

$$\begin{aligned} \sigma &\leq \mathbb{E}(z^2) \\ &= \mathbb{E}\left[\left(x - y \frac{\mathbb{E}(xy)}{\mathbb{E}(y^2)}\right)^2\right] \end{aligned}$$

## Aux 6

PJ) a)  $\text{Var}_\sigma(r) = \mathbb{E}(r^2) - \mathbb{E}(r)^2$

$$\frac{\partial}{\partial \theta} \mathbb{E}(r(x, \theta, h)) = \int_{\mathbb{R}} \frac{f(x, \theta+h) - f(x, \theta)}{f(x, \theta)} f(x, \theta) dx$$

$$= \int_{\mathbb{R}} f(x, \theta+h) - \int_{\mathbb{R}} f(x, \theta)$$

$$= 1 - 1 = 0$$

$$\bullet \text{Var}_g(r) = \mathbb{E}_g(r^2) - \mathbb{E}_g(r)^2$$

$$= I_{0,h} //$$

$$\bullet \text{Cov}_g(r, \hat{\theta}) = \mathbb{E}_g \left[ (r - \cancel{\mathbb{E}(r)}) (\hat{\theta} - \cancel{\mathbb{E}(\hat{\theta})}) \right]$$

$$= \mathbb{E}_g [r(\hat{\theta} - \theta)]$$

$$= \mathbb{E}_g(r\hat{\theta}) - \mathbb{E}_g(r\theta)$$

$$= \underbrace{\mathbb{E}_g(r\hat{\theta})}_{(1)} - \theta \cancel{\mathbb{E}_g(r)}$$

$$\textcircled{a} \quad \mathbb{E}_g(\hat{\tau}_{\hat{\theta}}) = \int_{\mathcal{R}} \left( \frac{f(x, \theta+h) - f(x, \theta)}{f(x, \theta)} \right) \hat{\theta}(x) f(x, \theta) dx$$

$$= \underbrace{\int_{\mathcal{R}} \hat{\theta}(x) f(x, \theta+h) dx}_{\mathbb{E}_{\theta+h}(\hat{\theta})} - \underbrace{\int_{\mathcal{R}} \hat{\theta}(x) f(x, \theta) dx}_{\mathbb{E}_g(\hat{\theta})}$$

$$= \mathbb{E}_{\theta+h}(\hat{\theta}) - \mathbb{E}_g(\hat{\theta})$$

$$= \theta+h - \theta = h //$$

$$\bullet \quad \text{Cov}(r, \hat{\theta})^2 \leq \underbrace{\text{Var}(r)} = \text{Var}(\hat{\theta}) \quad \text{✗}$$

$$h^2 \leq I_{\theta, h} = \text{Var}(\hat{\theta}) \quad \sqrt{I_{\theta, h}}$$

$$\bullet \quad \frac{h^2}{I_{\theta, h}} \leq \text{Var}(\hat{\theta}) \quad \sqrt{I_{\theta, h}}$$

\* Given  $X, Y$  var. Def  $Z = X - Y \frac{L(X|Y)}{E(Y^2)}$

$$0 \leq E(Z^2)$$

$$= E\left[\left(X - Y \frac{E(XY)}{E(Y^2)}\right)^2\right]$$

$$= E(X^2) - 2E(XY) \frac{E(XY)}{E(Y^2)} + \cancel{E(Y^2)} \frac{E(XY)^2}{E(Y^2)^2}$$

$$= E(X^2) - \frac{E(XY)^2}{E(Y^2)}$$

$$\therefore E(XY)^2 \leq E(X^2) E(Y^2) \quad \square$$

PS) b) En este caso  $f(x, \theta) = \frac{1}{\sigma} \mathbb{1}_{(0, \theta)}(x)$

$$\Rightarrow I_{\sigma, h} = \mathbb{E}(r^2) = \int_{\mathbb{R}} \left[ \frac{\frac{1}{\sigma+h} - \frac{1}{\sigma}}{\frac{1}{\sigma}} \right]^2 \frac{1}{\sigma} \mathbb{1}_{(0, \theta)}(x) dx$$

$$= \left( \frac{\frac{1}{\sigma+h} - \frac{1}{\sigma}}{\frac{1}{\sigma}} \right)^2 = \left( \frac{\sigma}{\sigma+h} - 1 \right)^2$$

$$= \left( \frac{\sigma - (\sigma+h)}{\sigma+h} \right)^2 = \left( \frac{-h}{\sigma+h} \right)^2 = \frac{h^2}{(\sigma+h)^2} \quad \square$$

PJ) c)  $\lim_{h \rightarrow 0^+} \frac{I_{0,h}}{h^2} = \lim_{h \rightarrow 0^+} \frac{h^2 / (0+h)^2}{h^2} = \lim_{h \rightarrow 0^+} \frac{1}{(0+h)^2} = \frac{1}{0^2}$  □



$$P2) a) T(X) = \frac{z}{\theta} \sum X_i$$

1) Es claro que  $T(X)$  es estricto decreciente s/r a  $\theta$

2) Sabemos que  $X_i \sim \exp(\theta)$

$$\Rightarrow \frac{z}{\theta} X_i \sim \exp\left(\frac{z}{\theta} \cdot \theta\right) \Rightarrow \frac{z}{\theta} X_i \sim \exp(z)$$

• Sabemos que suma de exponenciales es Gamma

$$\Rightarrow \sum \frac{z}{\theta} X_i = \frac{z}{\theta} \sum X_i = T(X) \sim \Gamma(n, z)$$


$$\Rightarrow f_{\frac{\theta}{\sigma^2} \chi^2} (t) = \frac{1}{2^n \Gamma(n)} t^{n-1} e^{-t/2} \mathbb{1}_{t>0}$$

↳ Esta ley no depende de  $\theta$

∴  $T(X)$  es un pivote

↳ También, de la def. del enunciado, es claro que es la densidad de una  $\chi^2$  con  $2n$  grados de libertad

$$\therefore T(X) \sim \chi^2(2n) \quad \square$$

PZ) b) Queremos  $t_1, t_2$  t.s.  $\mathbb{P}(t_1 \leq T(X) \leq t_2) = 1 - \alpha = 0,75$  ( $\alpha = 0,25$ )  BitPaper  
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$$\Rightarrow \mathbb{P}(T(X) \leq t_2) - \mathbb{P}(T(X) \leq t_1) = 1 - \alpha$$

• Si usamos  $t_2 = +\infty$   
 $t_1 = F_T^{-1}(\alpha)$  }  $\Rightarrow$  Nos da la igualdad deseada

Con esos valores  $\cdot \mathbb{P}(T(X) \leq t_2) = \mathbb{P}(T(X) > 0) = 1$

$$\cdot \mathbb{P}(T(X) \leq t_1) = F_T(t_1) = \bar{F}_T(F_T^{-1}(\alpha)) = \alpha$$

$$\circ t_1 \leq T(X) \leq t_2 \Leftrightarrow \frac{2\sum x_i}{t_2} \leq 0 \leq \frac{2\sum x_i}{t_1} \Leftrightarrow 0 < \sigma \leq \frac{2\sum x_i}{F_T^{-1}(\alpha)} \quad \square$$

$$c) \bar{X} = \frac{1}{n} \sum X_i \Leftrightarrow \sum X_i = n\bar{X}$$

- Usando esto:  $0 < \theta \leq \frac{2.7 \cdot 4.77}{F_T^{-1}(0.05)}$  2