

PRACCIÓN NOTURNA

1) $E(X) = \mu$ $V(X) = \sigma^2$

$\bar{X}_1 = \frac{1}{n-1} \sum_{i=1}^{n-1} x_i$ $\bar{X}_2 = \frac{1}{n} \sum_{i=1}^n x_i$

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

$E(\bar{X}_2) = \mu$ $\therefore b(\bar{X}_2) = 0$

$\therefore ECN(\bar{X}_2) = \frac{\sigma^2}{n}$

$ECN(\bar{X}_1) = V(\bar{X}_1) + b((\bar{X}_1))^2$

$E(\bar{X}_1) = \mu$ $\therefore b(\bar{X}_1) = 0$

$\therefore ECN(\bar{X}_1) = \frac{\sigma^2}{n-1}$

$ECN(\bar{X}_1) > ECN(\bar{X}_2)$ $\therefore \bar{X}_2$ es mejor estimador puntual que \bar{X}_1

calc. aux

$E(\bar{X}_1) = E\left(\frac{1}{n-1} \sum_{i=1}^{n-1} x_i\right) = \frac{1}{n-1} E\left(\sum_{i=1}^{n-1} x_i\right) =$

$\frac{1}{n-1} \sum_{i=1}^{n-1} E(x_i) = \frac{1}{n-1} \sum_{i=1}^{n-1} \mu = \frac{1}{n-1} (n-1) \mu = \mu$

(creo que costaba solo calcular varianza)

2) x_1, x_2, \dots, x_4 muestra aleatoria de v.a. X

$\mu = E(X)$ $\sigma^2 = V(X)$

$\hat{\mu}_1 = \frac{x_1 + x_2 + \dots + x_4}{4}$

$\hat{\mu}_2 = \frac{2x_1 - x_3 + x_4}{2}$

$\hat{\mu}_3 = \frac{2x_1 - x_3 + x_2}{3}$

a)

$$E(\hat{\mu}_1) = E\left(\frac{1}{5} \sum_{i=1}^5 X_i\right) = E(\bar{X}) = \mu$$

$\therefore \hat{\theta}_1$ es insesgado

$$\begin{aligned} E(\hat{\mu}_2) &= E\left(\frac{2X_1 - X_6 + X_4}{2}\right) = \frac{1}{2} E(2X_1 - X_6 + X_4) = \\ &= \frac{1}{2} \cdot (2E(X_1) - E(X_6) + E(X_4)) = \frac{1}{2} \cdot (2\mu - \mu + \mu) = \\ &= \mu - \frac{1}{2}\mu + \frac{1}{2}\mu = \mu \quad \therefore \hat{\theta}_2 \text{ es insesgado} \end{aligned}$$

$$\begin{aligned} E(\hat{\mu}_3) &= E\left(\frac{2X_1 - X_7 + X_3}{3}\right) = \frac{1}{3} E(2X_1 - X_7 + X_3) = \\ &= \frac{1}{3} [2E(X_1) - E(X_7) + E(X_3)] = \frac{1}{3} [2\mu - \mu + \mu] = \\ &= \frac{2}{3}\mu - \frac{1}{3}\mu + \frac{1}{3}\mu = \frac{2}{3}\mu \end{aligned}$$

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

$$\therefore ECN(\hat{\mu}_1) = V(\hat{\mu}_1) + (b(\hat{\mu}_1))^2 = V(\hat{\mu}_1) = \frac{\sigma^2}{4}$$

$$= \boxed{\frac{\sigma^2}{4}}$$

$$b(\hat{\mu}_1) = 0 \quad \downarrow \text{es insesgado}$$

$$\begin{aligned} V(\hat{\mu}_2) &= V\left(\frac{2X_1 - X_6 + X_4}{2}\right) = \left(\frac{1}{2}\right)^2 V(2X_1 - X_6 + X_4) = \\ &= \frac{1}{4} \cdot [4V(X_1) + V(X_6) + V(X_4)] = \frac{1}{4} \cdot [4\sigma^2 + \sigma^2 + \sigma^2] = \\ &= \sigma^2 + \frac{1}{4}\sigma^2 + \frac{1}{4}\sigma^2 = \frac{3}{2}\sigma^2 \end{aligned}$$

$$b(\hat{\mu}_2) = 0 \rightarrow \text{es insesgado}$$

$$\therefore \text{ECM}(\hat{\mu}_2) = V(\hat{\mu}_2) = \boxed{\frac{3}{2} \sigma^2}$$

$$\begin{aligned} V(\hat{\mu}_3) &= V\left(\frac{2x_1 - x_2 + x_3}{3}\right) = \left(\frac{1}{3}\right)^2 V(2x_1 - x_2 + x_3) = \\ &= \frac{1}{9} [4V(x_1) + V(x_2) + V(x_3)] = \frac{1}{9} [4\sigma^2 + \sigma^2 + \sigma^2] = \\ &= \frac{4}{9} \sigma^2 + \frac{1}{9} \sigma^2 + \frac{1}{9} \sigma^2 = \frac{6}{9} \sigma^2 = \frac{2}{3} \sigma^2 \end{aligned}$$

$$b(\hat{\mu}_3) = E(\hat{\mu}_3) - \mu = \frac{2}{3} \mu - \mu = -\frac{1}{3} \mu$$

$$\begin{aligned} \therefore \text{ECM}(\hat{\mu}_3) &= V(\hat{\mu}_3) + (b(\hat{\mu}_3))^2 = \frac{2}{3} \sigma^2 + \left(-\frac{1}{3} \mu\right)^2 = \\ &= \boxed{\frac{2}{3} \sigma^2 + \frac{\mu^2}{9}} \end{aligned}$$

$$c) \text{ECM}(\hat{\mu}_1) = \frac{1}{4} \sigma^2 \quad \text{ECM}(\hat{\mu}_2) = \frac{3}{2} \sigma^2 \quad \text{ECM}(\hat{\mu}_3) = \frac{2}{3} \sigma^2 + \frac{\mu^2}{9}$$

$$\text{NOTAR que } \frac{2}{3} \sigma^2 > \frac{1}{4} \sigma^2 \quad \therefore \frac{2}{3} \sigma^2 + \frac{\mu^2}{9} > \frac{1}{4} \sigma^2$$

$$\text{y que } \frac{3}{2} \sigma^2 > \frac{1}{4} \sigma^2$$

$\therefore \hat{\mu}_1$ es mejor estimador puntual que $\hat{\mu}_2$ y $\hat{\mu}_3$
mejor en el sentido de que todos los valores se acercan más a μ

3) sea x_1, x_2, \dots, x_n

a) $\hat{\mu}^2 = \bar{x}^2$ es estimador sesgado de μ^2

$$E(\hat{\mu}^2) = E(\bar{x}^2) = \frac{V(\bar{x})}{n} + \underbrace{(E(x))^2}_{\mu} = \frac{\sigma^2}{n} + \mu^2 \neq \mu^2$$

$$b) b(\hat{\mu}^2) = b(\bar{x}^2) = E(\bar{x}^2) - \mu^2 = \boxed{\frac{\sigma^2}{n}}$$

NOTA

c) a medida que aumenta n , disminuye el riesgo puesto que el denominador se va cada vez más grande (con el mismo numerador) y se reparten valores más pequeños, es decir, es más consistente porque se acerca cada vez más a 0.

4) a) Sea x_1, x_2, \dots, x_n una muestra aleatoria de un v.a. X , donde $X \sim P(\lambda)$. X : "nro diario de desconexiones".

$$L(x_1, x_2, x_3, \dots, x_n, \lambda) \stackrel{\text{indep.}}{=} P(X_1 = x_1) \cdot P(X_2 = x_2) \cdot P(X_3 = x_3) \cdot \dots \cdot P(X_n = x_n) = \frac{e^{-\lambda} \lambda^{x_1}}{x_1!} \cdot \frac{e^{-\lambda} \lambda^{x_2}}{x_2!} \cdot \dots \cdot \frac{e^{-\lambda} \lambda^{x_n}}{x_n!} = \frac{(e^{-\lambda})^n \lambda^{\sum_{i=1}^n x_i}}{\prod_{i=1}^n x_i!} = \frac{e^{-\lambda n} \lambda^{\sum_{i=1}^n x_i}}{\prod_{i=1}^n x_i!}.$$

Para facilitar cálculos se toma $\ln L(x_1, x_2, \dots, x_n, \lambda)$.

$$\begin{aligned} \ln L(x_1, x_2, \dots, x_n) &= \ln \left(\frac{e^{-\lambda n} \lambda^{\sum_{i=1}^n x_i}}{\prod_{i=1}^n x_i!} \right) = \\ &= \ln \left(e^{-\lambda n} \lambda^{\sum_{i=1}^n x_i} \right) - \ln \left(\prod_{i=1}^n x_i! \right) = \ln \left(e^{-\lambda n} \right) + \ln \left(\lambda^{\sum_{i=1}^n x_i} \right) - \\ &= \ln \left(\prod_{i=1}^n x_i! \right) = (-\lambda n) \cdot \frac{\ln e}{=1} + \left(\sum_{i=1}^n x_i \right) \ln \lambda - \ln \left(\prod_{i=1}^n x_i! \right) = \\ &= (-\lambda n) + \left(\sum_{i=1}^n x_i \right) \ln \lambda - \ln \left(\prod_{i=1}^n x_i! \right) = \end{aligned}$$

$$\frac{d}{d\lambda} \ln L(x_1, x_2, \dots, x_n, \lambda) = 0 \Rightarrow -n + \left(\sum_{i=1}^n x_i \right) \frac{1}{\lambda} - 0 = 0$$

$$\therefore n = \left(\sum_{i=1}^n x_i \right) \frac{1}{\lambda} \Rightarrow \lambda = \frac{1}{n} \sum_{i=1}^n x_i = \bar{x} \quad \text{se puede verificar que}$$

$$\therefore \lambda = \frac{1}{n} \sum_{i=1}^n x_i$$

$L(x_1, x_2, \dots, x_n, \lambda)$ tiene en $\lambda = \bar{x}$ un max. abs.

es irreducible por ser el \bar{X} , y es consistente porque el sesgo es 0 $\therefore b(\bar{X}) \rightarrow 0$ $V(\bar{X}) = \frac{\sigma^2}{n} \rightarrow 0$ $n \rightarrow \infty$

b) $\lambda = \bar{X} = \frac{1}{5} \sum_{i=1}^5 x_i = \frac{2+5+3+3+7}{5} = \boxed{4}$

c) Hallar ENV de $P(X \geq 3) = \frac{e^{-\lambda} \lambda^3}{3!}$

el ENV sera (prop. invariancia)

$$g(\hat{\lambda}) = \frac{e^{-\hat{\lambda}} \hat{\lambda}^3}{3!} = \frac{e^{-\bar{X}} \bar{X}^3}{3!}$$

estimación $\Rightarrow \frac{e^{-4} 4^3}{3!} = 0,195367$

$X_i \begin{cases} 1 & \text{si es out} \\ 0 & \text{c.c} \end{cases}$

5) a) X_1, X_2, \dots, X_n una muestra aleatoria de una v.a $B(1, p)$

E.N.V

indep.

$$L(X_1, X_2, \dots, X_n, p) \stackrel{\uparrow}{=} P(X_1=x_1) \cdot P(X_2=x_2) \dots P(X_n=x_n) =$$

$$= p^{x_1} (1-p)^{1-x_1} \cdot p^{x_2} (1-p)^{1-x_2} \dots p^{x_n} (1-p)^{1-x_n}$$

$$= p^{\sum_{i=1}^n x_i} \cdot (1-p)^{\sum_{i=1}^n (1-x_i)}$$

$$\ln L(X_1, X_2, \dots, X_n, p) = \ln \left(p^{\sum_{i=1}^n x_i} \right) + \ln \left((1-p)^{\sum_{i=1}^n (1-x_i)} \right) =$$

$$= \sum_{i=1}^n x_i \ln p + \left(n - \sum_{i=1}^n x_i \right) \ln (1-p)$$

$$\frac{d}{dp} \ln L(X_1, X_2, \dots, X_n, p) = 0 \Rightarrow \left(\sum_{i=1}^n x_i \right) \cdot \frac{1}{p} + \left(n - \sum_{i=1}^n x_i \right) \cdot \frac{1}{1-p} \cdot (-1) = 0$$

$$\Rightarrow \frac{\sum_{i=1}^n x_i}{p} - \frac{n - \sum_{i=1}^n x_i}{1-p} = 0 \Rightarrow \frac{\sum_{i=1}^n x_i}{p} = \frac{n - \sum_{i=1}^n x_i}{1-p}$$

$$\Rightarrow \frac{1-p}{p} = \frac{n - \sum_{i=1}^n x_i}{\sum_{i=1}^n x_i} \Rightarrow \frac{1}{p} - 1 = \frac{n}{\sum_{i=1}^n x_i} - 1 \Rightarrow p = \frac{\sum_{i=1}^n x_i}{n} = \bar{X}$$

NOTA

si x_i
es \neq
a 1 o
a 0
no
indep.

$\binom{1}{x_i}$

$$\therefore \hat{p} = \bar{X}$$

$$b) \quad n=100 \quad x=5 \quad \rightarrow \quad \sum_{i=1}^{100} x_i = 5$$

$$\text{estimación de } p \text{ es } \hat{p} = \bar{X} = \frac{1}{100} \cdot \sum_{i=1}^{100} x_i = \frac{5}{100} = 0,05$$

$$b2) \quad n=100 \quad \sum_{i=1}^{100} x_i = 5 \quad \hat{p} = \bar{X}$$

$$g(p) = (1-p)^6$$

$$\cdot \text{ENV } (1-p)^6$$

$$g(\hat{p}) = g(\bar{X}) = (1-\bar{X})^6$$

$$\text{estimación} \rightarrow (1-0,05)^6 = \boxed{0,735092}$$

6) X "proporción de tiempo que un estudiante emplea trabajando en su prueba de admisión"

$$f(x) = \begin{cases} (2\theta+1)x^{2\theta} & , 0 \leq x \leq 1 \\ 0 & , \text{oc} \end{cases}$$

$$\text{condición } \theta > -\frac{1}{2}$$

a) método de los momentos

$$\mu_1 = E(X) = \int_0^1 x \cdot [(2\theta+1) \cdot x^{2\theta}] = (1+2\theta) \frac{1}{2\theta+2}$$

$$\frac{1}{n} \sum_{i=1}^n y_i = \frac{1+2\theta}{2\theta+2} \Rightarrow$$

$$\Rightarrow \frac{1}{\bar{X}} = \frac{1+2\theta}{2\theta+2} \Rightarrow 1+2\theta = \bar{X} \cdot (2\theta+2) \Rightarrow$$

$$\Rightarrow 1+2\theta = 2\theta \cdot \bar{X} + 2\bar{X} \Rightarrow 2\theta = 2\theta \bar{X} + 2\bar{X} - 1$$

$$\Rightarrow 2\theta - 2\theta \bar{X} = 2\bar{X} - 1 \Rightarrow (2 - 2\bar{X})\theta = 2\bar{X} - 1 \Rightarrow$$

$$\theta = \frac{2\bar{x} - 1}{2 - 2\bar{x}}$$

$$\therefore \hat{\theta} = \frac{2 \cdot \left[\frac{1}{n} \sum_{i=1}^n x_i \right] - 1}{2 - 2 \left[\frac{1}{n} \sum_{i=1}^n x_i \right]}$$

← estimación

estimación

$$\frac{1}{n} \cdot \sum_{i=1}^n x_i = \frac{1}{10} \cdot \sum_{i=1}^{10} x_i = \frac{4}{5} = \bar{x}$$

$$\hat{\theta} = \frac{2 \cdot \frac{4}{5} - 1}{2 - 2 \cdot \frac{4}{5}} = \frac{\frac{3}{5}}{\frac{2}{5}} = \frac{3}{2} = 1,5$$

$$\therefore \hat{\theta} = 1,5 \text{ (estimación)}$$

b) EMV

$$\begin{aligned} L(x_1, x_2, \dots, x_n, \theta) &= f(x_1) \cdot f(x_2) \cdot \dots \cdot f(x_n) = \\ &= (2\theta + 1)x_1^{2\theta} \cdot (2\theta + 1)x_2^{2\theta} \cdot \dots \cdot (2\theta + 1)x_n^{2\theta} = \\ &= (2\theta + 1)^n \cdot \prod_{i=1}^n x_i^{2\theta} \end{aligned}$$

$$\ln L(x_1, x_2, \dots, x_n, \theta) = \ln((2\theta + 1)^n) + \sum_{i=1}^n \ln(x_i^{2\theta}) =$$

$$= n \cdot \ln(2\theta + 1) + 2\theta \sum_{i=1}^n \ln(x_i) =$$

$$\frac{d}{d\theta} \ln L(x_1, x_2, \dots, x_n, \theta) = 0$$

$$\frac{2n}{2\theta + 1} + 2 \sum_{i=1}^n \ln(x_i) = 0$$

$$\Rightarrow \frac{2n}{2\theta + 1} - 2 \sum_{i=1}^n \ln(x_i) \Rightarrow 2\theta + 1 = - \frac{n}{\sum_{i=1}^n \ln(x_i)}$$

$$\Rightarrow 2\theta = - \frac{n}{\sum_{i=1}^n \ln(x_i)} - 1 \Rightarrow \theta = \left[- \frac{n}{\sum_{i=1}^n \ln(x_i)} - 1 \right] : 2$$

NOTA

$$\hat{\theta} = \left[-\frac{n}{\sum_{i=1}^n \ln(x_i)} - 1 \right] : 2 \quad \leftarrow \text{estimación}$$

estimation

$$-\sum_{i=1}^{10} \ln(x_i) = 2,4295 \quad n=10$$

$$\hat{\theta} = \frac{\frac{10}{2,4295} - 1}{2} = 1,55804$$

4) a y b errores en teoría (σ^2 no es insignificante, también demostrado en teoría)

$$\hat{\mu} = \bar{x}$$

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

$$c) \mu = \bar{x} = 384,4$$

estimation

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} = 18,85841987$$

→ desviación estándar poblacional

$$d) P(X < 420) = ? \quad \cdot \mu = 384,4 \quad \cdot \sigma = 18,85841987$$

$$P(X < 420) = 0,94047$$

estimación