

Optimización analítica: otro ejemplo algo menos simple

Ejercicio

Estimar los parámetros $\Theta \equiv (\mu_1, \mu_2)$ de una gaussiana bivariada (en \mathbb{R}^2), en la que la matriz de covarianza

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix}$$

es conocida:

$$p(x_1, x_2; \mu_1, \mu_2) = A \cdot \exp \left(-B \left[\frac{(x_1 - \mu_1)^2}{\sigma_1^2} + \frac{(x_2 - \mu_2)^2}{\sigma_2^2} - \frac{2\sigma_{12}(x_1 - \mu_1)(x_2 - \mu_2)}{(\sigma_1\sigma_2)^2} \right] \right)$$

donde

$$A = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1 - (\sigma_{12}/\sigma_1\sigma_2)^2}}, \quad B = \frac{1}{2(1 - (\sigma_{12}/\sigma_1\sigma_2)^2)}$$

Otro ejercicio algo más complejo: Asumir que Σ tampoco es conocida; es decir estimar: $\Theta \equiv (\mu_1, \mu_2, \sigma_1, \sigma_2, \sigma_{12})$

3.1. (p.3.9, 0.5 puntos) Obtener los estimadores de máxima verosimilitud del vector media de una gaussiana bi-variada, cuya matriz de covarianza es fija y conocida partir de una muestra de de vectores bi-dimensionales x_1, x_2, \dots, x_N .

La matriz de covarianza es conocida: $\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix}$

$$p(x_1, x_2, \mu_1, \mu_2) = \underbrace{\frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\left(\frac{\sigma_{12}}{\sigma_1\sigma_2}\right)^2}}}_A \cdot e^{\underbrace{\left(-\frac{1}{2\left(1-\left(\frac{\sigma_{12}}{\sigma_1\sigma_2}\right)^2\right)}\right)}_B \cdot \underbrace{\left[\frac{(x_1-\mu_1)^2}{\sigma_1^2} + \frac{(x_2-\mu_2)^2}{\sigma_2^2} - \frac{2\sigma_{12}(x_1-\mu_1)(x_2-\mu_2)}{(\sigma_1\sigma_2)^2}\right]}_C}$$

$$L_s(\mu_1, \mu_2) \Rightarrow \log\left(\prod_{n=1}^N p(x_n; \mu_1, \mu_2)\right) \Rightarrow \log\left(\prod_{n=1}^N (A \cdot e^{-BC})\right)$$

$$\Rightarrow \log\left(A^N \cdot e^{-B \cdot \underbrace{\sum_{n=1}^N \left(\frac{(x_{n1}-\mu_1)^2}{\sigma_1^2} + \frac{(x_{n2}-\mu_2)^2}{\sigma_2^2} - \frac{2\sigma_{12}(x_{n1}-\mu_1)(x_{n2}-\mu_2)}{(\sigma_1\sigma_2)^2}\right)}_{C'}}\right)$$

$$\Rightarrow \log(A^N) + \log(e^{-BC'}) \Rightarrow \log(A^N) - BC' \Rightarrow \log\left(\frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\left(\frac{\sigma_{12}}{\sigma_1\sigma_2}\right)^2}}\right)^N - BC'$$

$$\Rightarrow N \log A - BC' \Rightarrow N \log 1 - N \log(2\pi\sigma_1\sigma_2\sqrt{1-\left(\frac{\sigma_{12}}{\sigma_1\sigma_2}\right)^2}) - BC'$$

$$\Rightarrow -N \log(2\pi\sigma_1\sigma_2\sqrt{1-\left(\frac{\sigma_{12}}{\sigma_1\sigma_2}\right)^2}) - \frac{1}{2\left(1-\left(\frac{\sigma_{12}}{\sigma_1\sigma_2}\right)^2\right)} \cdot \left(\sum_{n=1}^N \left(\frac{(x_{n1}-\mu_1)^2}{\sigma_1^2} + \frac{(x_{n2}-\mu_2)^2}{\sigma_2^2} - \frac{2\sigma_{12}(x_{n1}-\mu_1)(x_{n2}-\mu_2)}{(\sigma_1\sigma_2)^2}\right)\right)$$

derivada parcial en función μ_1

$$\frac{\partial Ls(\mu_1, \mu_2)}{\partial \mu_1} = 0 - \frac{1}{2 \left(1 - \left(\frac{\sigma_{12}}{\sigma_1 \sigma_2}\right)\right)} \cdot \left(\frac{1}{\sigma_1^2} \cdot \sum_{n=1}^N 2 \cdot (x_{n1} - \mu_1) + 0 - \frac{2\sigma_{12}}{(\sigma_1 \sigma_2)^2} \sum_{n=1}^N -(x_{n2} - \mu_2) \right) = 0$$

$$\Rightarrow - \frac{1}{2 \left(1 - \left(\frac{\sigma_{12}}{\sigma_1 \sigma_2}\right)\right)} \cdot \left(\frac{2}{\sigma_1^2} \right) \cdot \left(\underbrace{\sum_{n=1}^N (x_{n1} - \mu_1) + \frac{\sigma_{12}}{\sigma_2^2} \sum_{n=1}^N (x_{n2} - \mu_2)}_{\text{Debe ser 0}} \right) = 0$$

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nunca nunca serán 0

$$\Rightarrow \sum_{n=1}^N (x_{n1} - \mu_1) + \frac{\sigma_{12}}{\sigma_2^2} \sum_{n=1}^N (x_{n2} - \mu_2) = 0 \Rightarrow \underbrace{\sum_{n=1}^N x_{n1}}_{\text{lo llamaremos } S_1} - \sum_{n=1}^N \mu_1 + \frac{\sigma_{12}}{\sigma_2^2} \sum_{n=1}^N x_{n2} - \frac{\sigma_{12}}{\sigma_2^2} \sum_{n=1}^N \mu_2 = 0$$

lo llamaremos S_2

$$\Rightarrow \boxed{S_1 - N\mu_1 + \frac{\sigma_{12}}{\sigma_2^2} S_2 - \frac{\sigma_{12}}{\sigma_2^2} N\mu_2 = 0}$$

Derivada parcial en función de μ_2

$$\frac{\partial L_s(\mu_1, \mu_2)}{\partial \mu_2} = 0 - \frac{1}{2\left(1 - \left(\frac{\sigma_{12}}{\sigma_1 \sigma_2}\right)\right)} \cdot \left(\frac{1}{\sigma_2^2} \sum_{n=1}^N 2(x_{n2} - \mu_2) + \frac{2\sigma_{12}}{(\sigma_1 \sigma_2)^2} \sum_{n=1}^N (x_{n1} - \mu_1) \right) = 0$$

$$\Rightarrow - \frac{1}{2\left(1 - \left(\frac{\sigma_{12}}{\sigma_1 \sigma_2}\right)\right)} \cdot \left(\frac{1}{\sigma_2^2} \right) \cdot \left(\sum_{n=1}^N (x_{n2} - \mu_2) + \frac{\sigma_{12}}{\sigma_1^2} \sum_{n=1}^N (x_{n1} - \mu_1) \right) = 0$$

Nunca serán 0

Debe ser 0

$$\Rightarrow \sum_{n=1}^N (x_{n2} - \mu_2) + \frac{\sigma_{12}}{\sigma_1^2} \sum_{n=1}^N (x_{n1} - \mu_1) = 0 \Rightarrow \underbrace{\sum_{n=1}^N x_{n2}}_{\text{lo llamamos } S_2} - \sum_{n=1}^N \mu_2 + \frac{\sigma_{12}}{\sigma_1^2} \underbrace{\sum_{n=1}^N x_{n1}}_{\text{lo llamamos } S_1} - \frac{\sigma_{12}}{\sigma_1^2} \sum_{n=1}^N \mu_1 = 0$$

$$\Rightarrow S_2 - N\mu_2 + \frac{\sigma_{12}}{\sigma_1^2} S_1 - \frac{\sigma_{12}}{\sigma_1^2} N\mu_1 = 0$$

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SISTEMAS DE ECUACIONES CON LOS RESULTADOS

$$\begin{cases} S_1 - N\mu_1 + \frac{\sigma_{12}}{\sigma_2^2} S_2 - \frac{\sigma_{12}}{\sigma_2^2} N\mu_2 = 0 \\ S_2 - N\mu_2 + \frac{\sigma_{12}}{\sigma_1^2} S_1 - \frac{\sigma_{12}}{\sigma_1^2} N\mu_1 = 0 \end{cases}$$

Despejamos μ_1 en la primera ecuación

Sustituimos μ_1 en la segunda ecuación

$$\mu_1 = \frac{\sigma_{12}}{\sigma_2^2 N} S_2 - \frac{\sigma_{12} N\mu_2}{\sigma_2^2 N} + \frac{S_1}{N}$$

$$S_2 - N\mu_2 + \frac{\sigma_{12}}{\sigma_1^2} S_1 - \left(\frac{\sigma_{12}}{\sigma_1^2} N\right) \left(\frac{\sigma_{12} S_2}{\sigma_2^2 N} - \frac{\sigma_{12} N\mu_2}{\sigma_2^2 N} + \frac{S_1}{N}\right) = 0$$

SIMPLIFICAMOS

$$S_2 - N\mu_2 + \cancel{\frac{\sigma_{12}}{\sigma_1^2} S_1} - \left(\cancel{\frac{\sigma_{12}}{\sigma_1^2} N}\right) \left(\cancel{\frac{\sigma_{12} S_2}{\sigma_2^2 N}} - \frac{\sigma_{12} N\mu_2}{\sigma_2^2 N} + \cancel{\frac{S_1}{N}}\right) = 0$$

$$S_2 - N\mu_2 - \left(\frac{\sigma_{12}^2}{\sigma_1^2 \sigma_2^2}\right) (S_2 - N\mu_2) = 0 \Rightarrow (S_2 - N\mu_2) \underbrace{\left(1 - \frac{\sigma_{12}^2}{\sigma_1^2 \sigma_2^2}\right)}_{\substack{\text{debe ser } 0 \\ \text{en general no será nunca } 0}} = 0$$

$$S_2 - N\mu_2 = 0 \quad \mu_2 = \frac{S_2}{N} \Rightarrow \mu_2 = \frac{\sum_{n=1}^N x_{n2}}{N}$$

Habiendo obtenido que $\mu_2 = \frac{S_2}{N}$ en la segunda ecuación, sustituimos μ_2 en la primera ecuación:

$$S_1 - N\mu_1 + \frac{\sigma_{12}}{\sigma_2^2} S_2 - \frac{\sigma_{12}}{\sigma_2^2} N\mu_2 = 0 \Rightarrow S_1 - N\mu_1 + \frac{\sigma_{12}}{\sigma_2^2} S_2 - \frac{\sigma_{12} N}{\sigma_2^2} \cdot \frac{S_2}{N} = 0$$

Simplificamos

$$\Rightarrow S_1 - N\mu_1 + \frac{\sigma_{12}}{\sigma_2^2} S_2 - \frac{\sigma_{12} \cancel{N} S_2}{\sigma_2^2 \cancel{N}} = 0 \Rightarrow S_1 - N\mu_1 = 0$$

$$\Rightarrow \mu_1 = \frac{S_1}{N} \Rightarrow \frac{\sum_{n=1}^N X_{n1}}{N}$$

Resultados

$$\mu_1 = \frac{\sum_{n=1}^N X_{n1}}{N}$$

$$\mu_2 = \frac{\sum_{n=1}^N X_{n2}}{N}$$