

4) Sea X_1, X_2, \dots, X_n una muestra aleatoria de una población

$$f(x|\theta) = \frac{\theta}{(1+x)^{1+\theta}}; x \geq 0, \theta > 0$$

a) Halle el LRT para probar $H_0: \theta = \theta_0$ vs $H_1: \theta = \theta/\theta_0$

b) Halle el Test UMP y la respectiva región de Rechazo para el dato, para probar las hipótesis $H_0: \theta = 2$ vs $H_1: \theta = 1$

Solución: El espacio paramétrico θ consta de finitos por

$$\theta \in \mathbb{R}^+, \text{ donde } \Theta = \{\theta_0\} \text{ y } \Theta_0^c = (0, \theta_0) \cup (\theta_0, \infty)$$

Para hallar el LRT es necesario calcular el MLE.

$$L(\theta|x) = \prod_{i=1}^n f(x_i|\theta) = \prod_{i=1}^n \frac{\theta}{(1+x_i)^{1+\theta}} = \frac{\theta^n}{\left(\prod_{i=1}^n (1+x_i)\right)^{1+\theta}}$$

$$\ell(L(\theta|x)) = n \ln(\theta) - (1+\theta) \sum_{i=1}^n \ln(1+x_i)$$

Calculando puntos críticos, luego evaluando para ver si es máximo, claro o es max.

$$\frac{\partial \ell(L(\theta|x))}{\partial \theta} = \frac{n}{\theta} - \sum_{i=1}^n \ln(1+x_i) \Leftrightarrow \frac{n}{\theta} = \sum_{i=1}^n \ln(1+x_i)$$

$\hat{\theta}^*$ es el único de segunda Derivada

$$\frac{\partial^2 \ell(L(\theta|x))}{\partial \theta^2} = -\frac{n}{\theta^2} < 0, \text{ por tanto es } \hat{\theta}^* \text{ MLE para } \theta$$

$$\therefore \sup_{\theta \in \Theta} L(\theta|x) = L(\theta_0|x) \wedge \sup_{\theta \in \Theta} L(\theta|x) = L(\hat{\theta}^*|x)$$

$$\therefore \lambda(x) = \frac{L(\theta_0|x)}{L(\hat{\theta}^*|x)} = \frac{\theta_0^n}{\left[\prod_{i=1}^n (1+x_i)\right]^{1+\theta_0}}$$

$$\frac{\left(\frac{n}{\sum_{i=1}^n \ln(1+x_i)}\right)^n}{\left[\prod_{i=1}^n (1+x_i)\right]^{1+\hat{\theta}^*}}$$

se debe indicar por la forma de la expresión el MLE

$$= \frac{\theta^n \left[\prod_{i=1}^n (1+x_i) \right]^{1+\hat{\theta}^*}}{\left(\frac{\theta}{\sum_{i=1}^n \ln(1+x_i)} \right)^n \left(\prod_{i=1}^n (1+x_i) \right)^{1+\hat{\theta}_0}} = \frac{\theta^n \left[\prod_{i=1}^n (1+x_i) \right]^{\hat{\theta}^* - \hat{\theta}_0}}{n^n \left(\sum_{i=1}^n \ln(1+x_i) \right)^n}$$

$$= \left(\frac{\theta}{n} \right)^n \left[\prod_{i=1}^n (1+x_i) \right]^{\hat{\theta}^* - \hat{\theta}_0} \cdot \left[\sum_{i=1}^n \ln(1+x_i) \right]^{-n} = \text{Est LRT}$$

ⓑ Usando N-P, tenemos que: $\frac{F(X_1, \dots, X_n | 1)}{F(X_1, \dots, X_n | 3)} > k$

$$\therefore \frac{\frac{1^n}{\left[\prod_{i=1}^n (1+x_i) \right]^{1+1}}}{\frac{3^n}{\left[\prod_{i=1}^n (1+x_i) \right]^{1+3}}} \geq k \Leftrightarrow \frac{\left[\prod_{i=1}^n (1+x_i) \right]^2}{3^n \left[\prod_{i=1}^n (1+x_i) \right]^2} > k$$

$$\frac{\left(\prod_{i=1}^n (1+x_i) \right)^2}{3^n} > k \Leftrightarrow \left[\prod_{i=1}^n (1+x_i) \right]^2 > k 3^n \therefore \prod_{i=1}^n (1+x_i) > \sqrt{k 3^n}$$

$$\sum_{i=1}^n \ln(1+x_i) = \frac{1}{2} \ln(k 3^n) \quad \text{Sea } Y_i = \ln(1+x_i), \text{ entonces}$$

R (región de rechazo) cubra dada por

$$R = \left\{ (x_1, \dots, x_n) \mid \sum_{i=1}^n Y_i > \frac{1}{2} \ln(k 3^n) \right\}; \text{ si } P(Y \in R) = \star$$

$$\star = P\left(\sum_{i=1}^n Y_i > \frac{1}{2} \ln(k 3^n)\right) \Rightarrow \text{Para calcular esta prob. necesitamos saber cómo se distribuye } Y$$

Cambio de variable

$$Y_i = \ln(1+x_i) \Leftrightarrow x_i = e^{Y_i} - 1 \quad \wedge \quad \frac{dx_i}{dy_i} = e^{Y_i} \quad \text{Entonces, por 1.º cambio de v.}$$

$$f_{Y_i}(Y_i) = f_x(e^{Y_i} - 1) \left| \frac{dx_i}{dy_i} \right| = \frac{\theta}{(e^{Y_i})^{1+\theta}} e^{Y_i} = \theta e^{-Y_i} \quad \forall Y_i \in \mathbb{R}$$

$$\therefore Y_i \sim \exp(\theta), \text{ y por lo tanto } Y_i \text{ en (base, } \sum Y_i \sim \text{Gamma}(n, \frac{1}{\theta}))$$

Si $S = \sum_{i=1}^n Y_i \sim S \sim \text{Gamma}(n, 1/\theta)$; Finalmente

$$\alpha = P(S > \frac{1}{2} \ln(n \cdot 3^n) | \theta = 3) \Rightarrow (H_0 = \theta = 3) \text{ donde}$$

S_k un variatil sumador α de una Gamma y $S_k = \frac{1}{2} \ln(n \cdot 3^n)$

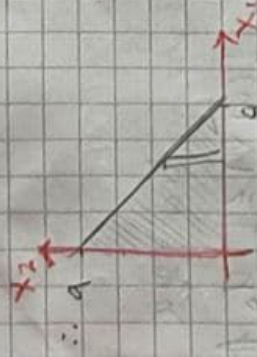
$$Asi, $S_k \Rightarrow 2S_k = \ln(n \cdot 3^n) \Rightarrow 2S_k = 3k; k = \frac{e^{2S_k}}{3^n}$$$

$$\therefore R = \{S | S > S_k\} \text{ con } S_k = \frac{1}{2} \ln(n \cdot 3^n)$$

(2) $C = \{ (x_1, x_2) | x_1 + x_2 > q \} \quad x_i \sim \exp(1/\theta) \cdot \theta = (0, \infty)$

Como piden la formula de potencia, $= x_i \cdot n \cdot \frac{1}{\theta} e^{-x_i/\theta}$

$$P(\theta) = P(x_1, x_2 \in C) = P(x_1 + x_2 > q) = 1 - P(x_1 + x_2 \leq q)$$



Como es una muestra de tamaño 2, tenemos que:

$$= 1 - \int_0^q \int_0^{q-x_2} \frac{1}{\theta} e^{-\frac{x_1}{\theta}} \cdot \frac{1}{\theta} e^{-\frac{x_2}{\theta}} dx_1 dx_2$$

$$= 1 - \int_0^q \int_0^{q-x_2} \frac{1}{\theta^2} e^{-\frac{x_1+x_2}{\theta}} dx_1 dx_2$$

$$\text{sea } u = -\frac{x_1}{\theta} \quad du = -\frac{1}{\theta} dx_1$$

$$= 1 - \int_0^q \left[-\frac{1}{\theta} e^{-\frac{x_2}{\theta}} \right]_0^{q-x_2} = 1 - \int_0^q \left[\frac{1}{\theta} e^{-\frac{x_2}{\theta}} \right]_0^{q-x_2} dx_2$$

$$= 1 + \frac{1}{\theta} \left[e^{-\frac{x_2}{\theta}} \right]_0^{q-x_2} = 1 + \frac{1}{\theta} \int_0^q e^{-\frac{x_2}{\theta}} dx_2$$

$$= 1 + \frac{1}{\theta} \left(\theta e^{-\frac{x_2}{\theta}} \right) \Big|_0^{q-x_2} = 1 + \frac{1}{\theta} \left(\theta e^{-\frac{q-x_2}{\theta}} - \theta e^{-\frac{0}{\theta}} \right) = 1 + \frac{1}{\theta} \left(\theta e^{-\frac{q}{\theta}} e^{\frac{x_2}{\theta}} - \theta \right)$$

$$= \frac{1}{\theta} e^{-\frac{q}{\theta}} + e = e \left(\frac{1}{\theta} + 1 \right) = \beta(\theta)$$

② El RT está definido por $\lambda(x) = \frac{\sup_{H_0} L(\theta|x)}{L(\bar{\theta}|x)}$ en $\bar{\theta} = \text{MLE}$

$$L(\theta|x) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(x_i - u)^2} = \left(\frac{1}{2\pi}\right)^{n/2} \cdot \theta \cdot e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - u)^2}$$

, Newton's sobre cuando se maximiza esta función, pero $L(\theta|x)$ no converge por todo...

Suponga $u \neq u_0$ con $\bar{\theta} = (-u, u_0)$
 \therefore Como $u \neq u_0$ bajo H_0 , entonces,

$$-u > u_0 \Leftrightarrow x_i - u_0 \leq x_i - u$$

$$\sum_{i=1}^n (x_i - u_0)^2 \leq \sum_{i=1}^n (x_i - u)^2$$

$$-\sum_{i=1}^n (x_i - u_0)^2 \geq -\sum_{i=1}^n (x_i - u)^2$$

$$\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - u_0)^2 \geq \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - u)^2$$

$$e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - u_0)^2} \geq e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - u)^2} \Rightarrow \text{Es obvio implica que } \forall u, L(u|x) \leq L(u_0|x)$$

Por tanto $\sup_{H_0} L(u|x) = L(u_0|x)$, Así

$$\lambda(x) = \frac{L(u_0|x)}{L(\bar{\theta}|x)} = \frac{\left(\frac{1}{2\pi}\right)^{n/2} \theta e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - u_0)^2}}{\left(\frac{1}{2\pi}\right)^{n/2} \sigma^n e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \bar{x})^2}}$$

$$= \frac{\exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - u_0)^2\right)}{\exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \bar{x})^2\right)} = \exp\left(\frac{1}{2\sigma^2} \left(\sum_{i=1}^n (x_i - \bar{x})^2 - \sum_{i=1}^n (x_i - u_0)^2\right)\right)$$

Ahora, se reduce lo si

$$\lambda(x) \leq c ; \exp\left(\frac{1}{2\sigma^2} \left(\sum_{i=1}^n (x_i - \bar{x})^2 - \sum_{i=1}^n (x_i - u_0)^2\right)\right) \leq c$$

$$(\sum (x_i - \bar{x})^2 - \sum (x_i - u_0)^2) \leq 2\sigma^2 \ln(c)$$

$$\sum x_i^2 - 2\bar{x} \sum x_i + n\bar{x}^2 - \sum x_i^2 + 2u_0 \sum x_i - nu_0^2 \leq 2\sigma^2 \ln(c)$$

$$\sum x_i^2 - 2n\bar{x} \sum \frac{x_i}{n} + n\bar{x}^2 - \sum x_i^2 + 2u_0 \sum x_i - nu_0^2 \leq 2\sigma^2 \ln(c)$$

$$\sum x_i^2 - n\bar{x}^2 - \sum x_i^2 + 2u_0 \sum x_i - nu_0^2 \leq 2\sigma^2 \ln(c)$$

$$-n\bar{x}^2 + 2u_0 \sum x_i \leq 2\sigma^2 \ln(c) + nu_0^2$$

$$-n\bar{x}^2 + 2nu_0\bar{x} \leq 2\sigma^2 \ln(c) + nu_0^2$$

$$\bar{x}^2 - 2u_0\bar{x} \geq \frac{-1}{n} (2\sigma^2 \ln(c) + nu_0^2)$$

$$\bar{x}^2 - 2u_0\bar{x} \geq \frac{-1}{n} (2\sigma^2 \ln(c) + nu_0^2)$$

$$\bar{x} - 2u_0\bar{x} + u_0^2 \geq \frac{-1}{n} (2\sigma^2 \ln(c) + nu_0^2) + u_0^2$$

$$(\bar{x} - u_0)^2 \geq \frac{-2\sigma^2 \ln(c)}{n} - u_0^2 + u_0^2$$

$$(\bar{x} - u_0)^2 \geq \frac{\sigma^2}{n} (-\ln(c)) \Leftrightarrow |\bar{x} - u_0| \geq \frac{\sigma}{\sqrt{n}} \sqrt{-\ln(c)}$$

$$\therefore \frac{|\bar{x} - u_0|}{\frac{\sigma}{\sqrt{n}}} > \frac{\sqrt{-\ln(c)}}{\sqrt{n}} \cdot \sqrt{n}$$

$$z_0 \rightarrow \infty, \text{ Para bien definido}$$

Sea $z = \frac{\bar{x} - u_0}{\frac{\sigma}{\sqrt{n}}} \sim N(0,1)$, se rechaza H_0 si $z > z_0$

(Por hipotesis solo se fue en ambas partes de la función)

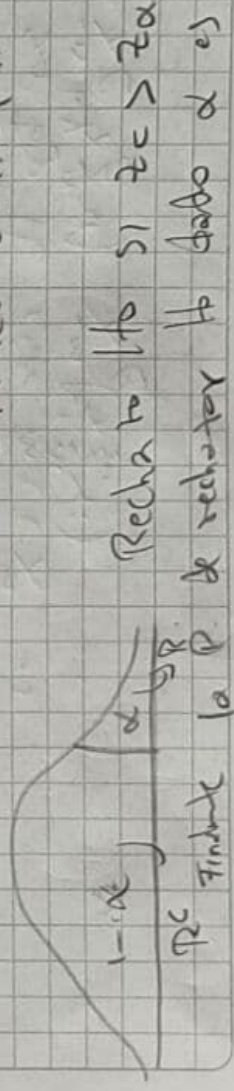
Aho, se fija lo P error tipo 1, \Leftrightarrow se fija α

$$\alpha = P(z > z_0 | u_0 = u) = P(N(0,1) > z_0)$$

$$P(z > z_0) = 1 - P(z \leq z_0) = P(\text{error tipo 1})$$

$$= P(\text{Rechazo } H_0 | H_0 \text{ es cierta})$$

$$\text{con } z_\alpha = P(z > z_\alpha)$$



$$\begin{aligned} \therefore \ln(\lambda | x, y) &= -n \ln(\lambda) - \frac{1}{\lambda} \sum_{i=1}^n x_i - m \ln(\lambda) - \frac{1}{\lambda} \sum_{j=1}^m y_j \\ &= (n+m) \ln(\lambda) - \frac{1}{\lambda} \left(\sum_{i=1}^n x_i + \sum_{j=1}^m y_j \right) \\ \frac{\partial}{\partial \lambda} &= \frac{(n+m)}{\lambda} + \frac{1}{\lambda^2} \left(\sum_{i=1}^n x_i + \sum_{j=1}^m y_j \right) = 0, \quad \hat{\lambda} = \frac{\left(\sum_{i=1}^n x_i + \sum_{j=1}^m y_j \right)}{(n+m)} \end{aligned}$$

Por tanto...

$$\lambda(x, y) = \frac{(n+m)^n}{\left(\sum_{i=1}^n x_i + \sum_{j=1}^m y_j \right)^n} \cdot \frac{(n+m)^m}{\left(\sum_{i=1}^n x_i + \sum_{j=1}^m y_j \right)^m} e^{-\frac{(n+m)}{\lambda}}$$

$$\frac{1}{\left(\frac{1}{n} \sum x_i \right)^n} \cdot \frac{1}{\left(\frac{1}{m} \sum y_j \right)^m} \cdot e^{-\frac{n}{\lambda}} \cdot e^{-\frac{m}{\lambda}}$$

$$= \left(\frac{n+m}{n} \right)^n \left(\frac{n+m}{m} \right)^m \left(\frac{\sum_{i=1}^n x_i}{\sum_{i=1}^n x_i + \sum_{j=1}^m y_j} \right)^n \cdot \left(\frac{\sum_{j=1}^m y_j}{\sum_{i=1}^n x_i + \sum_{j=1}^m y_j} \right)^m$$

✓ 1.2.1 por lo vs H,

$$\frac{1}{T} = \frac{\sum_{i=1}^n x_i}{\sum_{i=1}^n x_i + \sum_{j=1}^m y_j}, \quad \text{Si } \lambda(x, y) = \frac{(n+m)}{n^{\frac{n}{n+m}} m^{\frac{m}{n+m}}} T^{n+m} (1-T)^m, \text{ se}$$

scriba como un estadístico de prueba

4) Ya no es acb el 1-d, pero si sechato lo
 Es Ensi tipo 1, pero tanto no se sechato y es de
 sero Region sechato

$$X_1, \dots, X_n \sim \exp(1/\theta), \quad \theta > 0, \quad Y_1, \dots, Y_n \sim \exp(1/\lambda), \quad \lambda > 0$$

Nota que $H_0 = \theta = \lambda$ vs $H_1 = \theta \neq \lambda$.

Calculamos el LRT.

$$\lambda(x) = \sup_{\theta \in \Theta_0} L(\theta | x)$$

Por definicion, para todo
 Necesitamos el MLE

$$\sup_{\theta \in \Theta} L(\theta | x)$$

$$\begin{aligned} \therefore L(\theta, \lambda | x, y) &= \prod_{i=1}^n \frac{1}{\theta} e^{-\frac{x_i}{\theta}} \cdot \prod_{j=1}^m \frac{1}{\lambda} e^{-\frac{y_j}{\lambda}} \\ &= \frac{1}{\theta^n} e^{-\frac{1}{\theta} \sum_{i=1}^n x_i} \cdot \frac{1}{\lambda^m} e^{-\frac{1}{\lambda} \sum_{j=1}^m y_j} = \frac{1}{\theta^n \lambda^m} e^{-\frac{1}{\theta} \sum_{i=1}^n x_i - \frac{1}{\lambda} \sum_{j=1}^m y_j} \end{aligned}$$

$$\ell(\theta, \lambda | x, y) = -n \ln(\theta) - m \ln(\lambda) - \frac{1}{\theta} \sum_{i=1}^n x_i - \frac{1}{\lambda} \sum_{j=1}^m y_j$$

Ahora, $\frac{d}{d\theta} = -\frac{n}{\theta} + \frac{1}{\theta^2} \sum_{i=1}^n x_i = 0 \Rightarrow \hat{\theta}^* = \frac{1}{n} \sum_{i=1}^n x_i = \bar{x}$

$$\frac{\partial^2}{\partial \theta^2} = \frac{n}{\theta^2} - \frac{2}{\theta^3} \sum_{i=1}^n x_i < 0 \quad ; \quad \text{MLE Para } \hat{\theta} \text{ es } \theta$$

Analogamente... $\frac{\partial}{\partial \lambda} = -\frac{m}{\lambda} + \frac{1}{\lambda^2} \sum_{j=1}^m y_j = 0 \Rightarrow \hat{\lambda}^* = \frac{1}{m} \sum_{j=1}^m y_j = \bar{y}$

$$\frac{\partial^2}{\partial^2 \lambda} = \frac{m}{\lambda^2} - \frac{2m}{\lambda^3} \sum_{j=1}^m y_j < 0, \quad \hat{\lambda} = \bar{y}, \quad \text{el MLE Para } \lambda$$

Ahora, el sup log Hb, con MLE \hat{x}

$$L(x | x, y) = \frac{1}{\bar{x}^n} e^{-\frac{1}{\bar{x}} \sum_{i=1}^n x_i} \cdot \frac{1}{\bar{y}^m} e^{-\frac{1}{\bar{y}} \sum_{j=1}^m y_j}$$