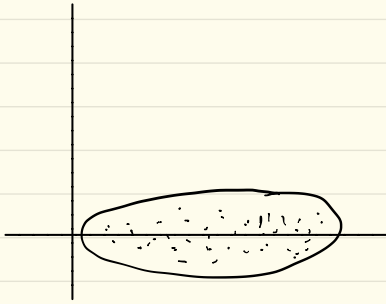



Dimensionality Reduction



$$\underline{x}_j \in \mathbb{R}^d$$

$$\downarrow$$
$$\underline{x}_j \in \mathbb{R}^k, \quad k < d$$

$$\text{Approx. error} = \|(x_1, x_2) - (x_1, 0)\|^2$$

PCA \rightarrow Principal Component Analysis

Form empirical correlation matrix $\frac{1}{n} \sum_{j=1}^n \underline{x}_j \underline{x}_j^T$

Find orthonormal eigenvectors of $\hat{R} \equiv k$ largest eigenvectors of \hat{R} .

Project data points onto space spanned by these vectors.

$$\underline{x}_1, \dots, \underline{x}_n \in \mathbb{R}^d, \quad \underline{X}_{d \times n} = [\underline{x}_1 \dots \underline{x}_n]$$

Let $V =$ k -dim subspace of \mathbb{R}^d

Let $\underline{f}_1, \underline{f}_2, \dots, \underline{f}_k =$ orthonormal basis for V

$$V = \text{span}(\underline{f}_1, \dots, \underline{f}_k)$$

$$\underline{f}_i^T \underline{f}_j = \begin{cases} 0 & i \neq j \\ 1 & i = j \end{cases}$$

$$\text{proj}_V(x_i) = \sum_{\ell=1}^k \langle x_i, f_\ell \rangle f_\ell$$

$$= \sum_{\ell=1}^k f_\ell (f_\ell^\top x_i)$$

$$F = [f_1 \dots f_k]$$

$$\downarrow d \times k$$

$$= \left(\sum_{\ell=1}^k f_\ell f_\ell^\top \right) x_i$$

$$F^\top F = I$$

$$= F F^\top x_i$$

$$\begin{array}{ccc} x_i \rightarrow & \text{proj}_V(x_i) = & \underbrace{F F^\top x_i}_{\in \mathbb{R}^d} \\ \in \mathbb{R}^d & \downarrow k\text{-dim} & \end{array}$$

$$\hat{x}_i : k\text{-dim approx to } x_i$$

Approximation Error

$$\|x_i - \hat{x}_i\|^2 = \|x_i - \text{proj}_V(x_i)\|^2$$

$$= \|x_i\|^2 - \|\text{proj}_V(x_i)\|^2$$

$$= \|x_i\|^2 - \|F F^\top x_i\|^2 \quad \left(\|a\|^2 = a^\top a = \text{Tr}(a a^\top) = \text{Tr}(a a^\top) \right)$$

$$= \|x_i\|^2 - \text{Tr}(F^\top x_i x_i^\top F)$$

Total Approx. Error

$$\begin{aligned} &= \sum_{j=1}^n \|x_j - \hat{x}_j\|^2 \\ &= \sum_{j=1}^n \|x_j\|^2 - \sum_{j=1}^n \text{Tr}(F^T x_j x_j^T F) \\ &= \quad \quad \quad \text{Tr}\{F^T (\sum_{j=1}^n x_j x_j^T) F\} \end{aligned}$$

$$\text{Total error}(F) = \underbrace{(\quad)}_{\substack{\text{doesn't depend} \\ \text{on } F}} - n \text{Tr}\{F^T \hat{R} F\}$$

Best k -dim subspace

$$\begin{aligned} &= \underset{F: F^T F = I_k}{\text{argmin}} \quad \left[(\quad) - n \text{Tr}(F^T \hat{R} F) \right] \\ &= \underset{F: F^T F = I_k}{\text{argmax}} \quad \text{Tr}(F^T \hat{R} F) \end{aligned}$$

Solution \rightarrow Rayleigh-Ritz Theorem

$$F = [u_1 \dots u_k] \quad \text{where}$$

$$\hat{R} = U \Lambda U^T, \quad U = [u_1 \dots u_k \dots u_d]$$

$$\Lambda = \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_d \end{pmatrix}, \quad \lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_d \geq 0$$

Summary of PCA

Given 1) $\mathbf{X} = [\mathbf{x}_1 \quad \mathbf{x}_n]_{d \times n}$

2) $k \leq \text{rank}(\mathbf{X})$

Steps

1) Eigen decomposition of empirical correlation matrix

$$\mathbf{X} \mathbf{X}^T = \mathbf{U} \mathbf{\Lambda} \mathbf{U}^T, \quad \mathbf{U} = [\mathbf{u}_1 \dots \mathbf{u}_d], \quad \mathbf{U}^{-1} = \mathbf{U}^T$$

$$\mathbf{\Lambda} = \begin{pmatrix} \lambda_1 & 0 \\ & \ddots \\ 0 & \lambda_d \end{pmatrix} \quad \lambda_1 \geq 0 \quad (\text{rank} \geq k)$$

2) Best k -dim subspace V_k^{best}

$$\mathbf{F} = [\mathbf{u}_1 \quad \mathbf{u}_k]_{d \times k}$$

$$\boxed{\mathbf{F}^T \mathbf{F} = \mathbf{I}_k}$$

$$V_k^{\text{best}} = \text{span}(\mathbf{f}_1, \dots, \mathbf{f}_k) = \text{span}(\mathbf{u}_1, \dots, \mathbf{u}_k)$$

Finished learning phase

3) Encode/Embed test sample

$$\mathbf{x} \in \mathbb{R}^d \longrightarrow \mathbf{y} = \underbrace{\mathbf{F}^T}_{k \times d} \underbrace{\mathbf{x}}_{d \times 1} \in \mathbb{R}^k$$

$$= \begin{pmatrix} \mathbf{u}_1^T \mathbf{x} \\ \vdots \\ \mathbf{u}_k^T \mathbf{x} \end{pmatrix}$$

Reconstruction of approximation

$$\text{Proj}_{V_{\text{best}}}(x) = \hat{x} = F_V = F F^T x \in \mathbb{R}^d$$

Approx. Error

$$\|x - \tilde{x}\|^2 = \|x\|^2 - \|\hat{x}\|^2 = \|x\|^2 - \|F^T x\|^2 = \|x\|^2 - \|y\|^2$$

Total approximation error of entire training set

$$= \sum_{j=1}^n \|x_j - \hat{x}_j\|^2 = \sum_{i=k+1}^d \lambda_i$$

$$X X^T v = \lambda v \quad \begin{array}{l} \text{eigenvector of } X X^T \\ v \neq 0 \quad \lambda > 0 \end{array}$$

$$\underbrace{(X^T X)}_u \underbrace{X^T v}_u = \lambda \underbrace{(X^T v)}_u \quad \text{(kernel PCA)}$$