

Examen

$$f_x(x) = \int_0^{\infty} f(x, y; \theta) dy = \int_0^{\infty} \theta^{-2} x^{\frac{1}{\theta}-1} e^{-\frac{y}{\theta}} dy \quad (1)$$

$$= \theta^{-2} x^{\frac{1}{\theta}-1} \int_0^{\infty} e^{-\theta^{-1}y} dy = -\theta^{-1} x^{\frac{1}{\theta}-1} e^{-\frac{y}{\theta}} \Big|_0^{\infty}$$

$$= \theta^{-1} x^{\frac{1}{\theta}-1} \quad \text{c'est la densité de la loi } \exp\left(\frac{1}{\theta}\right)$$

$0 < x < 1$

$$f_y(y) = \int_0^x f(x, y; \theta) dx = \theta^{-2} e^{-\frac{y}{\theta}} \int_0^x x^{\frac{1}{\theta}-1} dx = \theta^{-1} e^{-\frac{y}{\theta}} \left(x^{\frac{1}{\theta}} \right)' \Big|_0^x$$

$$= \theta^{-1} e^{-\frac{y}{\theta}} \quad \text{c'est la densité de la loi } \exp\left(\frac{1}{\theta}\right)$$

$y \geq 0$

b) $Z = -\log(x)$ soit g sa densité et G sa f de rep.

$$G(x) = P[Z < x] = P[-\log(x) < x] = P[X > e^{-x}] = 1 - P[X < e^{-x}]$$

La f de rep de x :

$$F_x(x) = \int_0^x \theta^{-1} t^{\frac{1}{\theta}-1} dt = \left[t^{\frac{1}{\theta}} \right]_0^x = x^{\frac{1}{\theta}}$$

Donc :

$$F_x(x) = \begin{cases} 0 & x < 0 \\ x^{\frac{1}{\theta}} & 0 \leq x < 1 \\ 1 & x \geq 1 \end{cases} \Rightarrow X \text{ prend que des valeurs positives}$$

$$G(z) = 1 - F_x(e^{-z}) = \begin{cases} 1 - e^{-\frac{z}{\theta}} & z > 0 \\ 0 & z < 0 \end{cases}$$

Sa densité :

$$g(z) = G'(z) = \theta^{-1} e^{-\frac{z}{\theta}} \mathbb{1}_{z > 0} = f_y(y)$$

c) la vraisemblance :

$$L_n(\theta) = \prod_{i=1}^n f(x_i, y_i; \theta) = \theta^{-2n} \left(\prod_{i=1}^n x_i \right)^{\frac{1}{\theta}-1} \cdot e^{-\frac{n\bar{y}_n}{\theta}}$$

$$\log L_n(\theta) = -2n \log \theta + \left(\frac{1}{\theta} - 1 \right) \cdot n \cdot \bar{z}_n - \frac{n\bar{y}_n}{\theta}$$

$$\frac{\partial \log L_n(\theta)}{\partial \theta} = -\frac{2n}{\theta} + \frac{1}{\theta^2} n \bar{z}_n + \frac{n\bar{y}_n}{\theta^2} = 0 \Rightarrow \theta_n = \frac{\bar{y}_n + \bar{z}_n}{2}$$

$$\frac{\partial \ln(\theta)}{\partial \theta} = \frac{2n}{\theta^2} - \frac{2}{\theta^3} n \bar{z}_n - \frac{2n}{\theta^3} \bar{y}_n = \frac{2n}{\theta^3} [\theta - \bar{z}_n - \bar{y}_n]$$

$$\frac{\partial^2 \log L_n(\hat{\theta}_n)}{\partial \theta^2} = \frac{2n}{\hat{\theta}_n^3} \left[\frac{\bar{y}_n + \bar{z}_n}{2} - (\bar{y}_n + \bar{z}_n) \right] = -\frac{2n}{\hat{\theta}_n^3} \frac{(\bar{y}_n + \bar{z}_n)}{2}$$

$$= -\frac{2n}{\hat{\theta}_n^3} < 0 \Rightarrow \hat{\theta}_n \text{ point de max.}$$

$$E(Y) = \frac{1}{\theta} \int_0^{\infty} y e^{-\frac{y}{\theta}} dy = -y e^{-\frac{y}{\theta}} \Big|_0^{\infty} + \int_0^{\infty} e^{-\frac{y}{\theta}} dy = \int_0^{\infty} e^{-\frac{y}{\theta}} dy$$

$$= -\theta e^{-\frac{y}{\theta}} \Big|_0^{\infty} = \theta \Rightarrow \boxed{E(Z) = \theta}$$

$$E(Y^2) = \frac{1}{\theta} \int_0^{\infty} y^2 e^{-\frac{y}{\theta}} dy = -y^2 e^{-\frac{y}{\theta}} \Big|_0^{\infty} + 2 \int_0^{\infty} y e^{-\frac{y}{\theta}} dy$$

$$= 2\theta E(Y) = 2\theta^2 \Rightarrow \boxed{\text{Var}(Y) = \text{Var}(Z) = \theta^2}$$

Propriétés :

$$E(\hat{\theta}_n) = \frac{E(Y) + E(Z)}{2} = \theta \Rightarrow \hat{\theta}_n \text{ sans biais}$$

Convergence :

$$\begin{array}{l} \bar{Y}_n \xrightarrow{\text{P.S.}} E(Y) = \theta \\ \bar{Z}_n \xrightarrow{\text{P.S.}} E(Z) = \theta \end{array} \left. \vphantom{\begin{array}{l} \bar{Y}_n \\ \bar{Z}_n \end{array}} \right\} \Rightarrow \hat{\theta}_n \xrightarrow{\text{P.S.}} \theta \text{ fort. consist}$$

Efficacité . X_i et Y_i indép $\Rightarrow Z_i$ et Y_i indép $\Rightarrow \bar{Z}_n$ et \bar{Y}_n indép

$$\text{Var}(\hat{\theta}_n) = \frac{1}{4} [\text{Var}(\bar{Y}_n) + \text{Var}(\bar{Z}_n)] = \frac{\text{Var}(\bar{Y}_n)}{2} = \frac{\theta^2}{2n}$$

L'information de Fisher :

$$I_1(\theta) = -E \left[\frac{\partial^2}{\partial \theta^2} \log f(x, y; \theta) \right] = -E \left[\frac{\partial^2}{\partial \theta^2} \left(-2 \log \theta + \left(\frac{1}{\theta} - 1 \right) \log X \right. \right.$$

$$\left. - \frac{Y}{\theta} \right) \Big] = -E \left[\frac{2}{\theta^2} - \frac{2}{\theta^3} Z - \frac{2Y}{\theta^3} \right] = \frac{2}{\theta^3} [E(Z) + E(Y) - \theta] = \frac{2}{\theta^2}$$

$$\Rightarrow \text{Var}(\hat{\theta}_n) = \frac{1}{n I_1(\theta)} \Rightarrow \hat{\theta}_n \text{ efficace.}$$

intervalle de conf. asymptotique ③

avec le TLC: $\sqrt{n} \frac{\bar{Y}_n - \theta}{\sigma} \xrightarrow[n \rightarrow \infty]{\mathcal{L}} \mathcal{N}(0,1)$ et $\sqrt{n} \frac{\bar{Z}_n - \theta}{\sigma} \xrightarrow{\mathcal{L}} \mathcal{N}(0,1)$ indépend

Alors: $S_1 = \sqrt{n} \frac{\bar{Y}_n + \bar{Z}_n}{\sigma} - 2 \xrightarrow[n \rightarrow \infty]{\mathcal{L}} \mathcal{N}(0,2)$

$$= 2\sqrt{n} \frac{\hat{\theta}_n}{\sigma} - 2 = 2 \left(\sqrt{n} \frac{\hat{\theta}_n}{\sigma} - 1 \right)$$

Donc: $S_2 = \sqrt{2} \left(\sqrt{n} \frac{\hat{\theta}_n}{\sigma} - 1 \right) \xrightarrow[n \rightarrow \infty]{\mathcal{L}} \mathcal{N}(0,1)$

Pour un niveau α fixé:

$$P \left[|S_2| < u_{1-\frac{\alpha}{2}} \right] = 1-\alpha \quad u_{1-\frac{\alpha}{2}} \text{ la fractile}$$

$$P \left[-u_{1-\frac{\alpha}{2}} < \sqrt{2} \left(\sqrt{n} \frac{\hat{\theta}_n}{\sigma} - 1 \right) < u_{1-\frac{\alpha}{2}} \right] = 1-\alpha \quad \text{d'ordre } 1-\frac{\alpha}{2} \text{ de la loi } \mathcal{N}(0,1)$$

$$P \left[n^{-1/2} \left(1 - \frac{u_{1-\alpha/2}}{\sqrt{2}} \right) < \frac{\hat{\theta}_n}{\sigma} < n^{-1/2} \left(1 + \frac{u_{1-\alpha/2}}{\sqrt{2}} \right) \right] = 1-\alpha$$

$$P \left[\frac{n^{1/2}}{\hat{\theta}_n} \left(1 + \frac{u_{1-\alpha/2}}{\sqrt{2}} \right)^{-1} < \theta < \frac{n^{1/2}}{\hat{\theta}_n} \left(1 - \frac{u_{1-\alpha/2}}{\sqrt{2}} \right)^{-1} \right] = 1-\alpha$$

Donc, l'intervalle de confiance asymptotique pour θ est:

$$\left[\frac{2\sqrt{n}}{\bar{Y}_n + \bar{Z}_n} \left(1 + \frac{u_{1-\alpha/2}}{\sqrt{2}} \right)^{-1} \quad ; \quad \frac{2\sqrt{n}}{\bar{Y}_n + \bar{Z}_n} \left(1 - \frac{u_{1-\alpha/2}}{\sqrt{2}} \right)^{-1} \right]$$

$$m_i + \varepsilon_{ij} \rightarrow \hat{m}_i = \bar{y}_{\cdot i} = \frac{1}{n_i} \sum_{j=1}^n y_{ij} = m_i + \bar{\varepsilon}_i \quad (4)$$

$$\frac{1}{\sqrt{n}} \sum_{i=1}^k (\varepsilon_i - m_i)^2, \quad \bar{\varepsilon}_i \sim W(0, \frac{1}{n_i}) \Rightarrow \varepsilon_i = \sqrt{n_i} \cdot \bar{\varepsilon}_i = \sqrt{n} \cdot \bar{\varepsilon}_i$$

$$\hat{m}_i = m_i + \sqrt{n_i} \cdot \frac{\varepsilon_i}{\sqrt{n_i}} \quad \hat{m}_i = m_i + \frac{\varepsilon_i}{\sqrt{n}} = m_i + \frac{\varepsilon_i}{\sqrt{n}}$$

$$T_n = \sqrt{n} \left(\sum_{i=1}^k \left(m_i + \frac{\varepsilon_i}{\sqrt{n}} \right)^2 - 1 \right) = \sqrt{n} \sum m_i^2 + 2 \sum_{i=1}^k \varepsilon_i m_i + \frac{1}{\sqrt{n}} \sum_{i=1}^k \varepsilon_i^2$$

$$c) \quad \frac{1}{\sqrt{n}} \sum_{i=1}^k \varepsilon_i^2 = \sqrt{n} \sum_{i=1}^k (\bar{\varepsilon}_i)^2 = \frac{1}{\sqrt{n}} \sum_{i=1}^k \left(\sum_{j=1}^n \varepsilon_{ij} \right)^2$$

On a que $\bar{\varepsilon}_i \xrightarrow{P} 0$

Parce que k est fixé, il suffit de montrer que: $\frac{1}{(\sqrt{n})^{1/4}} \varepsilon_i \xrightarrow{P} 0$

On applique B-Tchebychev.

$$\text{Sous } H_0: \sum m_i^2 - 1 = 0 \Rightarrow T_n = \frac{1}{\sqrt{n}} \sum_{i=1}^k \varepsilon_i^2 + 2 \sum_{i=1}^k \varepsilon_i m_i$$

$$\sum_{i=1}^k \varepsilon_i - m_i \sim W(0, \sum m_i^2) \Rightarrow T_n \xrightarrow{L} W(0, 4)$$

$$d) \quad \sqrt{n} (\sum m_i^2 - 1) \rightarrow \infty \Rightarrow T_n \rightarrow \infty$$

e) stat de test: On calcule:

$$T_n = \frac{1}{\sqrt{n}} \sum_{i=1}^k \varepsilon_i^2 \xrightarrow{H_0} W(0, 4)$$