0.1 P-PCA

在本节, 我们将学习概率视角的 PCA, 这被称为 P-PCA。

0.1.1 已知

$$x \in R^p, \ z \in R^q, \ q < p$$

$$\begin{cases} z \backsim N(0_q, I_q) \\ x = wz + \mu + \epsilon \\ \epsilon \backsim N(0_p, \sigma^2 I_p) \end{cases}$$

0.1.2 所求

0.1.3 推导

推导 x

$$E[x] = wE[z] + E[\mu] + E[\epsilon]$$

$$= \mu$$
(1)

$$Var[x] = wVar[z]w^{T} + Var[\mu] + Var[\epsilon]$$

$$= ww^{T} + 0 + \sigma^{2}I_{p}$$

$$= ww^{T} + \sigma^{2}I_{p}$$

$$\therefore x \sim N(\mu, ww^{T} + \sigma^{2}I_{p})$$
(2)

推导 x|z

构造分布 t

$$t = \begin{pmatrix} x \\ z \end{pmatrix}$$

$$E[t] = \begin{pmatrix} E[x] \\ E[z] \end{pmatrix}$$

$$= \begin{pmatrix} \mu l_p \\ 0_q \end{pmatrix}$$
(3)

$$cov(x, z) = E[(x - E[x])(z - E[z])^{T}]$$

$$= E[(x - \mu)z^{T}]$$

$$= E[(wz + \epsilon)z^{T}]$$

$$= E[wzz^{T}] + E[\epsilon z^{T}]$$

$$= wE[(z - E[z])(z - E[z])^{T}] + E[\epsilon z^{T}]$$

$$= wVar[z] + 0$$

$$= wI_{q}$$

$$= w$$

$$= w$$

$$= w$$

$$\therefore Var[t] = \begin{pmatrix} ww^T + \sigma^2 I_p & w \\ w^T & I_q \end{pmatrix}$$

$$\therefore t \sim N(\begin{bmatrix} \mu l_p \\ 0_q \end{bmatrix}, \begin{bmatrix} ww^T + \sigma^2 I_p & w \\ w^T & I_q \end{bmatrix})$$
(5)

构造分布 x.z 我们设

$$x.z = x - \Sigma_{xz} \Sigma_{zz}^{-1} z$$

$$\therefore x.z = x - wz$$

$$= (I_p -w) {x \choose z}$$

$$= (I_p -w) t$$
(6)

$$\therefore E[x.z] = \begin{pmatrix} I_p & -w \end{pmatrix} E[t]
= \begin{pmatrix} I_p & -w \end{pmatrix} \begin{pmatrix} \mu l_p \\ 0_q \end{pmatrix}
= \mu l_p$$
(7)

$$Var[x.z] = (I_p - w) Var[t] \begin{pmatrix} I_p \\ -w^T \end{pmatrix}$$

$$= (I_p - w) \begin{pmatrix} ww^T + \sigma^2 I_p & w \\ w^T & I_q \end{pmatrix} \begin{pmatrix} I_p \\ -w^T \end{pmatrix}$$

$$= (\sigma^2 I_p - 0) \begin{pmatrix} I_p \\ -w^T \end{pmatrix}$$

$$= \sigma^2 I_p$$
(8)

$$\therefore x.z \backsim N(\mu l_p, \sigma^2 I_p) \tag{9}$$

推导 x|z

$$\therefore x.z = x - \Sigma_{xz} \Sigma_{zz}^{-1} z$$

$$\therefore x|z = x.z + \Sigma_{xz} \Sigma_{zz}^{-1} z$$

$$= x.z + wz$$
(10)

这里 z 是已知的, 因此我们可以将 wz 视为常数。

$$E[x|z] = E[x.z] + wz$$

$$= \mu l_p + wz$$
(11)

$$Var[x|z] = Var[x.z] + 0$$

$$= \sigma^2 I_p$$
(12)

$$\therefore x|z \backsim N(\mu l_p + wz, \sigma^2 I_p) \tag{13}$$

推导 z|x

我们设

$$z.x = z - \Sigma_{zx} \Sigma_{xx}^{-1} x$$

$$= z - w^T \Sigma_{xx}^{-1} x$$

$$\Sigma = \Sigma_{xx}$$

$$\therefore z.x = z - w^T \Sigma^{-1} x$$
(14)

让我们对上式稍作变形:

$$z.x = z - w^{T} \Sigma^{-1} x$$

$$= (-w^{T} \Sigma^{-1} \quad I) \begin{pmatrix} x \\ z \end{pmatrix}$$

$$= (-w^{T} \Sigma^{-1} \quad I) t$$
(15)

$$E[z.x] = \begin{pmatrix} -w^T \Sigma^{-1} & I \end{pmatrix} \begin{pmatrix} \mu l_p \\ 0_q \end{pmatrix}$$
$$= -\mu w^T \Sigma^{-1}$$
(16)

$$Var[z.x] = \begin{pmatrix} -w^T \Sigma^{-1} & I \end{pmatrix} \begin{pmatrix} \Sigma & w \\ w^T & I \end{pmatrix} \begin{pmatrix} -(\Sigma^{-1})^T w \\ I \end{pmatrix}$$
$$= \begin{pmatrix} 0 & -w^T \Sigma^{-1} w + I \end{pmatrix} \begin{pmatrix} -\Sigma^{-1} w \\ I \end{pmatrix}$$
$$= -w^T \Sigma^{-1} w + I$$
 (17)

$$\therefore z.x \backsim N(-\mu w^T \Sigma^{-1}, -w^T \Sigma^{-1} w + I)$$
(18)

$$\therefore z.x = z - w^T \Sigma^{-1} x$$

$$\therefore z | x = z.x + w^T \Sigma^{-1} x$$
 (19)

$$E[z|x] = E[z.x] + w^{T} \Sigma^{-1} x$$

$$= -\mu w^{T} \Sigma^{-1} + w^{T} \Sigma^{-1} x$$

$$= w^{T} \Sigma^{-1} (x - \mu l_{p})$$

$$= w^{T} (ww^{T} + \sigma^{2} I)^{-1} (x - \mu l_{p})$$
(20)

$$Var[z|x] = Var[z.x] + 0$$

$$= -w^{T} \Sigma^{-1} w + I$$

$$= -w^{T} (ww^{T} + \sigma^{2} I)^{-1} w + I$$
(21)

$$\therefore z | x \backsim N(w^T (ww^T + \sigma^2 I)^{-1} (x - \mu l_p), -w^T (ww^T + \sigma^2 I)^{-1} w + I)$$
 (22)

0.1.4 总结

我们需要搜索的参数是:

$$\{w, \sigma, \mu\}$$

我们可以用 EM 算法求得他们,通过最大化 p(x|z),这意味着:

- 训练阶段我们计算 p(x|z)
- 推理阶段我们计算 p(z|x)