

Maximum Likelihood Estimation

(Estimación de Máxima Verosimilitud).

$$f(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\}$$

μ, σ : Parámetros que vamos a estimar,

Ejemplo: Probabilidad de pasar un examen con 10 personas.

$$P_1: 0.35$$

$$P_1: 0.66$$

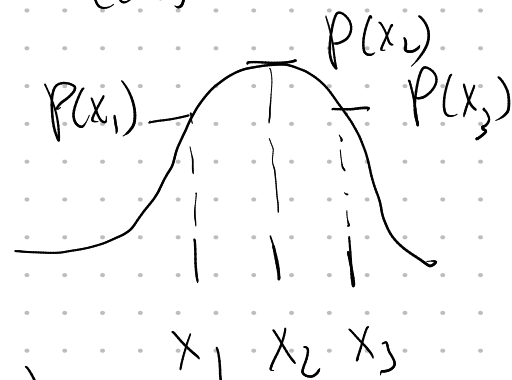
$$P_2: 0.01 \quad \text{Caso 1}$$

$$P_2: 0.48 \quad \text{Caso 2.}$$

Caso 2 es más probable por $P_1 P_2(\text{Caso 2}) > P_1 P_2(\text{Caso 1})$

Maximizar la verosimilitud

$$L = P(x_1) P(x_2) P(x_3)$$



x_1, \dots, x_N , con prob: $P(x_1) \dots P(x_N)$

Maximizar

$$P(x_1) P(x_2) \dots P(x_N) = \prod_{i=1}^N P(x_i)$$

$$P(\mu, \sigma | \{x_i\}) = \prod \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{(x_i - \mu)^2}{2\sigma^2}\right\}$$

$$\frac{\partial P}{\partial \mu} = 0 \quad , \quad \frac{\partial P}{\partial \sigma} = 0$$

$$P(\mu, \sigma | \{x_i\}) = \prod \frac{1}{\sqrt{2\pi} \sigma} \exp \left\{ \frac{(x_i - \mu)^2}{2\sigma^2} \right\}$$

$$\begin{aligned} \ell(\mu, \sigma) &= \log(P(\mu, \sigma)) = \log \left(\prod \frac{1}{\sqrt{2\pi} \sigma} \exp \left\{ \frac{(x_i - \mu)^2}{2\sigma^2} \right\} \right) \\ &= \sum_{i=1}^N \log \left(\frac{1}{\sqrt{2\pi} \sigma} \exp \left\{ \frac{(x_i - \mu)^2}{2\sigma^2} \right\} \right) \end{aligned}$$

$$\log(ab) = \log(a) + \log(b) \quad \log(\prod y_i) = \sum \log(y_i)$$

$$\ell(\mu, \sigma) = N \log \left(\frac{1}{\sqrt{2\pi}} \right) - N \log \sigma + \sum \log \left[\exp \left\{ \frac{(x_i - \mu)^2}{2\sigma^2} \right\} \right]$$

$$\begin{aligned} \sum_{i=1}^N \log \left(\frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sigma} \right) &= \sum_{i=1}^N \log \left(\frac{1}{\sqrt{2\pi}} \right) + \sum_{i=1}^N \log \left(\frac{1}{\sigma} \right) \\ &= N \log \left(\frac{1}{\sqrt{2\pi}} \right) + N \log(\sigma^{-1}) \\ &= N \log \left(\frac{1}{\sqrt{2\pi}} \right) - N \log(\sigma) \end{aligned}$$

$$\ell(\mu, \sigma) = N \log \left(\frac{1}{\sqrt{2\pi}} \right) - N \log \sigma + \sum \log \left\{ \exp \left(\frac{(x_i - \mu)^2}{2\sigma^2} \right) \right\}$$

$$\ell(\mu, \sigma) = N \log \left(\frac{1}{\sqrt{2\pi}} \right) - N \log \sigma + \sum \left(\frac{-(x_i - \mu)^2}{2\sigma^2} \right)$$

$$\frac{\partial \ell}{\partial \mu} = 0 + 0 + \sum \left(\frac{-(x_i - \mu)}{\sigma^2} \right) (-1) = 0$$

$$\frac{(-1)(-1)}{2\sigma^2} \sum (x_i - \mu) = 0$$

$$\sum (x_i - \mu) = 0 \Rightarrow \sum x_i - \sum_{i=1}^N \mu = 0$$

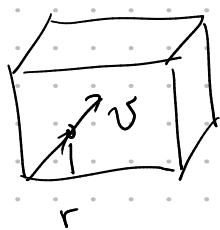
$$\sum x_i - N\mu = 0$$

$$\mu = \frac{\sum x_i}{N} : \text{promedio.}$$

$$\frac{\partial \ell(\mu, \sigma)}{\partial \sigma} \quad \sigma^2 = \frac{\sum (x_i - \mu)^2}{N} : \text{Varianza.}$$

Ejemplos de máxima verosimilitud.

Física Estadística



→ Espacio de Fase

El estado de equilibrio es el estado que maximiza la verosimilitud. A partir de esto se encuentra la temperatura T .

Redes Neuronales:

Datos



Etiquetas 0, 1

$$\prod P(c_d | x) \prod P(c_l | x)$$

Categorical cross entropy

Se entrena con gradiente descendente.

