

Normal Multivariada

Graciela Boente

Cuál es la conjunta?

- Z_1, \dots, Z_p i.i.d $Z_j \sim N(0, 1)$ $\mathbf{z} = (Z_1, \dots, Z_p)^T$

Cuál es su distribución conjunta?

$$f(\mathbf{z}) = f(z_1, z_2, \dots, z_p) = f_1(z_1) f_2(z_2) \cdots f_p(z_p)$$

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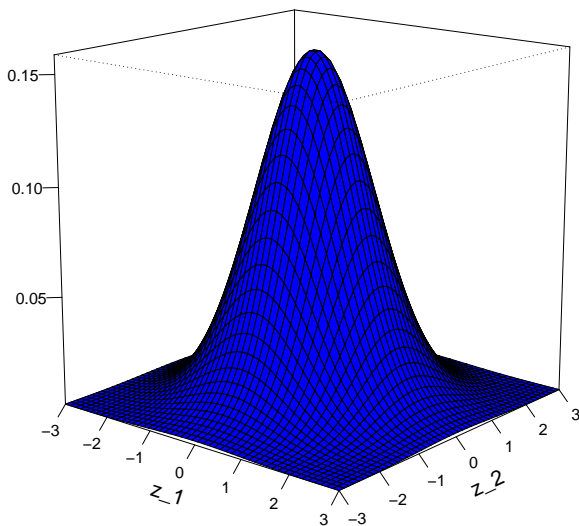
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Diremos que $\mathbf{z} \sim N(\mathbf{0}_p, \mathbf{I}_p)$

Normal Multivariada $p = 2$

Densidad de $\mathbf{Z} \sim N(\mathbf{0}_2, \mathbf{I}_2)$



Cuál es la conjunta?

- X_1, \dots, X_p i.i.d $X_j \sim N(0, \sigma_j^2)$ $\mathbf{X} = (X_1, \dots, X_p)^T$

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Sea $\Sigma = \text{diag}(\sigma_1^2, \dots, \sigma_p^2)$

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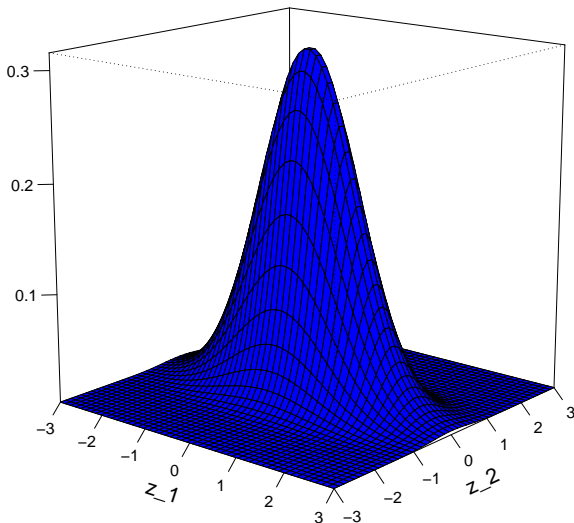
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Diremos que $\mathbf{X} \sim N(\mathbf{0}_p, \Sigma)$

Normal Multivariada $p = 2$

Densidad de $\mathbf{X} \sim N(\mathbf{0}_2, \Sigma)$, $\Sigma = \text{diag}(1, 0.25)$



Cuál es la conjunta?

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Sean $\Sigma = \text{diag}(\sigma_1^2, \dots, \sigma_p^2)$, $\mu = (\mu_1, \dots, \mu_p)^T$

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 \end{aligned}$$

Diremos que $\mathbf{X} \sim N(\mu, \Sigma)$

Definición 1

- Sea $\boldsymbol{\mu} \in \mathbb{R}^P$ y $\boldsymbol{\Sigma} \in \mathbb{R}^{P \times P}$ simétrica y definida positiva
Se dice que $\mathbf{x} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ si su densidad está dada por

$$f(\mathbf{x}) = \frac{1}{(2\pi)^{\frac{P}{2}}} \frac{1}{|\boldsymbol{\Sigma}|^{\frac{1}{2}}} \exp \left\{ -\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right\}$$

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- Si $\mathbf{x} \sim N(\mathbf{0}, \text{diag}(\lambda_1, \dots, \lambda_p))$

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- En particular, si $\mathbf{x} \sim N(\mathbf{0}, \mathbf{I}_p)$, x_1, \dots, x_p son i.i.d. $N(0, 1)$.
- Si $\mathbf{x} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ y $\mathbf{A} \in \mathbb{R}^{p \times p}$ es no singular \implies
 $\mathbf{Ax} + \mathbf{b} \sim N(\mathbf{A}\boldsymbol{\mu} + \mathbf{b}, \mathbf{A}\boldsymbol{\Sigma}\mathbf{A}^T)$

Caso $p = 2$

- Sea $\boldsymbol{\mu} \in \mathbb{R}^2$ y $\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}$ definida positiva ($|\rho| \neq 1$)

$$f(\mathbf{x}) = \frac{1}{2\pi} \frac{1}{\sigma_1\sigma_2(1-\rho^2)^{\frac{1}{2}}} \exp \left\{ -\frac{1}{2(1-\rho^2)} \left[\left(\frac{x_1 - \mu_1}{\sigma_1} \right)^2 + \left(\frac{x_2 - \mu_2}{\sigma_2} \right)^2 - 2\rho \left(\frac{x_1 - \mu_1}{\sigma_1} \right) \left(\frac{x_2 - \mu_2}{\sigma_2} \right) \right] \right\}$$

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Densidad

Datos generados

Propiedades

- Si $\mathbf{x} \sim N(\mathbf{0}, \mathbf{I}_p) \implies \varphi_{\mathbf{x}}(\mathbf{t}) = \exp\{-\frac{1}{2}\|\mathbf{t}\|^2\}$

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- $\mathbf{x} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \iff \mathbf{a}^T \mathbf{x} \sim N(\mathbf{a}^T \boldsymbol{\mu}, \mathbf{a}^T \boldsymbol{\Sigma} \mathbf{a}), \forall \mathbf{a} \in \mathbb{R}^p$

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- $\mathbf{x} = (x_1, \dots, x_p)^T \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \implies \mathbb{E}(\mathbf{x}) = \boldsymbol{\mu}$ y
 $\text{Cov}(\mathbf{x}) = (\text{Cov}(x_i, x_j))_{1 \leq i, j \leq p} = \boldsymbol{\Sigma}$

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- Sea $\mathbf{x} = (x_1, \dots, x_p)^T \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, entonces,
 x_1, \dots, x_p son independientes $\iff \boldsymbol{\Sigma}$ es diagonal.

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Se dice que \mathbf{x} es normal multivariada si y sólo si $\forall \mathbf{t} \in \mathbb{R}^p$ se tiene que $\mathbf{t}^T \mathbf{x}$ es normal univariada.

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Definición 3

Se dice que \mathbf{x} es normal multivariada si y sólo si $\exists \boldsymbol{\mu} \in \mathbb{R}^p$, $\boldsymbol{\Sigma} \in \mathbb{R}^{p \times p}$ simétrica $\boldsymbol{\Sigma} > 0$, tal que

$$\varphi_{\mathbf{x}}(\mathbf{t}) = \exp\{i\mathbf{t}^T \boldsymbol{\mu}\} \exp\{-\frac{1}{2}\mathbf{t}^T \boldsymbol{\Sigma} \mathbf{t}\}$$

Propiedades

Vimos que si $\mathbf{x} \sim N(\mathbf{0}, \Sigma)$, entonces

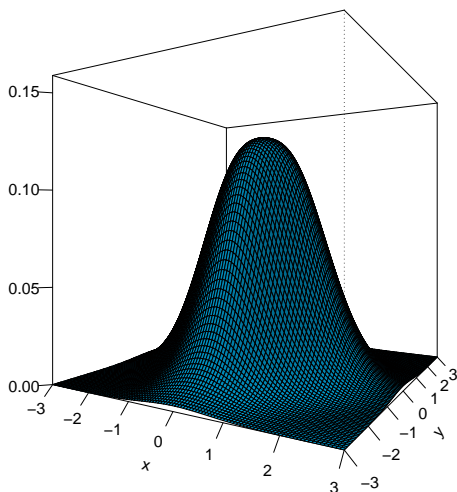
- x_1, \dots, x_p son independientes $\iff \Sigma$ es diagonal.
- $x_j \sim N(0, \sigma_{jj})$ donde $\Sigma = (\sigma_{ij})_{1 \leq i, j \leq p}$

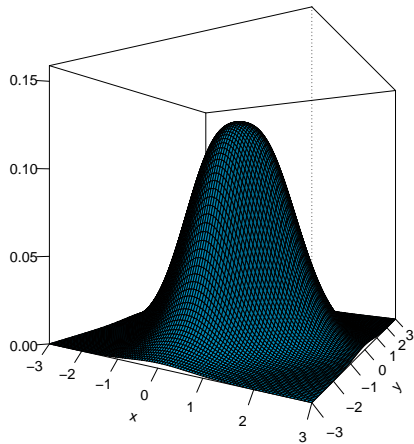
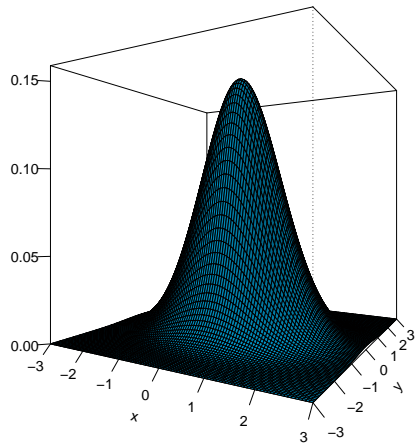
El siguiente ejemplo muestra que existen vectores aleatorios $\mathbf{x} = (x_1, x_2)$ tales que

- $\text{Cov}(\mathbf{x}) = \mathbf{I}_p$.
- $x_j \sim N(0, 1)$
- x_1 y x_2 no son independientes.

Sea \mathbf{x} con densidad

$$h(x, y) = \frac{1}{2\pi} \left\{ \left(\sqrt{2} e^{-\frac{x^2}{2}} - e^{-x^2} \right) e^{-y^2} + \left(\sqrt{2} e^{-\frac{y^2}{2}} - e^{-y^2} \right) e^{-x^2} \right\}$$



Densidad h Densidad $N(\mathbf{0}, \mathbf{I}_2)$ 

Propiedades

Sea $\mathbf{x} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ con $\boldsymbol{\Sigma} > 0$. Definamos

$$\mathbf{x} = \begin{pmatrix} \mathbf{x}^{(1)} \\ \mathbf{x}^{(2)} \end{pmatrix} \quad \boldsymbol{\mu} = \begin{pmatrix} \boldsymbol{\mu}^{(1)} \\ \boldsymbol{\mu}^{(2)} \end{pmatrix} \quad \boldsymbol{\Sigma} = \begin{pmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{pmatrix}$$

con $\mathbf{x}^{(i)}, \boldsymbol{\mu}^{(i)} \in \mathbb{R}^{p_i}$, $\boldsymbol{\Sigma}_{ij} \in \mathbb{R}^{p_i \times p_i}$, $p_1 + p_2 = p$.

Entonces,

a) $\mathbf{x}^{(1)} \sim N(\boldsymbol{\mu}^{(1)}, \boldsymbol{\Sigma}_{11})$ y $\mathbf{x}^{(2)} \sim N(\boldsymbol{\mu}^{(2)}, \boldsymbol{\Sigma}_{22})$.

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- Más aún, $\mathbf{x}^{(1)}$ y $\mathbf{x}^{(2)}$ son independientes $\iff \boldsymbol{\Sigma}_{21} = 0$.

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- Más aún, $\mathbf{x}^{(1)}$ y $\mathbf{x}^{(2)}$ son independientes $\iff \boldsymbol{\Sigma}_{21} = 0$.
- Dada $\mathbf{A} \in \mathbb{R}^{q \times p}$, $\text{rg}(\mathbf{A}) = q \implies \mathbf{Ax} \sim N(\mathbf{A}\boldsymbol{\mu}, \mathbf{A}\boldsymbol{\Sigma}\mathbf{A}^T)$.

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Sea $\mathbf{x} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ con $\boldsymbol{\Sigma} > 0$. Definamos

$$\mathbf{x} = \begin{pmatrix} \mathbf{x}^{(1)} \\ \mathbf{x}^{(2)} \end{pmatrix} \quad \boldsymbol{\mu} = \begin{pmatrix} \boldsymbol{\mu}^{(1)} \\ \boldsymbol{\mu}^{(2)} \end{pmatrix} \quad \boldsymbol{\Sigma} = \begin{pmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{pmatrix}$$

con $\mathbf{x}^{(i)}, \boldsymbol{\mu}^{(i)} \in \mathbb{R}^{p_i}$, $\boldsymbol{\Sigma}_{ij} \in \mathbb{R}^{p_i \times p_j}$, $p_1 + p_2 = p$.

Entonces,

- $\mathbf{x}^{(1)} \sim N(\boldsymbol{\mu}^{(1)}, \boldsymbol{\Sigma}_{11})$ y $\mathbf{x}^{(2)} \sim N(\boldsymbol{\mu}^{(2)}, \boldsymbol{\Sigma}_{22})$.
- Más aún, $\mathbf{x}^{(1)}$ y $\mathbf{x}^{(2)}$ son independientes $\iff \boldsymbol{\Sigma}_{21} = 0$.
- Dada $\mathbf{A} \in \mathbb{R}^{q \times p}$, $rg(\mathbf{A}) = q \implies \mathbf{Ax} \sim N(\mathbf{A}\boldsymbol{\mu}, \mathbf{A}\boldsymbol{\Sigma}\mathbf{A}^T)$.

En particular, si $\mathbf{x} \sim N(\mathbf{0}, \mathbf{I}_p)$ y $\mathbf{H} = (\mathbf{h}_1, \dots, \mathbf{h}_q) \in \mathbb{R}^{p \times q}$, es ortogonal incompleta, o sea, $\mathbf{H}^T \mathbf{H} = \mathbf{I}_q$, entonces $\mathbf{y} = \mathbf{H}^T \mathbf{x} \sim N(\mathbf{0}, \mathbf{I}_q)$.

Propiedades

- d) Sea $\mathbf{\Sigma} = \mathbf{H}\mathbf{\Lambda}\mathbf{H}^T$, con \mathbf{H} ortogonal y $\mathbf{\Lambda} = \text{diag}(\lambda_1, \dots, \lambda_p)$,
 $\lambda_1 \geq \dots, \lambda_p$.
Si $\mathbf{x} \sim N(\boldsymbol{\mu}, \mathbf{\Sigma}) \implies \mathbf{H}^T(\mathbf{x} - \boldsymbol{\mu}) \sim N(\mathbf{0}, \mathbf{\Lambda})$.

Propiedades

- d) Sea $\mathbf{\Sigma} = \mathbf{H}\mathbf{\Lambda}\mathbf{H}^T$, con \mathbf{H} ortogonal y $\mathbf{\Lambda} = \text{diag}(\lambda_1, \dots, \lambda_p)$,
 $\lambda_1 \geq \dots, \lambda_p$.
Si $\mathbf{x} \sim N(\boldsymbol{\mu}, \mathbf{\Sigma}) \implies \mathbf{H}^T(\mathbf{x} - \boldsymbol{\mu}) \sim N(\mathbf{0}, \mathbf{\Lambda})$.
- e) Si $\mathbf{x} \sim N(\boldsymbol{\mu}, \mathbf{\Sigma}) \iff \mathbf{x} = \mathbf{A}\mathbf{z} + \boldsymbol{\mu}$ con $\mathbf{z} \sim N(\mathbf{0}, \mathbf{I}_p)$ y
 $\mathbf{A}\mathbf{A}^T = \mathbf{\Sigma}$.

Propiedades

- d) Sea $\mathbf{\Sigma} = \mathbf{H}\mathbf{\Lambda}\mathbf{H}^T$, con \mathbf{H} ortogonal y $\mathbf{\Lambda} = \text{diag}(\lambda_1, \dots, \lambda_p)$,
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- e) Si $\mathbf{x} \sim N(\boldsymbol{\mu}, \mathbf{\Sigma}) \iff \mathbf{x} = \mathbf{A}\mathbf{z} + \boldsymbol{\mu}$ con $\mathbf{z} \sim N(\mathbf{0}, \mathbf{I}_p)$ y
 $\mathbf{A}\mathbf{A}^T = \mathbf{\Sigma}$.
- f) Si $\mathbf{x} \sim N(\boldsymbol{\mu}, \mathbf{\Sigma}) \implies (\mathbf{x} - \boldsymbol{\mu})^T \mathbf{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \sim \chi_p^2$
- g) Si $\mathbf{x} \sim N(\boldsymbol{\mu}, \mathbf{\Sigma}) \implies \mathbf{x}^T \mathbf{\Sigma}^{-1} \mathbf{x} \sim \chi_p^2(\delta^2)$ con $\delta^2 = \boldsymbol{\mu}^T \mathbf{\Sigma}^{-1} \boldsymbol{\mu}$

Propiedades

Lema 1. Sea $\mathbf{x} \sim N(\mathbf{0}, \sigma^2 \mathbf{I}_p)$ y sea $\mathbf{H}_1 = (\mathbf{h}_1, \dots, \mathbf{h}_q) \in \mathbb{R}^{p \times q}$ ortogonal incompleta, o sea,

$$\mathbf{H}_1^T \mathbf{H}_1 = \mathbf{I}_q$$

Sea $\mathbf{H} = (\mathbf{H}_1, \mathbf{H}_2)$ ortogonal, o sea, $\mathbf{H}^T \mathbf{H} = \mathbf{H} \mathbf{H}^T = \mathbf{I}_p$ Entonces

- $\mathbf{z} = \mathbf{H}_1^T \mathbf{x} \sim N(\mathbf{0}, \sigma^2 \mathbf{I}_q)$.
- \mathbf{z} es independiente de $\mathbf{x}^T \mathbf{x} - \mathbf{z}^T \mathbf{z}$.
- $\frac{\mathbf{x}^T \mathbf{x} - \mathbf{z}^T \mathbf{z}}{\sigma^2} \sim \chi_{p-q}^2$.