

Ejercicio 1

Si $L(\theta, t) = |t - \theta|$, entonces $\hat{\theta}_B$ es la mediana de $\pi(\theta | x_1, \dots, x_n)$

$$PEP(L(\theta, t)) = E(L(\theta, t) | x_1, \dots, x_n)$$

$$= \int_{-\infty}^{\infty} |t - \theta| \pi(\theta | x_1, \dots, x_n) d\theta$$

$$= \int_{-\infty}^t (t - \theta) \pi(\theta | x_1, \dots, x_n) d\theta$$

$$+ \int_t^{\infty} (\theta - t) \pi(\theta | x_1, \dots, x_n) d\theta$$

$$= \int_{-\infty}^t (t - \theta) \pi(\theta | x_1, \dots, x_n) d\theta - \int_t^{\infty} (t - \theta) \pi(\theta | x_1, \dots, x_n) d\theta$$

$$\frac{d}{dt} PEP(L(\theta, t)) = 1 \cdot \cancel{(t-t)} \pi(t | x_1, \dots, x_n) + \int_{-\infty}^t 1 \cdot \pi(\theta | x_1, \dots, x_n) d\theta$$

$$+ 1 \cdot \cancel{(t-t)} \pi(t | x_1, \dots, x_n) - \int_t^{\infty} 1 \cdot \pi(\theta | x_1, \dots, x_n) d\theta$$

$$= F(t) - (1 - F(t)) = 2F(t) - 1$$

$$2F(t) - 1 = 0 \Rightarrow F(t) = 1/2$$

$$\frac{d^2}{dt^2} P \in P(L(\theta, t)) = 2\pi(t | x_1, \dots, x_n) > 0$$

$$\hat{\theta}_B = t \quad \text{tal que} \quad F(t) = 1/2$$

$\hat{\theta}_B$ es la mediana a posteriori

Ejercicio 2

(x_1, \dots, x_N) m. a. s. de $\bar{x} \sim B(n, p)$, n conocido.

$$f_{\theta}(x) = \binom{n}{x} p^x (1-p)^{n-x} \quad p \in (0, 1)$$

$$f_{\theta}(x_1, \dots, x_N) = \prod_{j=1}^N \binom{n}{x_j} \cdot p^{\sum_{j=1}^N x_j} (1-p)^{nN - \sum_{j=1}^N x_j}$$

$$\pi(p) \sim \text{Beta}(a, b)$$

$$\pi(p) = \frac{1}{B(a, b)} p^{a-1} (1-p)^{b-1}$$

$$\begin{aligned} \pi(p | x_1, \dots, x_N) &\propto p^{\sum_{j=1}^N x_j} (1-p)^{nN - \sum_{j=1}^N x_j} \cdot p^{a-1} (1-p)^{b-1} \\ &= p^{\sum_{j=1}^N x_j + a - 1} (1-p)^{nN - \sum_{j=1}^N x_j + b - 1} \end{aligned}$$

$$\pi(p | x_1, \dots, x_N) \sim \text{Beta}\left(\sum_{j=1}^N x_j + a, nN - \sum_{j=1}^N x_j + b\right)$$

$$\begin{aligned}
 E(\varphi | x_1, \dots, x_N) &= \frac{\sum_{j=1}^N x_j + a}{\sum_{j=1}^N x_j + a + nN - \sum_{j=1}^N x_j + b} \\
 &= \frac{\sum_{j=1}^N x_j + a}{a + nN + b}
 \end{aligned}$$

Si $a = b = 1 \rightarrow \pi(\varphi)$ es no informativa y

$$E(\varphi | x_1, \dots, x_N) = \frac{\sum_{j=1}^N x_j + 1}{nN + 2}$$

El estimador de máxima verosimilitud es

$$\hat{\varphi}_{MV} = \frac{\sum_{j=1}^N x_j}{nN}$$