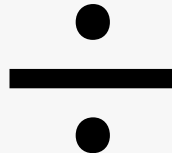
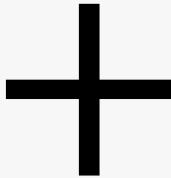


ITAM
Departamento de Estadística

Inferencia Estadística– Laboratorio #4
Estimación Puntual: Sesgo, Varianza, Error Cuadrático
Medio, Consistencia



1. Demuestra que

$$MSE(\hat{\theta}) = \mathbb{E}[(\hat{\theta} - \theta)^2] = V(\hat{\theta}) - B^2(\hat{\theta})$$

$B(\hat{\theta}) \equiv \text{sesgo}$

$$\text{Usamos } \hat{\theta} - \theta = \hat{\theta} - \underbrace{\mathbb{E}(\hat{\theta})}_{\text{Sumamos un cero}} + \mathbb{E}(\hat{\theta}) - \theta = [\hat{\theta} - \mathbb{E}(\hat{\theta})] + [\underbrace{\mathbb{E}(\hat{\theta}) - \theta}_{B(\hat{\theta})}]$$

$$\text{Así, } MSE_{\hat{\theta}} = \mathbb{E}[(\hat{\theta} - \theta)^2] = \mathbb{E}[(\hat{\theta} - \mathbb{E}(\hat{\theta})) + B(\hat{\theta})]^2$$

$$= \mathbb{E}[(\hat{\theta} - \mathbb{E}(\hat{\theta}))^2 + 2(\hat{\theta} - \mathbb{E}(\hat{\theta}))B(\hat{\theta}) + B^2(\hat{\theta})]$$

$$= \mathbb{E}[(\hat{\theta} - \mathbb{E}(\hat{\theta}))^2] + 2\mathbb{E}[(\hat{\theta} - \mathbb{E}(\hat{\theta}))B(\hat{\theta})] + \mathbb{E}[B^2(\hat{\theta})]$$

$$\mathbb{E}[\mathbb{E}(x)] = \mathbb{E}[x] \rightarrow = V(\hat{\theta}) + 2[\mathbb{E}(\hat{\theta}) - \mathbb{E}(\hat{\theta})]B(\hat{\theta}) + B^2(\hat{\theta})$$

$$= V(\hat{\theta}) + B^2(\hat{\theta})$$

2. Suponga que $\hat{\theta}$ es un estimador para un parámetro θ y $\mathbb{E}[\hat{\theta}] = a\theta + b$ para $a, b \neq 0$.

- En términos de a, b y θ . Encuentre $B(\hat{\theta})$
- Encuentre una función de $\hat{\theta}$, sea θ^* , que sea un estimador no sesgado para θ
- Usando este estimador insesgado, exprese $MSE(\hat{\theta}^*)$ como función de $V(\hat{\theta})$
- Dé un ejemplo de valores de a, b para los cuales se cumpla $MSE(\hat{\theta}^*) > MSE(\hat{\theta})$

$$(a) \text{ Sabemos } \mathbb{E}[\hat{\theta}] = a\theta + b$$

$$B(\hat{\theta}) = \mathbb{E}(\hat{\theta}) - \theta = a\theta + b - \theta = b + (a-1)\theta$$

$$(b) \text{ Queremos que } \mathbb{E}[\theta^*] = \theta, \text{ usamos } \mathbb{E}[\hat{\theta}] = a\theta + b$$

$$\text{y vemos que } \mathbb{E}\left[\frac{\hat{\theta} - b}{a}\right] = \theta \quad \therefore \quad \theta^* = \frac{\hat{\theta} - b}{a} \text{ es un estimador insesgado de } \theta$$

(c)

Como θ^* es insesgado se tiene que $B(\theta^*) = 0$ y por ej. (1)

$$MSE_{\theta^*} = V(\theta^*) + B^2(\theta^*)^0 = V(\theta^*) = V\left[\frac{\hat{\theta} - b}{a}\right]$$

$$= \frac{1}{a^2} V(\hat{\theta})$$

(d) Tenemos que encontrar a, b t.q.

$MSE(\theta^*) > MSE(\hat{\theta})$. Sabemos que $\mathbb{E}(\hat{\theta}) = a\theta + b$, $B(\hat{\theta}) = b + (a-1)\theta$

$$\text{y } MSE(\theta^*) = \frac{V(\hat{\theta})}{a^2} \rightarrow \text{por (c)}$$

$$\text{Ahora, } MSE_{\hat{\theta}} = V(\hat{\theta}) - B^2(\hat{\theta}) = V(\hat{\theta}) - [b + (a-1)\theta]^2$$

$$\therefore \frac{V(\hat{\theta})}{a^2} > V(\hat{\theta}) - [b + (a-1)\theta]^2 \Leftrightarrow a < 1 \wedge b < V(\hat{\theta})$$

TEOREMA: Sean X_1, \dots, X_n v.a.i.i.d con $X_i \sim F_X$
 \Rightarrow Si $W = \min\{X_1, \dots, X_n\}$ Sus acumuladas son:
 $Z = \max\{X_1, \dots, X_n\}$

$$(1) F_W(w) = 1 - [1 - F_X(w)]^n ; (2) F_Z(z) = [F_X(z)]^n$$

Dem.

$$(1) F_Z(z) = P(\max\{X_1, \dots, X_n\} \leq z) = P(X_1 \leq z, X_2 \leq z, \dots, X_n \leq z) \\ = \prod_{i=1}^n P(X_i \leq z) = [F_X(z)]^n$$

Si X_i es continua entonces $f_Z(z) = n [F_X(z)]^{n-1} f_X(z)$

$$(1) f_Z(z) = \frac{\partial}{\partial z} [F_X(z)]^n = n [F_X(z)]^{n-1} \frac{\partial}{\partial z} [F_X(z)] = n [F_X(z)]^{n-1} f_X(z)$$

$$(2) F_W(w) = P(\min\{X_1, \dots, X_n\} \leq w) = 1 - P(\min\{X_1, \dots, X_n\} > w) \\ = 1 - [P(X_1 > w, X_2 > w, \dots, P(X_n > w))] \\ = 1 - [P(X_1 > w) P(X_2 > w) \dots P(X_n > w)] \\ = 1 - \prod_{i=1}^n P(X_i > w) = 1 - \prod_{i=1}^n [1 - F_X(w)] = 1 - [1 - F_X(w)]^n$$

$\underbrace{\quad}_{1 - F_X(w)}$

Si X_i es continua entonces $f_W(w) = n [1 - F_X(w)]^{n-1} f_X(w)$

$$(2) f_W(w) = \frac{\partial}{\partial w} [1 - [1 - F_X(w)]^n] = -n [1 - F_X(w)]^{n-1} (-f_X(w)) \\ = n [1 - F_X(w)]^{n-1} f_X(w)$$

Recordar ↗

3. Suponga $Y_i, i = 1, 2, 3$ denotan una m.a. de una distribución exponencial con f.d.p $f(y) = \frac{1}{\theta} e^{-y/\theta}, y > 0$. Considere:

$$\hat{\theta}_1 = \frac{Y_1 + 2Y_2}{3}, \quad \hat{\theta}_2 = \min\{Y_1, Y_2, Y_3\}, \quad \hat{\theta}_3 = \bar{Y}$$

$$F(y) = 1 - e^{-y/\theta}, y \geq 0$$

(a) Determina cuál de estos estimadores es insesgado

(b) ¿Cuál tiene la varianza más pequeña?

$$(a) \quad E[\hat{\theta}_1] = E\left[\frac{Y_1 + 2Y_2}{3}\right] = \frac{1}{3} E[Y_1] + \frac{2}{3} E[Y_2] = \frac{1}{3} \theta + \frac{2}{3} \theta = \theta \quad \checkmark$$

$$\text{Sabemos que: } f_{Y(r)}(y) = \frac{n!}{(r-1)!(n-r)!} [F(y)]^{r-1} [1-F(y)]^{n-r} f(y)$$

$$\text{En particular } f_{Y(1)} = n [1-F(y)]^{n-1} f(y) = n [1 - 1 + e^{-y/\theta}]^{n-1} \cdot \frac{1}{\theta} e^{-y/\theta} \quad Y_i \sim \text{Exp}(\frac{1}{\theta})$$

$$\text{Con } n=3 \quad f_{Y(1)}(y) = \frac{3}{\theta} e^{-3y/\theta}, y \geq 0 \quad \xrightarrow{\quad} \text{Exp}\left(\frac{3}{\theta}\right) = \frac{n}{\theta} e^{-ny/\theta}$$

$$E[\hat{\theta}_2] = \frac{\theta}{3} \neq \theta \quad \left(\because \text{Si } Y \sim \text{Exp}\left(\frac{1}{\theta}\right) \Rightarrow E[Y] = \theta \right)$$

∴ No es insesgado

$$E(\hat{\theta}_3) = E(\bar{Y}) = E\left[\frac{Y_1 + Y_2 + Y_3}{3}\right] = \frac{1}{3} E[Y_1 + Y_2 + Y_3] = \frac{1}{3} 3 E[Y_1] = \theta \quad \text{es insesgado}$$

(b)

$$V(\hat{\theta}_1) = V\left[\frac{Y_1 + 2Y_2}{3}\right] = \frac{1}{9} (V[Y_1] + 4V[Y_2]) = \frac{1}{9} (\theta^2 + 4\theta^2) = \frac{5}{9} \theta^2$$

$$V(\hat{\theta}_2) = \frac{\theta^2}{9} \quad \because \quad \hat{\theta}_2 \sim \text{Exp}\left(\frac{3}{\theta}\right)$$

$$V(\hat{\theta}_3) = V\left[\bar{Y}\right] = V\left[\frac{Y_1 + Y_2 + Y_3}{3}\right] = \frac{1}{9} V[Y_1 + Y_2 + Y_3] = \frac{1}{9} (\theta^2 + \theta^2 + \theta^2) = \frac{\theta^2}{3}$$

Como $\hat{\theta}_2$ es sesgado es más eficiente comparar $V(\hat{\theta}_1)$ y $V(\hat{\theta}_3)$

$$\text{Vemos que } V(\hat{\theta}_1) = \frac{5\theta^2}{9} > \frac{\theta^2}{3} = V(\hat{\theta}_3) \quad \therefore \quad \hat{\theta}_3 \text{ es más eficiente.}$$

4. Si $Y \sim \text{Bin}(n, p)$. Demuestra que:

(a) $\hat{p}_1 = \frac{Y}{n}$ es insesgado.

(b) Sea $\hat{p}_2 = \frac{(Y+1)}{(n+2)}$ deduzca el sesgo de \hat{p}_2

(c) Dime los valores de p para los que $MSE(\hat{p}_1) < MSE(\hat{p}_2)$

$$\text{Caus } Y \sim \text{Bin}(n, p) \Rightarrow E[Y] = np, \quad V(Y) = np(1-p)$$

$$(a) \quad E[\hat{p}_1] = E\left[\frac{Y}{n}\right] = \frac{1}{n} E[Y] = \frac{np}{n} = p$$

$$(b) \quad E[\hat{p}_2] = E\left[\frac{Y+1}{n+2}\right] = \frac{1}{n+2} E[Y+1] = \frac{np+1}{n+2}$$

$$B(\hat{p}_2) = E(\hat{p}_2) - p = \frac{np+1}{n+2} - p = \frac{np+1 - (n+2)p}{n+2}$$

$$(c) \quad MSE_{\hat{p}_1} = V(\hat{p}_1) = V\left(\frac{Y}{n}\right) = \frac{np(1-p)}{n^2} = \frac{p(1-p)}{n}$$
$$= \frac{np+1 - np - 2p}{n+2} = \frac{1-2p}{n+2}$$

$$MSE_2 = V(\hat{p}_1) + B^2(\hat{p}_2)$$

$$= \frac{np(1-p)}{(n+2)^2} + \frac{(1-2p)^2}{(n+2)^2} = \frac{np(1-p) + (1-2p)^2}{(n+2)^2}$$

$$\therefore MSE_{\hat{p}_1} = \underbrace{\frac{p(1-p)}{n}}_{>0} < \underbrace{\frac{np(1-p)}{(n+2)^2}}_{>0} + \frac{(1-2p)^2}{(n+2)^2}$$

$$\Leftrightarrow 0 < \frac{(1-2p)^2}{(n+2)^2} \Leftrightarrow 0 < (1-2p)^2 \Leftrightarrow 0 < \widehat{1-2p} \Leftrightarrow p < \frac{1}{2}$$

$0 \leq p \leq 1$

5. Suponga que $X_i, Y_i, i = 1, 2, \dots, n$ son m.a.'s independientes provenientes de poblaciones con medias μ_1, μ_2 y varianzas σ_1, σ_2 respectivamente. Demuestre que $\bar{X} - \bar{Y}$ es un estimador consistente de $\mu_1 - \mu_2$

Vamos a ver si es insesgado.

$$E[\bar{X} - \bar{Y}] = E[\bar{X}] - E[\bar{Y}] = E\left[\frac{\sum X_i}{n}\right] - E\left[\frac{\sum Y_i}{n}\right] = \frac{1}{n}(E[\sum X_i] - E[\sum Y_i])$$

independencia \rightarrow

$$= \frac{1}{n}(n\mu_1 - n\mu_2) = \mu_1 - \mu_2 \checkmark$$

$$V(\bar{X} - \bar{Y}) = V(\bar{X}) + V(\bar{Y}) - 2\text{Cov}(\bar{X}, \bar{Y}) \xrightarrow{0 \because X \perp Y}$$

$$= V(\bar{X}) + V(\bar{Y}) = V\left(\frac{1}{n} \sum X_i\right) + V\left(\frac{1}{n} \sum Y_i\right)$$

$$= \frac{1}{n^2} V(\sum X_i) + \frac{1}{n^2} V(\sum Y_i) = \frac{1}{n^2} \left[\sum V(X_i) + \sum_{i \neq j} \text{Cov}(X_i, X_j) \right] + \frac{1}{n^2} \left[\sum V(Y_i) + \sum_{i \neq j} \text{Cov}(Y_i, Y_j) \right]$$

$$\Rightarrow \lim_{n \rightarrow \infty} V(\bar{X} - \bar{Y}) = \lim_{n \rightarrow \infty} \frac{\sigma_1^2 + \sigma_2^2}{n} = \frac{\sigma_1^2 + \sigma_2^2}{n}$$

$$= 0 \checkmark \therefore \bar{X} - \bar{Y} \text{ es consistente}$$

Otra forma

$$\lim_{n \rightarrow \infty} E[\bar{X} - \bar{Y}] = \lim_{n \rightarrow \infty} \mu_1 - \mu_2 = \mu_1 - \mu_2$$

6. Se dice que $\hat{\theta}$, un estimador insesgado de θ es consistente en $MSE(\hat{\theta})$ si $\lim_{n \rightarrow \infty} MSE(\hat{\theta}) = 0$.

(a) Pruebe que $\hat{\theta}$ es consistente en $MSE(\hat{\theta})$ si y sólo si $\lim_{n \rightarrow \infty} V(\hat{\theta}) = 0$

(b) Pruebe que consistencia en MSE implica consistencia en probabilidad.

(c) Use estos dos incisos para demostrar que $\hat{\theta}$ es consistente si $\lim_{n \rightarrow \infty} E(\hat{\theta}) = \theta$

(a)

\Rightarrow Nos dicen que $\hat{\theta}$ es insesgado $\therefore B(\hat{\theta}) = 0 \Rightarrow \lim_{n \rightarrow \infty} B(\hat{\theta}_n) = 0$

Como $\hat{\theta}$ también es consistente en $MSE_{\hat{\theta}}$

$$\lim_{n \rightarrow \infty} MSE_{\hat{\theta}_n} = \lim_{n \rightarrow \infty} V(\hat{\theta}_n) + \cancel{B^2(\hat{\theta}_n)}^0 = \lim_{n \rightarrow \infty} V(\hat{\theta}_n) = 0 \quad \checkmark$$

\Leftarrow Si $\hat{\theta}$ es consistente por dfn $\lim_{n \rightarrow \infty} V(\hat{\theta}_n) = 0$ y como $\lim_{n \rightarrow \infty} B(\hat{\theta}_n) = 0$

se tiene que $\lim_{n \rightarrow \infty} V(\hat{\theta}_n) + \lim_{n \rightarrow \infty} B^2(\hat{\theta}_n) = 0 = \lim_{n \rightarrow \infty} MSE_{\hat{\theta}_n} \quad \checkmark$

(b) p.d $\lim_{n \rightarrow \infty} MSE_{\hat{\theta}} = 0 \Rightarrow \lim_{n \rightarrow \infty} P\{|\hat{\theta} - \theta| > \epsilon\} = 0$

Sabemos que $\hat{\theta}_n$ es insesgado y consistente en $MSE_{\hat{\theta}}$. Sea $\epsilon > 0$

y aplicamos Desigualdad de Markov Recordar (Lab 1) $P\{g(x) \geq k\} \leq \frac{E(g(x))}{k}$

Tomamos como $g(\theta) = \hat{\theta}_n - \theta$ y $k = \epsilon$

¿Por qué esto es cierto? \checkmark
Hint: Ley Débil de grandes #s

$$\Rightarrow 0 \leq P\{|\hat{\theta}_n - \theta| \geq \epsilon\} \leq \frac{E[(\hat{\theta}_n - \theta)^2]}{\epsilon^2} = \frac{MSE[\hat{\theta}_n]}{\epsilon^2}$$

Axioma
Kolmogorov

Como $\hat{\theta}_n$ es consistente en MSE entonces $\lim_{n \rightarrow \infty} MSE_{\hat{\theta}_n} = 0$

$$\therefore \lim_{n \rightarrow \infty} P\{|\hat{\theta}_n - \theta| \geq \epsilon\} \leq \lim_{n \rightarrow \infty} \frac{MSE_{\hat{\theta}_n}}{\epsilon^2} = \lim_{n \rightarrow \infty} \frac{V(\hat{\theta}_n)}{\epsilon^2} = 0$$

(c)

Ahora, si θ es consistente en $MSE_{\hat{\theta}_n}$ se tiene que converge en probabilidad

$$\lim_{n \rightarrow \infty} MSE_{\hat{\theta}_n} = \lim_{n \rightarrow \infty} \underbrace{V(\hat{\theta}_n)}_{\geq 0} + \lim_{n \rightarrow \infty} \underbrace{B^2(\hat{\theta}_n)}_{\geq 0} = 0 \Leftrightarrow \lim_{n \rightarrow \infty} V(\hat{\theta}_n) = 0 \quad \text{y} \quad \lim_{n \rightarrow \infty} B^2(\hat{\theta}_n) = 0 \quad (*)$$

Si analizamos $(*)$ se tiene que

$$\lim_{n \rightarrow \infty} B^2(\hat{\theta}_n) = 0 \Leftrightarrow \lim_{n \rightarrow \infty} B(\hat{\theta}_n) = \lim_{n \rightarrow \infty} E(\hat{\theta}_n) - \lim_{n \rightarrow \infty} \theta \Rightarrow \lim_{n \rightarrow \infty} E(\hat{\theta}_n) = \theta$$

$\hookrightarrow \therefore B'(\hat{\theta}_n) \geq 0$

7. Sea X_i $i = 1, 2, \dots, n$ una m.a de $X_i \sim U(0, \theta) \quad \forall i$, use el ejercicio anterior para demostrar que $T = X_{(n)}$ es consistente.

Sabemos que $\hat{\theta}_n$ es consistente si $\lim_{n \rightarrow \infty} E(\hat{\theta}_n) = \theta$

Se puede demostrar que $F_{X_{(n)}} = [F_X(x)]^n = \left(\frac{x}{\theta}\right)^n \Rightarrow f_{X_{(n)}} = \frac{n}{\theta} \left(\frac{x}{\theta}\right)^{n-1}$

Tenemos $T = X_{(n)}$

$$E[T] = \int_0^\theta x \cdot \frac{n}{\theta} \left(\frac{x}{\theta}\right)^{n-1} dx = \frac{n}{\theta^n} \int_0^\theta x^n dx = \frac{n}{\theta^n} \frac{x^{n+1}}{n+1} \Big|_0^\theta = \frac{n}{\theta^n} \frac{\theta^{n+1}}{n+1} = \frac{n\theta}{n+1}$$

$$\Rightarrow \lim_{n \rightarrow \infty} E[T] = \lim_{n \rightarrow \infty} E[X_{(n)}] = \lim_{n \rightarrow \infty} \frac{n\theta}{n+1} = \theta \lim_{n \rightarrow \infty} \frac{n}{n+1}$$

$$= \theta \lim_{n \rightarrow \infty} \frac{1}{1 + \frac{1}{n}} = \theta$$