Multivariate Gaussian distribution

You

Ngày 22 tháng 9 năm 2021

$Homework_2$ 1

Ex1: Proof p(x) is normal.

$$p(x|\mu, \sigma^2) = \frac{1}{(2\pi)^{\frac{D}{2}} |\sum_{1}|^{\frac{1}{2}}} exp\left\{ \frac{-1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu) \right\}$$

1.2Proof

Đặt

$$\begin{split} \Delta^2 &= \frac{-1}{2} (x - \mu)^T . \Sigma^{-1} . (x - \mu) \\ &= \frac{-1}{2} (x^T - \mu^T) . \Sigma^{-1} . (x - \mu) \\ &= \frac{-1}{2} x^T \Sigma^{-1} x + \frac{1}{2} x^T \Sigma^{-1} \mu + \frac{1}{2} \mu^T \Sigma^{-1} x - \frac{1}{2} \mu^T \Sigma^{-1} \mu \end{split}$$

Trong đó: *

$$\frac{1}{2}\mu^T\Sigma^{-1}\mu = constant$$

vì (1*D).(D*D).(D*1) = Constant

$$\frac{1}{2}x^{T}\Sigma^{-1}\mu + \frac{1}{2}\mu^{T}\Sigma^{-1}x$$

Ta có: $(\frac{1}{2}x^T\Sigma^{-1}\mu)^T=\frac{1}{2}\mu^T(\Sigma^{-1})^Tx$ (since $(ABC)^T=C^TB^TA^T$) mà + Σ đối xứng nên $\Sigma^{-1}=(\Sigma^{-1})^T=\Sigma+\frac{1}{2}x^T\Sigma^{-1}\mu=constant$ (do (1*D).(D*D).(D*1)) Vậy $\Delta=\frac{-1}{2}x^T\Sigma^{-1}x+x^T\Sigma^{-1}\mu+constant$

Ta có: Σ đối xứng nên:

$$\Sigma = \sum_{i=1}^{D} \lambda_{i} u_{i} u_{i}^{T} - > \Sigma^{-1} = \sum_{i=1}^{D} \frac{1}{\lambda_{i}} u_{i} u_{i}^{T}$$

Proof: vì u_i là các eigenvecto nên theo tính chất $u^T.u=0$ -> $\sum_{i=1}^D u_i.u_i^T=I$ and: Σ đối xứng nên các eigenvalues sẽ là số thực. and: $\Sigma^T=\Sigma^{-1}$

$$\Delta^{2} = \frac{-1}{2} (x - \mu)^{T} \cdot \Sigma^{-1} \cdot (x - \mu)$$

$$(1) = \frac{-1}{2} (x - \mu)^T \sum_{i=1}^{D} \frac{1}{\lambda_i} u_i u_i^T (x - \mu)$$

Set: $y_i = u_i^T(x - \mu)$ Since y_i có giá trị là một số thực (do (1*D)(D*1) nên $y_i = y_i^T = (u_i^T(x - \mu))^T = (u_i^T(x - \mu))^T = (u_i^T(x - \mu))^T$ $(x-\mu)^T u_i$

$$(1) <=> \Delta^2 = \frac{-1}{2} \sum_{i=1}^{D} \frac{1}{\lambda_i} (x - \mu)^T u_i u_i^T (x - \mu)$$

$$=\sum_{i=1}^D \frac{-y_i^2}{2\lambda_i}$$

$$|\Sigma|^{\frac{1}{2}} = \prod_{i=1}^D \lambda_j^{\frac{1}{2}}$$

(trong đó λ_j là cac eigenvalues va $\det(A)$ bằng tich cac eigenvalues)

$$\begin{split} p(y) &= \frac{1}{(2\pi)^{\frac{D}{2}} \prod_{j=1}^{D} \lambda_{j}^{\frac{1}{2}}} e^{\sum_{j=1}^{D} \frac{-y_{j}^{2}}{2\lambda_{j}}} \\ &= \prod_{j=1}^{D} (\frac{1}{2\pi\lambda_{j}})^{\frac{1}{2}} e^{\sum_{j=1}^{D} \frac{-y_{j}^{2}}{2\lambda_{j}}} \\ &= \prod_{j=1}^{D} (\frac{1}{2\pi\lambda_{j}})^{\frac{1}{2}} \cdot \prod_{j=1}^{D} e^{\frac{-y_{j}^{2}}{3\lambda_{i}}} \\ &= \prod_{j=1}^{D} (\frac{1}{2\pi\lambda_{j}})^{\frac{1}{2}} e^{\frac{-y_{j}^{2}}{2\lambda_{j}}} \\ &\int_{-\infty}^{\infty} p(y) dy = \prod_{j=1}^{D} \int_{-\infty}^{\infty} \frac{1}{(2\pi\lambda_{j})^{\frac{1}{2}}} \cdot e^{\frac{-y_{j}^{2}}{2\lambda_{i}}} dy_{j} \end{split}$$

+) pick j = 1 and set $\lambda=\sigma^2->\int_{-\infty}^\infty \frac{1}{\sqrt{2\pi\sigma^2}}.e^{\frac{-y^2}{2\sigma^2}}=1$. Thus:

$$\int_{-\infty}^{\infty} p(y)dy = 1 => Normality$$

1.3 Conditional Gaussion distribution

Set $x = \begin{pmatrix} x_a \\ x_b \end{pmatrix}$ and $\mu = \begin{pmatrix} \mu_a \\ \mu_b \end{pmatrix}$ and $\Sigma = \begin{bmatrix} \Sigma_{aa} & \Sigma_{ab} \\ \Sigma_{ba} & \Sigma_{bb} \end{bmatrix}$ Đặt: matrix $A = \Sigma^{-1} = \begin{bmatrix} ccA_{aa} & A_{ab} \\ A_{ba} & A_{bb} \end{bmatrix}$ Since Σ đối xứng nên Σ_{aa} và Σ_{bb} cũng đối xứng Tìm $p(x_a|x_b)$ Ta có:

$$\Delta^{2} = \frac{-1}{2}(x - \mu)^{T}.\Sigma^{-1}.(x - \mu)$$

$$= \frac{-1}{2}.\left(\begin{matrix} x_{a} - \mu_{a} \\ x_{b} - \mu_{b} \end{matrix}\right)^{T}.\left(\begin{matrix} A_{aa} & A_{ab} \\ A_{ba} & A_{bb} \end{matrix}\right).\left(\begin{matrix} x_{a} - \mu_{a} \\ x_{b} - \mu_{b} \end{matrix}\right)$$
Set: $(x_{a} - \mu_{a})^{T} = C_{1} (x_{b} - \mu_{b})^{T} = C_{2} (x_{a} - \mu_{a}) = D_{1} (x_{b} - \mu_{b}) = D_{2} \text{ thay vào } \Delta^{2} \text{ c\'o}$:
$$= \frac{-1}{2}.\left(\begin{matrix} C_{1} \\ C_{2} \end{matrix}\right)^{T}.\left(\begin{matrix} A_{aa} & A_{ab} \\ A_{ba} & A_{bb} \end{matrix}\right).\left(\begin{matrix} D_{1} \\ D_{2} \end{matrix}\right)$$

$$= \frac{-1}{2}((C_{1}A_{aa} + C_{2}A_{ba} - C_{1}A_{ab} + C_{2}A_{bb}).\left(\begin{matrix} D_{1} \\ D_{2} \end{matrix}\right)$$

$$= \frac{-1}{2}[(C_{1}A_{aa} + C_{2}A_{ba}).D_{1} + (C_{1}A_{ab} + C_{2}A_{bb}).D_{2}]$$

$$= \frac{-1}{2}(C_{1}A_{aa}D_{1} + C_{2}A_{ba}D_{1} + C_{1}A_{ab}D_{2} + C_{2}A_{bb}D_{2})$$

$$\Delta^{2} = \frac{-1}{2}(x_{a} - \mu_{a})^{T}A_{aa}(x_{a} - \mu_{a}) - \frac{1}{2}(x_{b} - \mu_{b})^{T}A_{ba}(x_{a} - \mu_{a}) - \frac{1}{2}.(x_{a} - \mu_{a})^{T}A_{ab}(x_{b} - \mu_{b})^{T}A_{bb}(x_{b} - \mu_{b})$$

trong đó; $-\frac{1}{2}(x_b - \mu_b)^T A_{bb}(x_b - \mu_b) = constant$ do (1*b).(b*b).(b*1) thuộc R $\frac{1}{2}(x_b - \mu_b)^T A_{ba}(x_a - \mu_a) = \frac{1}{2}.(x_a - \mu_a)^T A_{ab}(x_b - \mu_b)$ do đây là 2 ma trận chuyển vị. Vậy :

$$\Delta^2 = \frac{-1}{2}(x_a - \mu_a)^T A_{aa}(x_a - \mu_a) - (x_a - \mu_a)^T A_{ab}(x_b - \mu_b) + constant$$

$$= \frac{-1}{2}x_a^T A_{aa}x_a + \frac{1}{2}x_a^T A_{aa}\mu_a + \frac{1}{2}\mu_a^T A_{aa}x_a - \frac{1}{2}\mu_a^T A_{aa}\mu_a - (x_a - \mu_a)^T A_{ab}(x_b - \mu_b) + constant$$

trong đó: $\frac{1}{2}\mu_a^T A_{aa} x_a = \frac{1}{2}x_a^T A_{aa} \mu_a$ and $\frac{1}{2}\mu_a^T A_{aa} \mu_a = constant$

$$\Delta^{2} = \frac{-1}{2} x_{a}^{T} A_{aa} x_{a} + x_{a}^{T} A_{aa} \mu_{a} - (x_{a} - \mu_{a})^{T} A_{ab} (x_{b} - \mu_{b}) + constant$$

$$= \frac{-1}{2}x_a^T A_{aa} x_a + x_a^T A_{aa} \mu_a - x_a^T A_{ab} (x_b - \mu_b) + u_a^T A_{ab} (x_b - \mu_b) + constant$$

$$= \frac{-1}{2}x_a^T A_{aa} x_a + x_a^T . (A_{aa} \mu_a - A_{ab} (x_b - \mu_b)) + constant$$

Compare with Gaussian distribution: $\Delta = \frac{-1}{2}x^T\Sigma^{-1}x + x^T\Sigma^{-1}\mu + constant$

$$A_{aa} = \Sigma^{-1} = > \Sigma_{a|b} = A_{aa}^{-1}$$

$$\Sigma^{-1}\mu = A_{aa}\mu_a - A_{ab}(x_b - \mu_b)$$

Nhân 2 vế với $\Sigma = A_{aa}^{-1}$ ta được:

$$\Sigma \Sigma^{-1} \mu_{a|b} = A_{aa}^{-1} A_{aa} \mu_a - A_{aa}^{-1} A_{ab} (x_b - \mu_b)$$

$$\mu_{a|b} = \mu_a - A_{aa}^{-1} A_{ab} (x_b - \mu_b)$$

By using Schur complement:

$$A_{aa} = (\Sigma_{aa} - \Sigma_{ab}\Sigma_{bb}^{-1}\Sigma_{ba})^{-1}$$

$$A_{ab} = -(\Sigma_{aa} - \Sigma_{ab}\Sigma_{bb}^{-1}\Sigma_{ba})^{-1}\Sigma_{ab}\Sigma_{bb}^{-1}$$

Thus: $\Sigma_{a|b} = A_{aa}^{-1} = \Sigma_{aa} - \Sigma_{ab}\Sigma_{bb}^{-1}\Sigma_{ba}$

$$\mu_{a|b} = \mu_a - (\Sigma_{aa} - \Sigma_{ab}\Sigma_{bb}^{-1}\Sigma_{ba})(-(\Sigma_{aa} - \Sigma_{ab}\Sigma_{bb}^{-1}\Sigma_{ba})^{-1}\Sigma_{ab}\Sigma_{bb}^{-1}(x_b - \mu_b)$$

$$\mu_{a|b} = \mu_a + \Sigma_{ab} \Sigma_{bb}^{-1} (x_b - \mu_b)$$

$$p(x_a|x_b) = N(x_{a|b}|\mu_{a|b}, \Sigma_{a|b})$$