

Distribución Gaussiana Condicional para una Gaussiana Multivariada.

Distribución normal Multivariada.

Suponiendo $X = \begin{bmatrix} x_a \\ x_b \end{bmatrix}$, $\mu = \begin{bmatrix} \mu_a \\ \mu_b \end{bmatrix}$; $\Sigma = \begin{bmatrix} \Sigma_{aa} & \Sigma_{ab} \\ \Sigma_{ba} & \Sigma_{bb} \end{bmatrix}$

Donde $N(X|\mu, \Sigma) = \frac{1}{(2\pi)^{p/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2} (X-\mu)^T \Sigma (X-\mu)\right)$

Con $\Sigma_{ab} = \Sigma_{ba}^T$

A partir de la matriz de precisión:

$$\Delta = \Sigma^{-1}; \quad \Delta = \begin{bmatrix} \Delta_{aa} & \Delta_{ab} \\ \Delta_{ba} & \Delta_{bb} \end{bmatrix}$$

Para $P(X_b | X_a)$, con $p(X) = p(X_a, X_b)$

$$-\frac{1}{2} (X-\mu)^T \Sigma (X-\mu) = -\frac{1}{2} \begin{bmatrix} x_a, x_b \end{bmatrix}^T \begin{bmatrix} \mu_a, \mu_b \end{bmatrix}^T \begin{bmatrix} \Sigma_{aa} & \Sigma_{ab} \\ \Sigma_{ba} & \Sigma_{bb} \end{bmatrix}^{-1} \begin{bmatrix} x_a - \mu_a \\ x_b - \mu_b \end{bmatrix}$$

$$-\frac{1}{2} (X-\mu)^T \Sigma (X-\mu) = -\frac{1}{2} \begin{bmatrix} x_a - \mu_a, x_b - \mu_b \end{bmatrix}^T \begin{bmatrix} \Delta_{aa} & \Delta_{ab} \\ \Delta_{ba} & \Delta_{bb} \end{bmatrix} \begin{bmatrix} x_a - \mu_a \\ x_b - \mu_b \end{bmatrix}$$

$$-\frac{1}{2} [X^T \Sigma^{-1} X - X^T \Sigma^{-1} \mu - \mu^T \Sigma^{-1} X + \mu^T \Sigma^{-1} \mu] = -\frac{1}{2} X^T \Sigma^{-1} X + \frac{1}{2} X^T \Sigma^{-1} \mu - \frac{1}{2} \mu^T \Sigma^{-1} \mu$$

$X^T \Sigma^{-1} \mu = \mu^T \Sigma^{-1} X = \langle \mu, X \rangle \Sigma^{-1}$, con $\Sigma > 0 \rightarrow$ Definida positiva.

Por lo tanto:

$$\underbrace{-\frac{1}{2} X^T \Sigma^{-1} X}_{\text{Cuadrático}} + \underbrace{X^T \Sigma^{-1} \mu}_{\text{lineal}} - \underbrace{\frac{1}{2} \mu^T \Sigma^{-1} \mu}_{\text{Constante}} = \frac{1}{2} \begin{bmatrix} x_a - \mu_a, x_b - \mu_b \end{bmatrix}^T \begin{bmatrix} \Delta_{aa} & \Delta_{ab} \\ \Delta_{ba} & \Delta_{bb} \end{bmatrix} \begin{bmatrix} x_a - \mu_a \\ x_b - \mu_b \end{bmatrix}$$

$$\begin{aligned} -\frac{1}{2} X^T \Sigma^{-1} X + X^T \Sigma^{-1} \mu + cte &= -\frac{1}{2} \left[(x_a - \mu_a)^T \Delta_{aa} + (x_b - \mu_b)^T \Delta_{ba}, (x_a - \mu_a)^T \Delta_{ab} \right. \\ &\quad \left. + (x_b - \mu_b)^T \Delta_{bb} \right] \begin{bmatrix} x_a - \mu_a \\ x_b - \mu_b \end{bmatrix} \\ &= -\frac{1}{2} \left[(x_a - \mu_a)^T \Delta_{aa} (x_a - \mu_a) + (x_b - \mu_b)^T \Delta_{ba} (x_a - \mu_a) \right. \\ &\quad \left. + (x_a - \mu_a)^T \Delta_{ab} (x_b - \mu_b) + (x_b - \mu_b)^T \Delta_{bb} (x_b - \mu_b) \right] \end{aligned}$$

$\mu_{b|a}$ y $\Sigma_{b|a}$ Completando cuadrados.

$$p(x) = p([x_a, x_b]), \quad p(x_b | x_a) = N(x_b | \mu_{b|a}, \Sigma_{b|a})$$

Reescribiendo exponencial.

$$A_{ab}^T = A_{ba}$$

$$-\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) = -\frac{1}{2} x_a^T \Delta_{aa} x_a + x_a^T \Delta_{aa} \mu_a + \frac{1}{2} \mu_a^T \Delta_{aa} \mu_a$$

$$\dots = -\frac{1}{2} x_b^T \Delta_{ba} x_a + \frac{1}{2} x_b^T \Delta_{ba} \mu_a + \frac{1}{2} \mu_b^T \Delta_{ba} x_a - \frac{1}{2} \mu_b^T \Delta_{ba} \mu_a$$

$$-\frac{1}{2} x_a^T \Delta_{ab} x_b + \frac{1}{2} x_a^T A_{ab} \mu_b + \frac{1}{2} \mu_a^T A_{ab} x_b - \frac{1}{2} \mu_a^T \Delta_{ab} \mu_b$$

$$-\frac{1}{2} x_b^T \Delta_{bb} x_b + x_b^T A_{bb} \mu_b - \frac{1}{2} \mu_b^T A_{bb} \mu_b$$

Para determinar $p(x_b | x_a)$ se encuentra la dependencia de x_b con x_a asumiendo x_a constante.

Término cuadrático en x_b : $-\frac{1}{2} x_b^T \Delta_{bb} x_b$

Del término cuadrático $\Sigma_{b|a} = \Delta_{bb}^{-1}$

Términos lineales en x_b :

$$-\frac{1}{2} x_b^T \Delta_{ba} x_a + \frac{1}{2} x_b^T \Delta_{ba} \mu_a - \frac{1}{2} x_a^T A_{ab} x_b + \frac{1}{2} \mu_a^T A_{ab} x_b + x_b^T A_{bb} \mu_b$$

Se tiene que

$$x_b^T A_{bb} \mu_b - \frac{1}{2} x_b^T \Delta_{ba} x_a + \frac{1}{2} x_b^T A_{ba} \mu_a - \frac{1}{2} x_a^T A_{ab} x_b + \frac{1}{2} \mu_a^T A_{ab} x_b$$

$$x_b^T A_{bb} \mu_b + (-x_b^T \Delta_{ba} x_a) + x_b^T A_{ba} \mu_a$$

$$x_b^T (A_{bb} \mu_b + \Delta_{ba} (\mu_a - x_a))$$

Donde $\Delta_{ba} = \Delta_{ab}$

Se busca despejar término donde

$$\cancel{X_b^T} \cancel{\Sigma_{b|a}^{-1}} \mu_{b|a} = \cancel{X_b^T} (\Delta_{bb} \mu_b + (\Delta_{ba} (\mu_a - x_a)))$$

$$\Sigma_{b|a}^{-1} = \Delta_{bb}$$

$$\Sigma_{b|a}^{-1} \mu_{b|a} = \Sigma_{b|a}^{-1} \mu_b + (\Delta_{ba} (\mu_a - x_a))$$

$$\cancel{\Sigma_{b|a}^{-1}} \cancel{\Sigma_{b|a}^{-1}} \mu_{b|a} = \cancel{\Sigma_{b|a}^{-1}} \cancel{\Sigma_{b|a}} \mu_b + (\Delta_{ba} (\mu_a - x_a))$$

$$\mu_{b|a} = \cancel{\Sigma_{b|a}^{-1}} \cancel{\Sigma_{b|a}} \mu_b + \Sigma_{ba}^{-1} (\mu_a - x_a) \Sigma_{b|a}$$

$$\Delta_{ba} = \Sigma_{ba}^{-1}$$

$$\mu_{b|a} = \mu_b + \Sigma_{b|a} \Sigma_{ba}^{-1} (\mu_a - x_a)$$

$$\Sigma_{b|a} = \Delta_{bb}^{-1}$$

$$\mu_{b|a} = \mu_b + \Delta_{bb}^{-1} \Delta_{ba} (\mu_a - x_a)$$

$$P(X_b | X_a) = N(X_b | \mu_{b|a}, \Sigma_{b|a})$$

$$\Sigma^{-1} = \begin{bmatrix} \Sigma_{aa} & \Sigma_{ab} \\ \Sigma_{ba} & \Sigma_{bb} \end{bmatrix}^{-1} = \Delta = \begin{bmatrix} \Delta_{aa} & \Delta_{ab} \\ \Delta_{ba} & \Delta_{bb} \end{bmatrix}$$

Matriz⁻¹ por partes

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} = \begin{bmatrix} M & -MBD^{-1} \\ -D^{-1}CM & D^{-1} + D^{-1}CMBD^{-1} \end{bmatrix}$$

$$M = (A - BD^{-1}C)^{-1}$$

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

$$\Sigma_{b|a} = \Sigma_{bb}^{-1} + \Sigma_{bb}^{-1} \Sigma_{ba} (\Sigma_{aa} - \Sigma_{ab} \Sigma_{bb}^{-1} \Sigma_{ba}) \Sigma_{ab} \Sigma_{bb}^{-1}$$