

## Práctica 6. - Matemática 3.

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

$$= \frac{1}{n-1} \sum_{i=1}^m \mu = \frac{1}{n-1} m\mu = \frac{\mu n}{n-1}$$

$$V(\bar{X}_1) = V\left(\frac{1}{n-1} \sum_{i=1}^m x_i\right) = \left(\frac{1}{n-1}\right)^2 \cdot V\left(\sum_{i=1}^m x_i\right)$$

$$= \frac{1^2}{(n-1)^2} \cdot \sum_{i=1}^m V(x_i) = \frac{1}{(n-1)^2} \sum_{i=1}^m \sigma^2$$

$$= \frac{1}{(n-1)^2} \cdot n\sigma^2 = \frac{n\sigma^2}{n-1}$$

$$ECM(\bar{X}_1) = \{E[\bar{X}_1 - E(\bar{X}_1)]^2 + V(\bar{X}_1)\}$$

$$= (\mu - \mu)^2 + \frac{n\sigma^2}{n-1} = \frac{n\sigma^2}{n-1}$$

$$\cdot E(\bar{X}_2) = E\left(\frac{1}{n} \sum_{i=1}^n x_i\right) = \frac{1}{n} \cdot \sum_{i=1}^n E(x_i) = \frac{1}{n} \cdot n \cdot \mu$$

$$= \mu$$

$$V(\bar{X}_2) = V\left(\frac{1}{n} \sum_{i=1}^n x_i\right) = \frac{1}{n} \sum_{i=1}^n V(x_i) = \frac{1}{n} n V(x_i)$$

$$= \frac{1}{n} n \sigma^2 = \sigma^2$$

$$ECM(\bar{X}_2) = \{E[\bar{X}_2 - E(\bar{X}_2)]^2 + V(\bar{X}_2)\}$$

$$= (\mu - \mu)^2 + \sigma^2 = \sigma^2$$

$\therefore \bar{X}_2$  es el mejor estimador porque tiene menor ECM.

$$2) a) E(\theta_1) = E\left(\frac{x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7}{7}\right) = \text{Por linealidad de la esperanza}$$

$$= \frac{E(x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7)}{7} = \text{Por linealidad de la esp.}$$

$$= \frac{E(X_1) + E(X_2) + E(X_3) + E(X_4) + E(X_5) + E(X_6) + E(X_7)}{7}$$

$$= \frac{7E(X_1)}{7} = E(X_1) = \mu$$

~~scribble~~

$$E(\theta_2) = E\left(\frac{2X_1 - X_6 + X_4}{2}\right) = \frac{E(2X_1 - X_6 + X_4)}{2} =$$

$$= \text{Por linealidad} = \frac{E(2X_1) - E(X_6) + E(X_4)}{2} =$$

$$= \frac{2E(X_1) - E(X_6) + E(X_4)}{2} = \frac{2\mu}{2} = \mu$$

$$E(\theta_3) = E\left(\frac{2X_1 - X_7 + X_3}{3}\right) = \frac{E(2X_1 - X_7 + X_3)}{3} =$$

$$= \text{por linealidad} = \frac{2E(X_1) - E(X_7) + E(X_3)}{3} =$$

$$= \frac{2\mu}{3} = \frac{2}{3}\mu$$

$\therefore \theta_1$  y  $\theta_2$  son insesgales.

$$b) V(\theta_1) = V\left(\frac{X_1 + X_2 + \dots + X_7}{7}\right) = \left(\frac{1}{7}\right)^2 V(X_1 + X_2 + \dots + X_7) =$$

$$= \text{por independencia} = \frac{1}{49} [V(X_1) + V(X_2) + \dots + V(X_7)] =$$

$$= \frac{1}{49} \cdot 7 \cdot \sigma^2 = \frac{1}{7} \sigma^2$$

$$V(\theta_2) = V\left(\frac{2X_1 - X_6 + X_4}{2}\right) = \left(\frac{1}{2}\right)^2 [V(2X_1) - V(X_6) + V(X_4)] =$$

↓  
por ind.



$$= \frac{1}{4} [2V(X_1) - V(X_6) + V(X_4)] = \frac{1}{4} [2\sigma^2 - \sigma^2 + \sigma^2];$$

$$= \frac{2\sigma^2}{4} = \frac{1}{2} \sigma^2$$

$$V(\theta_3) = V\left(\frac{2X_1 - X_7 + X_3}{3}\right) = \left(\frac{1}{3}\right)^2 [V(2X_1) - V(X_7) + V(X_3)] =$$

↓  
por ind.

$$= \frac{1}{9} [2\sigma^2 - \sigma^2 + \sigma^2] = \frac{2}{9} \sigma^2$$

$$\begin{aligned} ECM(\theta_1) &= E(\theta_1 - E(\theta_1))^2 + V(\theta_1) = E(\theta_1 - \mu)^2 + \frac{1}{7} \sigma^2 = \\ &= \text{por linealidad} = (E(\theta_1) - E(\mu))^2 + \frac{1}{7} \sigma^2 = \\ &= (\mu - \mu)^2 + \frac{1}{7} \sigma^2 = \frac{1}{7} \sigma^2 \end{aligned}$$

$$\begin{aligned} ECM(\theta_2) &= E(\theta_2 - E(\theta_2))^2 + V(\theta_2) = E(\theta_2 - \mu)^2 + \frac{1}{2} \sigma^2 = \\ &= \text{por linealidad} = (\mu - \mu)^2 + \frac{1}{2} \sigma^2 = \frac{1}{2} \sigma^2 \end{aligned}$$

$$\begin{aligned} ECM(\theta_3) &= E(\theta_3 - E(\theta_3))^2 + V(\theta_3) = E\left(\theta_3 - \frac{2}{3}\mu\right)^2 + \frac{2}{9} \sigma^2 = \\ &= \text{por linealidad} = \left(\frac{2}{3}\mu - \frac{2}{3}\mu\right)^2 + \frac{2}{9} \sigma^2 = \frac{2}{9} \sigma^2 \end{aligned}$$

$$\therefore \frac{2}{9} \sigma^2 = \frac{2}{9} \sigma^2$$

c)  $\therefore \text{Mezor}[ECM(\theta_1), ECM(\theta_2), ECM(\theta_3)] = ECM(\theta_1) =$

$$= \frac{1}{7} \sigma^2$$

3) a)  $E(x_i) = \mu$  ;  $V(x_i) = \sigma^2$  ,  $V(\bar{x}) = \frac{\sigma^2}{n}$

$$\hookrightarrow E(\bar{x}^2) = V(\bar{x}) + (E(\bar{x}))^2 = V\left(\frac{\sum_{i=1}^n x_i}{n}\right) + \left(E\left(\frac{\sum_{i=1}^n x_i}{n}\right)\right)^2 =$$

$$= \frac{V(n x_i)}{n^2} + \left(\frac{E(n x_i)}{n}\right)^2 = \frac{n V(x_i)}{n^2} + \left(\frac{n E(x_i)}{n}\right)^2$$

$$= \frac{n \sigma^2}{n^2} + \mu^2 = \frac{\sigma^2}{n} + \mu^2 \quad \text{por linealidad}$$

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

$\hookrightarrow \bar{x}^2$  es un estimador sesgado de  $\mu^2$  ya que  $\mu^2 \neq \frac{\sigma^2}{n} + \mu^2$ .

c)  $\lim_{n \rightarrow \infty} \left(\frac{\sigma^2}{n}\right) = 0$

4) 'nº diario de desconexiones occidentales de un servidor'  
 $\sim P(\lambda)$ .  $= N \sim P(\lambda)$

a) EMV( $\lambda$ ):  $P(N=k) = \frac{e^{-\lambda} \cdot \lambda^k}{k!}$  ,  $k=0,1,\dots$

$$\rightarrow L(\lambda) = P(N_1=k_1) \cdot P(N_2=k_2) \cdot \dots \cdot P(N_n=k_n)$$

$$= \prod_{i=1}^n \left( \frac{e^{-\lambda} \cdot \lambda^{k_i}}{k_i!} \right) = \frac{e^{-\lambda n} \cdot \lambda^{\sum_{i=1}^n k_i}}{\prod_{i=1}^n k_i!}$$

distribuya

$$= \ln \left( \frac{e^{-\lambda n} \cdot \lambda^{\sum_{i=1}^n k_i}}{\prod_{i=1}^n k_i!} \right)$$

$$= \ln(e^{-\lambda n} \cdot \lambda^{\sum_{i=1}^n k_i}) - \ln\left(\prod_{i=1}^n (k_i!)\right) = \text{prop. de productos del log.} =$$

prop. de derivadas de logaritmos.



$$\begin{aligned}
 &= \ln(e^{-2n}) + \ln(\lambda^{\sum_{i=1}^n (k_i)}) - \ln(\prod_{i=1}^n (k_i!)) = \text{prop. de potencias del log.} = \\
 &= -2n \cdot \ln(e) + \sum_{i=1}^n (k_i) \cdot \ln(\lambda) - \ln(\prod_{i=1}^n (k_i!)) = \\
 &= -2n \cdot 1 + \sum_{i=1}^n (k_i) \ln(\lambda) - \underbrace{\sum_{i=1}^n \ln(k_i!)}_{\text{prop. de productos del log.}}
 \end{aligned}$$

derivando e igualando a 0 para maximizar:

$$\frac{\partial \ln L(\lambda)}{\partial \lambda} = -n + \frac{\sum_{i=1}^n (k_i)}{\lambda} - 0 \stackrel{?}{=} 0$$

$$\frac{\sum_{i=1}^n (k_i)}{\lambda} = n \quad \text{medio muestral: } \frac{\sum_{i=1}^n (k_i)}{n}$$

$$\sum_{i=1}^n (k_i) = n\lambda = \bar{X}$$

Sumando las observaciones  $(2, 5, 3, 3, 7)$ :  $\frac{20}{5} = 4$   
 $n=5$  observaciones  $\nearrow$  b

$$E(\bar{X}) \stackrel{?}{=} \lambda \rightarrow E\left(\frac{\sum_{i=1}^n (k_i)}{n}\right) = \frac{E(\sum_{i=1}^n (k_i))}{n} =$$

$$\begin{aligned}
 &\xrightarrow{\text{por linealidad de la esp.}} \\
 &= \frac{n E(k_i)}{n} = \frac{n E(\lambda)}{n} = E(\lambda) = \lambda \quad \therefore \text{Es un estimador insesgado.} \\
 &\quad \downarrow \text{reemplazando por } \lambda
 \end{aligned}$$

$$c) \lim_{n \rightarrow \infty} E(\bar{X}) \stackrel{?}{=} \lambda \quad y \quad \lim_{n \rightarrow \infty} V(\bar{X}) \stackrel{?}{=} 0 ?$$

$$\begin{aligned} \hookrightarrow \lim_{n \rightarrow \infty} \frac{n E(\lambda)}{n} &= \lim_{n \rightarrow \infty} E(\lambda) = \\ &= \lambda \quad \checkmark \end{aligned}$$

$$\hookrightarrow \lim_{n \rightarrow \infty} (V(\bar{X})) =$$

$$\lim_{n \rightarrow \infty} V\left(\frac{\sum_{i=1}^n (k_i)}{n}\right)$$

$$\downarrow = \lim_{n \rightarrow \infty} \frac{V(\sum_{i=1}^n (k_i))}{n^2}$$

por ind.

$$= \lim_{n \rightarrow \infty} \frac{V(n k_i)}{n^2} =$$

$$= \lim_{n \rightarrow \infty} \frac{n V(k_i)}{n^2} =$$

$$= \lim_{n \rightarrow \infty} \frac{n \lambda}{n^2} = \lim_{n \rightarrow \infty} \frac{\lambda}{n}$$

$$= 0 \quad \checkmark$$

$\hookrightarrow \therefore \lambda_i$ , es consistente el estimador.

b) Hecho.

$$\begin{aligned} c) P(N \geq 3) &= 1 - P(N < 3) = 1 - (P(N=0) + P(N=1) + P(N=2)) = \\ &= 1 - \left( \frac{e^{-\lambda} \cdot \lambda^0}{0!} + \frac{e^{-\lambda} \cdot \lambda^1}{1!} + \frac{e^{-\lambda} \cdot \lambda^2}{2!} \right) = 1 - \left( e^{-\lambda} \left( 1 + \lambda + \frac{\lambda^2}{2} \right) \right) \end{aligned}$$

Factor  
Común

$$\Rightarrow \hat{P}_{EMV}(\geq 3 | \hat{\lambda}_{EMV}) = 1 - e^{-\hat{\lambda}_{EMV}} \left( 1 + \hat{\lambda}_{EMV} + \frac{\hat{\lambda}_{EMV}^2}{2} \right)$$

$$= 1 - e^{-4} (1 + 4 + 8) = 1 - 0,238 = 0,762.$$

5) a)  $X \sim B(1, p)$ .

$$P(X=k) = \binom{1}{k} p^k (1-p)^{1-k}, \quad k=0,1,\dots$$

$$L(k_1, k_2, \dots, k_n; p) = p^{\sum_{i=1}^n (k_i)} (1-p)^{n - \sum_{i=1}^n (k_i)}$$

$$\ln L(p) = \sum_{i=1}^n (k_i) \ln(p) + (n - \sum_{i=1}^n (k_i)) \ln(1-p)$$

aplicando prop.  
del log.

derivando:  $\frac{\partial \ln L(p)}{\partial p} = 0$

$$\frac{\sum_{i=1}^n (k_i)}{p} - \frac{n - \sum_{i=1}^n (k_i)}{1-p} = 0$$

$$\frac{\sum_{i=1}^n (k_i)}{p} = \frac{n - \sum_{i=1}^n (k_i)}{1-p}$$

$$\frac{1}{p} = \frac{n}{n - \sum_{i=1}^n (k_i)}$$

$$\hat{p}_{EMV} = \frac{\sum_{i=1}^n (k_i)}{n}$$

b) i)  $\hat{p}_{EMV} = \frac{5}{100} = 0,05$

ii)  $\hat{p}_{EMV} = (1 - \hat{p}_{EMV})^6 = (1 - 0,05)^6 = 0,95^6 \approx 0,735$



$$6) a) \mu = \int_{-\infty}^{+\infty} x \cdot (2\theta+1)x^{2\theta} dx = \int_0^1 (2\theta+1)x^{2\theta+1} dx$$

$$= (2\theta+1) \left( \frac{x^{2\theta+2}}{2\theta+2} \right) \Big|_0^1 = (2\theta+1) \left( \frac{1}{2\theta+2} - 0 \right) = \frac{2\theta+1}{2\theta+2}$$

$$n = \text{observaciones} = 10. \rightarrow \bar{X} = \frac{\sum(\text{observaciones})}{n}$$

$$= \frac{7,8}{10} = 0,78$$

$$\frac{2\theta+1}{2\theta+2} = 0,78$$

$$2\theta+1 = (2\theta+2)0,78$$

$$2\theta - 1,56\theta = 1,56 - 1$$

$$\theta_{MM} = \frac{14}{11} \approx 1,2727$$

$$b) \underbrace{LMV(\theta_{MM})}_{L(\theta)} = \prod_{i=1}^n ((2\theta+1)x_i^{2\theta}) = (2\theta+1)^n \cdot \prod_{i=1}^n (x_i^{2\theta})$$

$$\ln L(\theta) = \ln((2\theta+1)^n) + \ln\left(\prod_{i=1}^n (x_i^{2\theta})\right) = \text{prop. log. (producto)} =$$

$$= n \cdot (\ln(2\theta+1)) + \sum_{i=1}^n (\ln(x_i^{2\theta})) = \text{prop. log. (pot.)} =$$

$$= n \cdot \ln(2\theta+1) + \sum_{i=1}^n (2\theta \ln(x_i)) = \text{prop. de la sumatoria} =$$

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

$$\frac{\partial \ln L(\theta)}{\partial \theta} = 0 \rightarrow \frac{\partial (n \cdot \ln(2\theta+1) + 2\theta \sum_{i=1}^n (\ln(x_i)))}{\partial \theta} \stackrel{=0}{\rightarrow}$$

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

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



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

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

$$\begin{aligned} \hat{\theta}_{EMV} &= \frac{1}{2} \cdot \left( \frac{-10}{((-0,08) + (-0,24) + (-0,11) + (-0,43) + (-0,15) + (-0,76) + (-0,31) + (-0,03) + (-0,06) + (-0,26))} - 1 \right) \\ &= \frac{1}{2} \left( \frac{-10}{-2,42} - 1 \right) \approx \cancel{1,55761} \approx 1,55761 \end{aligned}$$