

# Principal Component Analysis

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$$\mathcal{D} = \{x^{(1)}, \dots, x^{(n)}\}$$

$$x^{(i)} \in \mathbb{R}^d$$

$$X \in \mathbb{R}^d \quad X \sim P$$

$$x^{(i)} \sim P \quad \text{i.i.d.}$$

$$E(X) = \mu$$

$$E(X - \mu)(X - \mu)^T = C$$

$$a^* = \arg \min_a E(\|X - a\|^2) = \mu$$

$$\tilde{X} = \gamma u \quad \begin{array}{l} u \in \mathbb{R}^d \\ \|u\| = 1 \end{array}$$

Let

$$\mu = 0 \rightarrow E(X) = 0$$

$$E(XX^T) = C$$

$$\gamma^* = \arg \min_{\gamma} \|X - \gamma u\|^2$$

$$= \arg \min_{\gamma} \|X\|^2 - 2\gamma u^T X + \gamma^2$$

$$\gamma^* = u^T X$$

$$\hat{x} = (x^T u) u$$

$$E(\|x - \hat{x}\|^2)$$

$$= E(\|x\|^2) - 2E(x^T \hat{x})$$

$$= E(\|x\|^2) - 2u^T C u + E(\|\hat{x}\|^2)$$

$$= \text{Tr}(C) - u^T C u$$

$$\min_u E(\|x - \hat{x}\|^2)$$

$$= \min_u \text{Tr}(C) - u^T C u$$

$$\Rightarrow \max_{\substack{u \\ \|u\|_2 = 1}} u^T C u$$

Use Cauchy Schwartz

$$u^T v \leq \|u\| \|v\|$$

$$v = \lambda u$$

$$Cu = \lambda u$$

$$u^T v = \lambda \|u\|^2 = \lambda, \quad v = \lambda u$$

Largest value is  $\lambda_1$ .

$$\lambda_1 > \lambda_2 > \dots > \lambda_d \geq 0$$

$$Cu_1 = \lambda_1 u_1.$$

$$u = u_1.$$

$$\hat{x} = (x^T u) u_1.$$

$$\gamma_1 = x^T u_1$$
$$\gamma = x^T v$$

$$E \|x - \gamma_1 u_1 - \gamma v\|^2$$

$$= E (\|x - \gamma_1 u_1\|^2)$$
$$+ E (\gamma^2 \|v\|^2)$$

$$- 2E (x - \gamma_1 u_1)^T (\gamma v)$$

$$= E(\|x - \gamma_1 u_1\|^2)$$

$$- 2 E \gamma_1 (x^T u)$$

$$+ 2 E(\gamma_1 \gamma) u_1^T u$$

$$+ E(\gamma^2) [E(\gamma \gamma_1) = 0]$$

$$= E(\|x - \gamma_1 u_1\|^2)$$

$$- E(\gamma^2)$$

$$\min_v E(\|x - \gamma_1 u_1 - \gamma v\|^2)$$

$$= \min_v E(\|x - \gamma_1 u_1\|^2) - E(\gamma^2)$$

$$\text{argmin}_v E(\|x - \gamma_1 u_1 - \gamma v\|^2)$$

$$= \text{argmin}_v E(\|x - \gamma_1 u_1\|^2) - E(\gamma^2)$$

$$= \text{argmax}_v E(\gamma^2) = u^T C v$$

$$E(\gamma, \gamma) = 0 \Rightarrow u_1^T C v = 0$$

$$v_2 u_2 \Rightarrow E(Y^2) = \lambda_2$$

$$Y_2 \begin{bmatrix} Y_1 \\ Y_2 \\ Y_n \end{bmatrix} = \begin{bmatrix} u_1^T X \\ u_2^T X \\ u_n^T X \end{bmatrix}$$



# Canonical Component Analysis.

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$$X \in \mathbb{R}^{d_1} \quad Y \in \mathbb{R}^{d_2}$$

$$Z = \begin{bmatrix} X \\ Y \end{bmatrix} \quad E(Z) = \begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix}$$

$$E(X) = \mu_x \quad E(Y) = \mu_y$$

$$\text{cov}(Z) = \begin{bmatrix} C_{xx} & C_{xy} \\ C_{yx} & C_{yy} \end{bmatrix}$$

$$C_{xy} = C_{yx}^T$$

$$\text{cov}(Z) = E \left( (Z - E(Z)) (Z - E(Z))^T \right)$$

$$R = U^T X \quad S = V^T Y.$$

$$E(X) = 0, \quad E(Y) = 0$$

$$\begin{aligned} \rho_{RS} &= \frac{E(RS)}{\sqrt{\text{var}(R)} \sqrt{\text{var}(S)}} \\ &= \frac{U^T E(XY^T) V}{\sqrt{V^T E(Y Y^T) V} \sqrt{U^T E(X X^T) U}} = \rho_{uv} \end{aligned}$$

$$E(Y Y^T) = C_{YY}$$

$$E(X X^T) = C_{XX}$$

$$E(X Y^T) = C_{XY}$$

$$\rho(u, v) = \frac{u^T C_{XY} v}{\sqrt{v^T C_{YY} v} \sqrt{u^T C_{XX} u}}$$

$$\max_{u, v} \rho(u, v)$$

$$\|u\| = 1$$

$$\|v\| = 1$$

$$C_{xx}^{\frac{1}{2}} u = a$$

$$C_{yy}^{\frac{1}{2}} v = b$$

$$u = C_{xx}^{-1/2} a, \quad v = C_{yy}^{-1/2} b$$

$$\rho(a, b) = \frac{a^T C_{xx}^{-1/2} C_{xy} C_{yy}^{-1/2} b}{\|a\| \|b\|}$$

$$A = C_{xx}^{-1/2} C_{xy} C_{yy}^{-1/2}$$

$$\frac{a^T A b}{\|a\| \|b\|} \leq \frac{\|a\| \|Ab\|}{\|a\| \|b\|} = \frac{\|Ab\|}{\|b\|}.$$

$$\frac{b^T A^T A b}{\|b\|^2} \text{ is maximized at}$$

$$A^T A b = \lambda b$$

$$A^T A = C_{yy}^{-1/2} C_{yx} C_{xx}^{-1} C_{xy} C_{yy}^{-1/2}$$

$$\lambda_1, \lambda_2, \dots, \lambda_{d_2}$$

$\lambda_1$  is the largest  
eigenvalue of  $A^T A$

$q_1$  be the eigenvector

$$\frac{a^T A b}{\|a\| \|b\|} \leq \frac{\|a\| \|Ab\|}{\|a\| \|b\|} = \frac{\|Ab\|}{\|b\|} = \sqrt{\lambda_1}$$


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$$A \in \mathbb{R}^{l \times m}$$

$$A = \sum_{i=1}^r \sigma_i f_i g_i^T \quad r = \min(l, m)$$

$$f_i \in \mathbb{R}^l, g_i \in \mathbb{R}^m$$

$$f_i^T f_j = \begin{cases} 0 & i \neq j \\ 1 & i = j \end{cases} \quad \left| \quad g_i^T g_j = \begin{cases} 0 & i \neq j \\ 1 & i = j \end{cases} \right.$$

$$j = 1, \dots, r$$

$$A g_i = \sigma_i f_i \quad i = 1, \dots, r$$

$$f_j^T A = \sigma_j g_j^T \quad \left| \quad A^T f_i = \sigma_i g_i \right.$$

$$A^T A g_i = \sigma_i A^T f_i = \sigma_i^2 g_i$$

$$A A^T f_i = \sigma_i A g_i = \sigma_i^2 f_i$$

$$f_j^T A g_i = 0$$

$$b = g_1$$

$$v = C_{yy}^{-1/2} b = C_{yy}^{-1/2} g_1$$

$$Ab = \mu a$$

$(b, a)$  are singular vector pairs.

$$A = C_{xx}^{-1/2} C_{xy} C_{yy}^{-1/2}$$

$$A = \sum_{i=1}^r \sigma_i f_i g_i^T$$

$$A g_i = \sigma_i f_i$$

$$a = f_1 \quad u = C_{xx}^{-1/2} f_1$$

Second pair is to choose

$u, v$  such that

$u^T X$  and  $u_1^T X$  are un-correlated  
 $v^T Y$  and  $v_1^T Y$  are uncorrelated

$$\rho(u, v) = \frac{u^T C_{XY} v}{\sqrt{v^T C_{YY} v} \sqrt{u^T C_{XX} u}}$$

$$\max_{u, v} \rho(u, v)$$

$$\|u\| = 1, \quad \text{cov}(v^T Y, v_1^T Y) = 0$$

$$\|v\| = 1, \quad \text{cov}(u^T X, u_1^T X) = 0$$

$$v^T C_{YY} v_1 = 0 \quad u^T C_{XX} u_1 = 0$$

$$C_{xx}^{1/2} u = a$$

$$C_{yy}^{1/2} v = b$$

$$a_1 = C_{xx}^{1/2} u_1$$

$$b_1 = C_{yy}^{1/2} v_1$$

$$\begin{array}{l} u^T C_{xx}^{1/2} C_{xx}^{1/2} u_1 = 0 \\ a^T a_1 = 0 \end{array}$$

$$\begin{array}{l} v^T C_{yy}^{1/2} C_{yy}^{1/2} v_1 = 0 \\ b^T b_1 = 0 \end{array}$$

$$\rho(a, b) = \frac{a^T C_{xx}^{-1/2} C_{xy} C_{yy}^{-1/2} b}{\|a\| \|b\|}$$

$$a^T a_1 = 0, \quad b^T b_1 = 0$$

$$\max_{a, b} \rho(a, b)$$

$$a = f_2, \quad b = g_2$$

$$u = C_{xx}^{-1/2} f_2, \quad v = C_{yy}^{-1/2} g_2$$



$$\tilde{X} = \begin{pmatrix} u_1^T X \\ \vdots \\ u_k^T X \end{pmatrix} \quad \tilde{Y} = \begin{pmatrix} v_1^T Y \\ \vdots \\ v_k^T Y \end{pmatrix}$$

$$\text{cov}(u_l^T X, u_m^T X)$$

$$\text{cov}(v_l^T Y, v_m^T Y) = 0$$

$$= u_l^T C_{XX} u_m = 0$$

$$v_l^T C_{YY} v_m = 0$$

$$\text{cov}(u_l^T X, v_m^T Y)$$

$$= u_l^T C_{XY} v_m$$

$$= f_l^T C_{XX}^{-1/2} C_{XY} C_{YY}^{-1/2} g_m$$

$$l \neq m$$

$$= 0$$