

Lecture October 23

Principal component analysis (PCA): Favorite dim-reduction algorithm.

Fitting a low-dimensional subspace of dim $d \ll D$ to a set of (multivariate)

points $\{x_1 \dots x_N\}$ in a high dim space \mathbb{R}^D

covariance matrix \mathbb{C}

$$x \in \mathbb{R}^n$$

$$y \in \mathbb{R}^n$$

$$\mathbb{C}[x, y] = \begin{bmatrix} \text{cov}[x, x] & \text{cov}[x, y] \\ \text{cov}[y, x] & \text{cov}[y, y] \end{bmatrix}$$

$$\text{cov}[x, y] = \frac{1}{n} \sum_{i=0}^{n-1} (x_i - \bar{x})(y_i - \bar{y})$$

$$\text{var}[x] = \frac{1}{n} \sum_{i=0}^{n-1} (x_i - \bar{x})^2$$

$$\mathbb{C}[\underline{x}, \underline{y}] = \begin{bmatrix} \text{var}[x] & \text{cov}[x, y] \\ \text{cov}[y, x] & \text{var}[y] \end{bmatrix}$$

$$\text{corr}[x, y] = \frac{\text{cov}[x, y]}{\sqrt{\text{var}[x] \text{var}[y]}}$$

correlation matrix $K[X, Y]$

$$K[X, Y] = \begin{bmatrix} 1 & \text{cor}[X, Y] \\ \text{cor}[X, Y] & 1 \end{bmatrix}$$

in general $X \in \mathbb{R}^{n \times p}$

$$X = \begin{bmatrix} x_{00} & x_{01} & \dots & x_{0p-1} \\ x_{10} & & & \\ \vdots & & & \\ x_{n-10} & \dots & x_{n-1p-1} \end{bmatrix}$$

$$X = [x_0 \ x_1 \ x_2 \ \dots \ x_{p-1}]$$

Note : many texts define
 $X \in \mathbb{R}^{p \times n}$

$$C[X] = \begin{bmatrix} \text{var}[x_0] & \text{cov}[x_0, x_1] & \dots & \text{cov}[x_0, x_p] \\ \text{cov}[x_1, x_0] & \text{var}[x_1] & & \\ & & \ddots & \\ \text{cov}[x_{p-1}, x_0] & & & \text{var}[x_p] \end{bmatrix}$$

$$C \in \mathbb{R}^{p \times p}$$

$$C[X] = \frac{1}{n} X^T X = E[\bar{X} \bar{X}^T]$$

$$\left[\begin{array}{l} X \in \mathbb{R}^{p \times n} \\ C[\bar{X}] = \frac{1}{n} X X^T \end{array} \right.$$

$$X = \begin{bmatrix} x_{00} & x_{01} \\ x_{10} & x_{11} \end{bmatrix} = \begin{bmatrix} x_0 & x_1 \end{bmatrix}$$

$$\begin{aligned} E[\bar{X} \bar{X}^T] &= \frac{1}{n} X^T X = \frac{1}{n} \begin{bmatrix} x_{00}^2 + x_{01}^2 & x_{00}x_{10} + x_{01}x_{11} \\ x_{10}x_{00} + x_{11}x_{01} & x_{10}^2 + x_{11}^2 \end{bmatrix} \\ &= \begin{bmatrix} \text{var}[x_0] & \text{cov}[\bar{x}_0, \bar{x}_1] \\ \text{cov}[\bar{x}_1, \bar{x}_0] & \text{var}[\bar{x}_1] \end{bmatrix} \\ &= C[\bar{X}] \end{aligned}$$

X = Feature matrix,

$n \gg p$: seldom to perform PCA

$n \leq p$: PCA of interest if $p > 10^2$

$p \gg n$ PCA is normally applied,

Toward - the PCA theorem

$$C[\bar{X}] = E[\bar{X}^T \bar{X}]$$

(recall @LS/Ridge
 $\text{var}[\hat{\beta}] \propto (X^T X)^{-1}$)

orthogonal transformation

$$S; \quad S^T S = S S^T = \mathbf{1} \quad S^T = S^{-1}$$

$$S = [s_0, s_1, \dots, s_{p-1}]$$

$$s_i \in \mathbb{R}^p \quad s_i^T s_j = \delta_{ij}$$

$S^T C[\bar{X}] S = C[\bar{Y}]$ has
 diagonal elements

$$[\lambda_0, \lambda_1, \dots, \lambda_{p-1}]$$

$$C[\bar{Y}] = E[(S \bar{X})^2]$$

X has been normalized by
 subtracting the mean value,

$$S^T C[\bar{X}] S = \underline{S^T E[\bar{X}^T \bar{X}] S}$$

$$S^T C[Y] S = S^T E[X^T X] S$$

$$S^T C[Y] S = \underbrace{E[X^T X]}_{\frac{1}{n} X^T X} S \in \mathbb{R}^{p \times p}$$

$C[Y]$ is diagonal, $\lambda_0 > \lambda_1 > \lambda_2 \dots \lambda_{p-1}$

$$S_i^T \lambda_i = C[X] S_i^T$$

S_i are eigenvectors of $C[X]$ and λ_i are the eigenvalues.

orthogonal transformation

$$S \in \mathbb{R}^{2 \times 2}$$

$$S = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}$$

$$S^T A S = D = [\lambda_1, \lambda_2]$$

$$S^T S = \mathbb{I}$$

$$A x = \lambda x \quad (\det(A - \lambda I) = 0)$$

$$S^T A x = \lambda S^T x$$

$$\uparrow \\ \mathbb{I} = S S^T$$

$$\boxed{S^T A S = D}$$

$$D \cdot \underbrace{S^T X} = X \underbrace{S^T X}$$

PCA Theorem

X - multivariate random variable with zero mean $X \in \mathbb{R}^D$

d - integer $d < D$

The d -principal components of $X, Y \in \mathbb{R}^D$ are defined as the d -orthogonal (uncorrelated) linear components of X

$$y_i' = S_i X \in \mathbb{R}^D$$

$$S_i \in \mathbb{R}^D$$

S_i are eigenvectors of the correlation matrix.

The variance of y_i' is maximum subject to

normalized subject to

$$S_i^T S_i = \underline{1} \quad / \quad S_i^T S_j = \delta_{ij}$$

$$\text{var}(y_1) \geq \text{var}(y_2) \geq \text{var}(y_3)$$

$$\dots \text{var}(y_d) > 0$$

$$S_1^* = \arg \max_{S_1 \in \mathbb{R}^D} \text{var}(S_1 x)$$

$$\text{subject to } S_1^T S_1 = \underline{1}$$

S_i are the orthogonal
eigenvectors of $C[x]$

$$= E[\bar{x} \bar{x}^T]$$