u, z} \log |A| \text{ s.t.}$ 
 $B = \begin{pmatrix} A & -u \\ -u^T & z \end{pmatrix}$ 
 $B = B^T$

$B \succcurlyeq 0$

$y_i^T B y_i \leq 1 \text{ for all } i$

$A^* \ B^* \ u^* \ z^* \text{ opt} \rightarrow \boxed{x_i^T A x_i - 2u^T x_i + z \leq 1}$

$\text{Def. } \underline{x_c^* = A^{*-1} u^*}$

$\Rightarrow x_i^T A^* x_i - 2(A^* x_c^*)^T x_i + x_c^{*T} A^* x_c^* \leq 1$ 
 $z^* - u^{*T} A^{*-1} u^* \geq 0$

$z^* \geq u^{*T} A^{*-1} u^*$

$z^* = \underline{u^{*T} A^{*-1} u^*}$

$\underline{(x_i - x_c^*)^T A^* (x_i - x_c^*) \leq 1}$

# Ex: manifold learning

- Given points  $x_1, \dots, x_m \in \mathbb{R}^n \leftarrow \text{big}$
- Find points  $y_1, \dots, y_m \in \mathbb{R}^d \leftarrow \underline{d \ll n}$
- Preserving **local geometry**
  - neighbor edges  $N \quad (i,j) \in N \Leftrightarrow \text{preserve geometry between } x_i, x_j$
  - distances  $\|x_i - x_j\| = \|y_i - y_j\| \quad (i,j) \in N$
- If we preserve distances among  $x_i, x_j, x_\ell$   
we also preserve angles  $(x_i - x_j) \cdot (x_i - x_\ell)$

$$x_i \in \mathbb{R}^n \rightarrow z_i \in \mathbb{R}^n \rightarrow y_i \in \mathbb{R}^d$$

## Step 1: “embed” $\mathbb{R}^n$ into $\mathbb{R}^n$

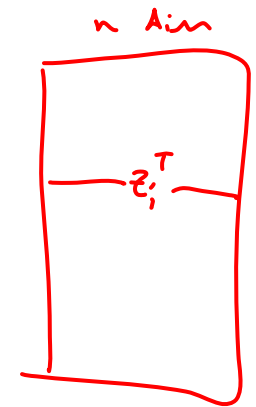
- While preserving local distances, move points to make manifold as flat as possible

$$\begin{aligned} \bullet \max \quad & \sum_{i=1}^m \sum_{j=1}^m \|z_i - z_j\|^2 = 2m \sum_i z_i^T z_i - 2 \sum_i \sum_j z_i^T z_j \\ \text{s.t.} \quad & \|z_i - z_j\| = \|x_i - x_j\| \quad \forall (i,j) \in N \\ & \sum_{i=1}^m z_i = \vec{0} \end{aligned}$$

Handwritten notes and simplifications:

- For the objective function:  $\sum_i \sum_j z_i^T z_j = \sum_i z_i^T (\sum_j z_j) = \sum_i z_i^T \vec{0} = 0$
- The objective function simplifies to:  $\sum_{i=1}^m \sum_{j=1}^m \|z_i - z_j\|^2 = 2m \sum_i z_i^T z_i$

Step 2: reduce to  $\mathbb{R}^d$   $\mathbf{z}$   
 $m \times s$



- Now that manifold is flat, just use PCA:

Define  $U, S$ ;  $S$  diagonal,  $\sum_i \mathbf{z}_i \mathbf{z}_i^T \approx \underbrace{U S U^T}$   
 $\mathbb{R}^{n \times d}$   $\mathbb{R}^{d \times d}$

Take  $\mathbf{y}_i = U^T \mathbf{z}_i = U S$

$$\mathbf{Z} \mathbf{Z}^T = \mathbf{K} = \mathbf{Q} \mathbf{\Sigma} \mathbf{Q}^T$$

$$\mathbf{Z} = \mathbf{Q} \sqrt{\mathbf{\Sigma}}$$

# Maximizing variance

- $\max \sum_i \underline{z_i^T z_i} \quad \text{s.t.} \quad \underline{\sum_i z_i = \vec{0}} \quad \underline{\|z_i - z_j\|^2 = \|x_i - x_j\|^2 \quad (i,j) \in \mathcal{N}}$

$K = \text{"kernel matrix"} \quad K_{ij} = z_i \cdot z_j \quad \underline{K = Z Z^T} \Rightarrow K \succeq 0$

$$\|z_i - z_j\|^2 = z_i \cdot z_i - 2z_i \cdot z_j + z_j \cdot z_j = \underline{K_{ii} - 2K_{ij} + K_{jj}} = \|x_i - x_j\|^2$$

$$\rightarrow \sum_{i=1}^n \sum_{j=1}^n K_{ij} = 0 \Leftrightarrow \sum_i \sum_j z_i^T z_j = 0 \quad \forall (i,j) \in \mathcal{N}$$

$$\Leftrightarrow \left( \sum_i z_i^T \right) \left( \sum_j z_j \right) = 0 \Leftrightarrow \sum_i z_i = \vec{0}$$

- $\max \text{tr}(K) \quad \text{s.t.} \quad \sum_{i,j} K_{ij} = 0 \quad K \succeq 0 \quad K = K^T$   
 $\left\{ \begin{array}{l} K_{ii} - 2K_{ij} + K_{jj} = \|x_i - x_j\|^2 \quad \forall (i,j) \in \mathcal{N} \end{array} \right.$

# Summary

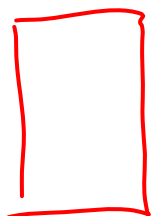
- Solve SDP to “embed”  $R^n$  into  $R^n$
- Use PCA to embed  $R^n$  into  $R^d$
- Called “semidefinite embedding” or “maximum variance unfolding”
- Problems?



# Problem: solving SDP

- Kernel matrix  $K \approx XX^T$
- Idea: suppose we know a subspace that preserves geometry

$$\tilde{K} \approx \underbrace{AA^T XX^T AA^T}_{J} \approx A \underbrace{JA^T}_{\text{smaller}} = \tilde{K}$$

$\uparrow$   $A$  (column orthogonal)  


$$\tilde{K} \succcurlyeq 0 \iff J \succcurlyeq 0$$

# Side note: non-Euclidean

$$K_{ii} - 2K_{ij} + K_{jj} = d(x_i, x_j) \text{ might not be feasible}$$

- If original distances are not Euclidean, might not be able to duplicate them exactly in Euclidean  $\mathbb{R}^n$
- Would need to soften constraints:  
**approximately** preserve local distances

$$K_{ii} - 2K_{ij} + K_{jj} \leq d(x_i, x_j) \quad \forall (i, j) \in N$$