

Tarea #3

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1) Sea $x = (x_1, x_2)$ tal que $f(x_1, x_2) = (2\pi)^{-1/2} |\Sigma|^{-1/2} \exp\left\{-\frac{1}{2}(x-\mu)'\Sigma^{-1}(x-\mu)\right\}$

con $\mu = (\mu_1, \mu_2)'$ vector de medias y $\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}$ tal que $\text{var}(x_1) = \sigma_{11}$
 $\text{var}(x_2) = \sigma_{22}$

obtenga la distribución condicional de x_1 a $x_2 = x_2$.

$$\text{cov}(x_1, x_2) = \sigma_{12} = \sigma_{21}$$

Preliminares:

1) pd $|\Sigma|^{1/2} = \sigma_{11}^{1/2} \sigma_{22}^{1/2} \sqrt{1-p^2}$ con $p = \text{corr}(x_1, x_2)$

dem:

Por un lado tenemos que $|\Sigma|^{1/2} = \left| \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix} \right|^{1/2} = (\sigma_{11}\sigma_{22} - \sigma_{12}\sigma_{21})^{1/2} = (\sigma_{11}\sigma_{22} - \sigma_{12}^2)^{1/2}$ (1)

Por otro lado sea $p = \text{corr}(x_1, x_2) = \frac{\text{cov}(x_1, x_2)}{\sqrt{\text{var}(x_1)} \sqrt{\text{var}(x_2)}} = \frac{\sigma_{12}}{\sigma_{11}^{1/2} \sigma_{22}^{1/2}}$ (2)

entonces:

$$\begin{aligned} \sigma_{11}^{1/2} \sigma_{22}^{1/2} \sqrt{1-p^2} &= \sigma_{11}^{1/2} \sigma_{22}^{1/2} \sqrt{1 - \left(\frac{\sigma_{12}}{\sigma_{11}^{1/2} \sigma_{22}^{1/2}} \right)^2} = \sigma_{11}^{1/2} \sigma_{22}^{1/2} \sqrt{\frac{\sigma_{11}\sigma_{22} - \sigma_{12}^2}{\sigma_{11}\sigma_{22}}} \\ &= (\sigma_{11}\sigma_{22} - \sigma_{12}^2)^{1/2} \stackrel{(1)}{=} |\Sigma|^{1/2} // \end{aligned}$$

$\therefore |\Sigma|^{1/2} = \sigma_{11}^{1/2} \sigma_{22}^{1/2} \sqrt{1-p^2}$ (3)

ii) Notar que $1-p^2 = \frac{\sigma_{11}\sigma_{22} - \sigma_{12}^2}{\sigma_{11}\sigma_{22}}$ (4)

3) pd $f(x_1, x_2)$ se puede reescribir en términos de p como:

$$f(x_1, x_2) = (2\pi)^{-1} [\sigma_{11}\sigma_{22}(1-p^2)]^{-1/2} \exp \left\{ -\frac{1}{2} (1-p)^{-1} \left[\left(\frac{x_1 - \mu_1}{\sigma_{11}^{1/2}} \right)^2 - 2p \left[\frac{x_1 - \mu_1}{\sigma_{11}^{1/2}} \right] \left[\frac{x_2 - \mu_2}{\sigma_{22}^{1/2}} \right] + \left[\frac{x_2 - \mu_2}{\sigma_{22}^{1/2}} \right]^2 \right] \right\}$$

Dem:

$$f(x_1, x_2) = (2\pi)^{-2/2} |\Sigma|^{-1/2} \exp \left\{ -\frac{1}{2} (x - \mu)' \Sigma^{-1} (x - \mu) \right\}$$

$$\text{de (3)} = (2\pi)^{-1} (\sigma_{11} \sigma_{22} \sqrt{1-\rho^2})^{-1/2} \exp \left\{ -\frac{1}{2} (x_1 - \mu_1, x_2 - \mu_2) \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \begin{pmatrix} \sigma_{22} & -\sigma_{21} \\ -\sigma_{12} & \sigma_{11} \end{pmatrix} \begin{pmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{pmatrix} \right\}$$

$$\text{de (4)} = (2\pi)^{-1} (\sigma_{11} \sigma_{22} (1-\rho^2))^{-1/2} \exp \left\{ -\frac{1}{2} \frac{1}{\sigma_{11} \sigma_{22} (1-\rho^2)} (x_1 - \mu_1, x_2 - \mu_2) \begin{pmatrix} \sigma_{22} & -\sigma_{21} \\ -\sigma_{12} & \sigma_{11} \end{pmatrix} \begin{pmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{pmatrix} \right\}$$

$$= (2\pi)^{-1} (\sigma_{11} \sigma_{22} (1-\rho^2))^{-1/2} \exp \left\{ -\frac{1}{2} \frac{1}{\sigma_{11} \sigma_{22} (1-\rho^2)} [\sigma_{22} (x_1 - \mu_1)^2 - 2\sigma_{12} (x_1 - \mu_1)(x_2 - \mu_2) + \sigma_{11} (x_2 - \mu_2)^2] \right\}$$

$$= (2\pi)^{-1} (\sigma_{11} \sigma_{22} (1-\rho^2))^{-1/2} \exp \left\{ -\frac{1}{2(1-\rho^2)} \left[\left(\frac{x_1 - \mu_1}{\sigma_{11}^{1/2}} \right)^2 - \frac{2\sigma_{12}}{\sigma_{11}^{1/2} \sigma_{22}^{1/2}} \left[\frac{x_1 - \mu_1}{\sigma_{11}^{1/2}} \right] \left[\frac{x_2 - \mu_2}{\sigma_{22}^{1/2}} \right] - \left(\frac{x_2 - \mu_2}{\sigma_{22}^{1/2}} \right)^2 \right] \right\}$$

$$\text{de (2)} = (2\pi)^{-1} [\sigma_{11} \sigma_{22} (1-\rho^2)]^{-1/2} \exp \left\{ -\frac{1}{2(1-\rho^2)} \left[\left(\frac{x_1 - \mu_1}{\sigma_{11}^{1/2}} \right)^2 - 2\rho \left(\frac{x_1 - \mu_1}{\sigma_{11}^{1/2}} \right) \left(\frac{x_2 - \mu_2}{\sigma_{22}^{1/2}} \right) - \left(\frac{x_2 - \mu_2}{\sigma_{22}^{1/2}} \right)^2 \right] \right\} //$$

Distribución Condicional de X_1 en $X_2 = x_2$

$$f(x_1 | x_2 = x_2) = \frac{f(x_1, x_2 = x_2)}{f(x_2 = x_2)}$$

$$= \frac{(2\pi)^{-1} [\sigma_{11} \sigma_{22} (1-\rho^2)]^{-1/2} \exp \left\{ -\frac{1}{2(1-\rho^2)} \left[\left(\frac{x_1 - \mu_1}{\sigma_{11}^{1/2}} \right)^2 - 2\rho \left(\frac{x_1 - \mu_1}{\sigma_{11}^{1/2}} \right) \left(\frac{x_2 - \mu_2}{\sigma_{22}^{1/2}} \right) - \left(\frac{x_2 - \mu_2}{\sigma_{22}^{1/2}} \right)^2 \right] \right\}}{(2\pi)^{-1/2} \sigma_{22}^{-1/2} \exp \left\{ -\frac{1}{2} \left(\frac{x_2 - \mu_2}{\sigma_{22}^{1/2}} \right)^2 \right\}}$$

$$\propto \exp \left\{ -\frac{1}{2\sigma_{11}(1-\rho^2)} \left[x_1^2 - 2x_1\mu_1 - 2\rho\sigma_{11}^{1/2} x_1 \left(\frac{x_2 - \mu_2}{\sigma_{22}^{1/2}} \right) \right] \right\}$$

$$= \exp \left\{ -\frac{1}{2\sigma_{11}(1-\rho^2)} \left[x_1^2 - 2 \left(\mu_1 - \rho \frac{\sigma_{11}^{1/2}}{\sigma_{22}^{1/2}} (x_2 - \mu_2) \right) x_1 \right] \right\}$$

$$\propto \exp \left\{ -\frac{1}{2\sigma_{11}(1-\rho^2)} \left[x_1^2 - 2 \left(\mu_1 - \rho \frac{\sigma_{11}^{1/2}}{\sigma_{22}^{1/2}} (x_2 - \mu_2) \right) x_1 + \left(\mu_1 - \rho \frac{\sigma_{11}^{1/2}}{\sigma_{22}^{1/2}} (x_2 - \mu_2) \right)^2 \right] \right\}$$

$$= \exp \left\{ -\frac{1}{2\sigma_{11}(1-\rho^2)} \left[x_1 - \left(\mu_1 - \rho \frac{\sigma_{11}^{1/2}}{\sigma_{22}^{1/2}} (x_2 - \mu_2) \right) \right]^2 \right\}$$

que coincide con el kernel de una normal con media $\mu_{1|2} = \mu_1 - \rho \frac{\sigma_{11}^{1/2}}{\sigma_{22}^{1/2}} (x_2 - \mu_2)$ & varianza $\Sigma_{1|2} = \sigma_{11} (1-\rho^2)$, que sustituyendo el valor de ρ es equivalente a tener

$$X_1 | X_2 = x_2 \sim N \left(\mu_1 - \sigma_{12} \sigma_{22}^{-1} (x_2 - \mu_2); \sigma_{11} - \sigma_{12} \sigma_{22}^{-1} \sigma_{12} \right) //$$

2) Sea $\underline{X} = (x_1, x_2)$ un vector de dimensión p tal que x_1 es de dimensión p_1 y x_2 es de dimensión p_2 y $\underline{X} \sim N_p(\underline{x} | \underline{\mu}, \underline{\Sigma})$ con $p = p_1 + p_2$.
Obtener la distribución condicional de x_1 en $x_2 = x_2$.

Preliminares: (recuperado de Graybill, F. (1961))

* Teorema: Si A es una matriz simétrica, positiva definida tal que $A = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}$ y si B es la inversa de A tal que $B = \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix}$ y si $B_{11} \neq A_{11}$ son ambas de dimensión $m_1 \times m_1$, se satisface que

$$A_{11}^{-1} = B_{11} - B_{12} B_{22}^{-1} B_{21}$$

$$\text{y } A_{11} B_{12} = -A_{12} B_{22}$$

Dem: Dado que $A = B^{-1}$ entonces $AB = I$ por lo tanto

$$\begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix} = \begin{pmatrix} I & 0 \\ 0 & I \end{pmatrix} \quad (1)$$

De (1) se pueden obtener las siguientes ecuaciones matriciales:

$$A_{11} B_{11} + A_{12} B_{21} = I \quad \text{y} \quad A_{11} B_{12} + A_{12} B_{22} = 0 \quad (2)$$

De (3) obtenemos de $A_{12} = -A_{11} B_{12} B_{22}^{-1}$ (4) y también de $A_{11} B_{12} = -A_{12} B_{22}$ (5)

sustituyendo (4) en (2) y premultiplicando por A_{11}^{-1} tenemos

$$A_{11} B_{11} + [-A_{11} B_{12} B_{22}^{-1} B_{21}] = I$$

$$\Rightarrow A_{11}^{-1} A_{11} B_{11} - A_{11}^{-1} A_{11} B_{12} B_{22}^{-1} B_{21} = A_{11}^{-1} I$$

$$\Rightarrow B_{11} - B_{12} B_{22}^{-1} B_{21} = A_{11}^{-1}$$

Dado que A_{11} y B_{22} son matrices spd y son los menores principales de A y B respectivamente, se tiene que A_{11}^{-1} y B_{22}^{-1} existen. //

Distribución condicional de x_1 en $x_2 = x_2$:

Sea $\underline{X} = (x_1, x_2)$ donde x_1 es dimensión p_1 y x_2 es de dimensión p_2 , tal que $\underline{X} \sim N_{p_1+p_2}(\underline{x} | \underline{\mu}, \underline{\Sigma})$ con $\underline{\mu} = (\underline{\mu}_1, \underline{\mu}_2)$ y $\underline{\Sigma} = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}$ la matriz de varianzas y covarianzas por bloques.

Sea $\underline{\Sigma}^{-1} = \begin{bmatrix} \Sigma_{11}^{-1} & \Sigma_{12}^{-1} \\ \Sigma_{21}^{-1} & \Sigma_{22}^{-1} \end{bmatrix}$ la matriz inversa de $\underline{\Sigma}$.

Entonces, la distribución condicional de X_1 dado $X_2 = x_2$ está dada por:

$$f(x_1 | x_2 = x_2) = \frac{f(x_1, x_2 = x_2)}{f(x_2 = x_2)}$$

$$= \frac{(2\pi)^{-(p_1+p_2)/2} |\Sigma|^{-1/2} \exp\left\{-\frac{1}{2}(x-\mu)' \Sigma^{-1}(x-\mu)\right\}}{(2\pi)^{p_2/2} |\Sigma_{22}|^{-1/2} \exp\left\{-\frac{1}{2}(x_2-\mu_2)' \Sigma_{22}^{-1}(x_2-\mu_2)\right\}}$$

$$\propto \exp\left\{-\frac{1}{2}(x-\mu)' \Sigma^{-1}(x-\mu) + \frac{1}{2}(x_2-\mu_2)' \Sigma_{22}^{-1}(x_2-\mu_2)\right\}$$

$$= \exp\left\{-\frac{1}{2}(x_1-\mu_1, x_2-\mu_2)' \begin{bmatrix} \Sigma_{11}^{-1} & \Sigma_{12}^{-1} \\ \Sigma_{21}^{-1} & \Sigma_{22}^{-1} \end{bmatrix} \begin{bmatrix} x_1-\mu_1 \\ x_2-\mu_2 \end{bmatrix} + \frac{1}{2}(x_2-\mu_2)' \Sigma_{22}^{-1}(x_2-\mu_2)\right\}$$

$$= \exp\left\{-\frac{1}{2}\left[(x_1-\mu_1)' \Sigma_{11}^{-1}(x_1-\mu_1) + 2(x_1-\mu_1)' \Sigma_{12}^{-1}(x_2-\mu_2) + (x_2-\mu_2)' \Sigma_{22}^{-1}(x_2-\mu_2)\right] + \frac{1}{2}(x_2-\mu_2)' \Sigma_{22}^{-1}(x_2-\mu_2)\right\}$$

$$= \exp\left\{-\frac{1}{2}\left[(x_1-\mu_1)' \Sigma_{11}^{-1}(x_1-\mu_1) + 2(x_1-\mu_1)' \Sigma_{12}^{-1}(x_2-\mu_2)\right]\right\}$$

$$\propto \exp\left\{-\frac{1}{2}\left[x_1' \Sigma_{11}^{-1} x_1 - 2x_1' \Sigma_{11}^{-1} \mu_1 + 2x_1' \Sigma_{12}^{-1}(x_2-\mu_2)\right]\right\}$$

$$= \exp\left\{-\frac{1}{2}\left[x_1' \Sigma_{11}^{-1} x_1 - 2x_1' \Sigma_{11}^{-1}(\mu_1 - \Sigma_{11} \Sigma_{12}^{-1}(x_2-\mu_2))\right]\right\}$$

Del teorema anterior, se sigue que $\Sigma_{11}^{-1} = \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}$ y de $\Sigma_{11} \Sigma_{12}^{-1} = -\Sigma_{12} \Sigma_{22}^{-1}$ entonces

$$\begin{aligned} f(x_1 | x_2 = x_2) &\propto \exp\left\{-\frac{1}{2}\left[x_1'(\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})x_1 - 2x_1'(\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})(\mu_1 + \Sigma_{12} \Sigma_{22}^{-1}(x_2 - \mu_2))\right]\right\} \\ &\propto \exp\left\{-\frac{1}{2}\left[x_1'(\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})x_1 - 2x_1'(\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})(\mu_1 + \Sigma_{12} \Sigma_{22}^{-1}(x_2 - \mu_2))\right] + (\mu_1 + \Sigma_{12} \Sigma_{22}^{-1}(x_2 - \mu_2))'(\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})(\mu_1 + \Sigma_{12} \Sigma_{22}^{-1}(x_2 - \mu_2))\right\} \\ &= \exp\left\{-\frac{1}{2}\left[\left[x_1 - (\mu_1 + \Sigma_{12} \Sigma_{22}^{-1}(x_2 - \mu_2))\right]'(\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})\left[x_1 - (\mu_1 + \Sigma_{12} \Sigma_{22}^{-1}(x_2 - \mu_2))\right]\right]\right\} \end{aligned}$$

Que coincide con el kernel de una normal multivariada de orden p_1 . Esto es

$$x_1 | x_2 = x_2 \sim N_{p_1}(x_{1|2}, \Sigma_{11|2}) \text{ donde } \mu_{1|2} = \mu_1 + \Sigma_{12} \Sigma_{22}^{-1}(x_2 - \mu_2)$$

$$\text{y } \Sigma_{11|2} = \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}$$