

Ex 5:

$$f_{\theta}(x) = \frac{1+\theta x}{2} 1_{[-1,1]}(x)$$

$$\begin{aligned} 1) E_{\theta}(X) &= \int \frac{x+\theta x^2}{2} dx \\ &= \left[x^2 + \frac{\theta x^3}{3} \right]_{-1}^1 = \frac{\theta}{6} + \frac{\theta}{6} = \boxed{\frac{\theta}{3}} \end{aligned}$$

$$\bar{x} = \frac{\hat{\theta}}{3} \Rightarrow \hat{\theta} = 3\bar{x}$$

$$\begin{aligned} E(\hat{\theta}) &= 3E(\bar{x}) = 3 \frac{\sum E(x_i)}{n} \\ &= 3 \cdot n \cdot \underbrace{\left(\frac{\theta}{3}\right)}_{\wedge} = \theta \end{aligned}$$

sans biais.

$$\begin{aligned} \text{Var}(\hat{\theta}) &= \text{Var}(3\bar{x}) \\ &= 9 \text{Var}(\bar{x}) \\ &= \frac{9}{n^2} \text{Var}\left(\sum x_i\right) = \frac{9}{n^2} \sum \text{Var}(x_i) \\ &= \frac{9}{n^2} \sum \left(\int_{-1}^1 \frac{t^2(1+\theta t)}{2} dt - \frac{\theta^2}{9} \right) \\ &= \frac{9}{n^2} \sum \left(\left[\frac{t^3}{6} + \frac{\theta t^4}{4} \right]_{-1}^1 - \frac{\theta^2}{9} \right) \\ &= \frac{9}{n^2} \left(\frac{n}{3} - \frac{n\theta^2}{9} \right) \\ &= \left(\frac{3}{n} - \frac{\theta^2}{n} \right) \end{aligned}$$

Ex 1

1) L'esperance de X ; f_θ

$$f_\theta(x) = \theta(1+\theta)x^{\theta-1}(1-x) \mathbb{1}_{[0,1]}(x)$$

$$E[X] = \int_0^1 x f(x) dx$$

$$= \int_0^1 \theta(1+\theta)x^\theta(1-x) dx$$

$$= \theta(\theta+1) \left[\frac{x^{\theta+1}}{\theta+1} - \frac{x^{\theta+2}}{\theta+2} \right]_0^1$$

$$= \theta(\theta+1) \left[\frac{1}{\theta+1} - \frac{1}{\theta+2} \right]$$

$$= \theta - \frac{\theta(\theta+1)}{\theta+2} = \frac{\theta^2 + 2\theta - \theta^2 - \theta}{\theta+2}$$

$$= \frac{\theta}{\theta+2}$$

De telle sorte que la méthode de moment est $\hat{\theta}$
 solution des moments de $\hat{\theta}$;
 solution de $\bar{x} = \frac{\hat{\theta}}{\hat{\theta} + 2}$

$$\Rightarrow \hat{\theta} = \bar{x} (\hat{\theta} + 2)$$

$$\Rightarrow \hat{\theta} = \bar{x} \hat{\theta} + 2\bar{x} \Rightarrow (1 - \bar{x}) \hat{\theta} = 2\bar{x}$$

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

Commencant par calculer la formule de Fisher

$$\ln(f(x, \theta)) = \ln(\theta) + \ln(1 + \theta) + (\theta - 1) \ln(x) + \ln(1 - x)$$

Soit

$$\frac{\partial}{\partial x} (\ln f(x, \theta)) = \frac{1}{\theta} + \frac{1}{1 + \theta} - \ln(x)$$

De telle sorte que

$$\frac{\partial}{\partial \theta} \log f_{\theta}(x) = -\frac{1}{\theta^2} - \frac{1}{(1 + \theta)^2}$$

et donc si

$$X \sim f_{\theta};$$

$$I(\theta) = -n E_{\theta} \left[\frac{\partial \log f_{\theta}(x)}{\partial \theta^2} \right]$$

$$= \left(\frac{\theta^2 + (\theta + 1)^2}{\theta^2 (\theta + 1)^2} \right) n$$

La borne de Cramer Rao est ici

$$\frac{(\theta+1)^2 \theta^2}{n[\theta^2 + (\theta+1)^2]}$$

Et si on regarde la différence entre
Var($\hat{\theta}$) et cette borne on obtient

$$\frac{\theta(\theta+2)^2}{2n(\theta+3)} - \frac{(\theta+1)^2 \theta^2}{n(\theta^2 + (\theta+1)^2)}$$

$$= \frac{\theta(\theta^2 + 4 + 4\theta)(\theta^2 + (\theta+1)^2) - 2\theta^2(\theta+1)^2(\theta+3)}{2n(\theta+3)(\theta^2 + (\theta+1)^2)}$$

$$= \frac{\theta[2\theta^4 - 2\theta^4 + (2+8-6-4)\theta^3 + (8+1+2-2-6)\theta^2 + (4+8-6)\theta + 4]}{2n(\theta+3)(\theta^2 + (\theta+1)^2)}$$

$$= \frac{3\theta^2 + 6\theta + 4}{2n(\theta+3)(\theta^2 + (\theta+1)^2)} > 0$$

Tous les termes du ratio étant positive
cette estimateur n'est pas efficace.

EX 2:

$\theta \in (0,1)$; $a, b \in \mathbb{R}_+$

$$X_i = \begin{cases} U_i \sim \mathcal{U}([0, a]) \text{ avec prob } \theta \\ V_i \sim \mathcal{U}([0, b]) \text{ avec prob } 1 - \theta \end{cases}$$

N nbre d'observation de X_i ; $0 < X_i < a$

$$1) N = \sum 1_{(0 < X_i < a)}$$

Posons $Y_i = 1_{(0 < X_i < a)}$

~~Ces~~ les variables X_i sont indépendantes

les variables Y_i le sont également

Et ~~ce~~ on a des variables Y_i sont
des variables distribuées suivant une loi

Bernoulli, N suit une loi binomiale

plus précisément $N \sim \mathcal{B}(n, p = P(Y=1))$

or ici:

$$\begin{aligned}
 p &= P(X \leq a) \\
 &= P(X \leq a | X = U_1) \cdot P(X = U_1) \\
 &\quad + P(X \leq a | X = U_2) \cdot P(X = U_2) \\
 &= P(U_1 \leq a) \cdot \theta + P(U_2 \leq a) \cdot (1 - \theta)
 \end{aligned}$$

Soit : $p = \theta + \frac{a}{b} (1 - \theta) = \frac{b-a}{b} \theta + \frac{1}{b}$

f est linéaire de θ

Pour l'estimateur du maximum de vraisemblance de θ on peut utiliser une propriété que nous avons vu lorsqu'on reparamétrise un modèle statistique

Si \hat{p} est l'estimateur du maximum de vraisemblance de p ,

et si $\theta = g(p)$ alors l'estimateur du maximum de vraisemblance de θ est $\hat{\theta} = g(\hat{p})$.

Ici, on utilise le fait que l'estimation du maximum de vraisemblance de la probabilité dans un modèle binomial est la proportion.

Autrement dit, \hat{p} est la proportion d'observations inférieures à a , i.e.

$$\hat{p} = \frac{1}{n} \sum_{i=1}^n \mathbb{1}(x_i < a)$$

Et à partir de là on en déduit l'estimateur de maximum de vraisemblance de θ puisque $\hat{\theta}$ est solution de:

$$\frac{b-a}{b} \hat{\theta} + \frac{1}{b} = \frac{1}{n} \sum \mathbb{1}(x_i < a)$$

$$\hat{\theta} = \left(\frac{1}{n} \sum \mathbb{1}(x_i < a) - \frac{1}{b} \right) \frac{b}{b-a}$$

Ex 3. Soit m , median de $f(x)$

$$\int_0^m f_\theta(x) dx = 0.5$$

$$\int_0^m \frac{2x}{\theta^2} dx = 0.5$$

$$\frac{x^2}{\theta^2} \Big|_0^m = 0.5 \Rightarrow m^2 = 0.5 \theta^2$$
$$\Rightarrow m = \sqrt{\frac{1}{2}} \theta$$

$$\mathcal{L}(x_1, \dots, x_n, \theta) = \begin{cases} \frac{2^n}{\theta^{2n}} \prod x_i & \text{si } \max(x_i) \geq \theta \\ 0 & \text{si } \max(x_i) < \theta \end{cases}$$

$$= \frac{2^n}{\theta^{2n}} \prod x_i \mathbb{1}(\max(x_i) \geq \theta)$$

Alors $\theta = \max(x_i)$

$$m = \sqrt{\frac{1}{2}} \max(x_i)$$

Ex4:

La surface du cercle S:

$$S = \pi \left(\frac{d}{2} \right)^2 ; \quad d = d_0 + \varepsilon ;$$

$$\varepsilon \sim N(0, \sigma^2)$$

$$d, d_0 \sim N(0, \sigma^2)$$

$d \sim N(d_0, \sigma^2)$; un estimateur de d_0, σ ,

D'après la méthode des max de vrais.

estimateur de d_0 ; $\hat{d}_0 = \frac{\sum d_i}{n}$

$$\hat{\sigma}_0^2 = \frac{1}{n} \sum_{i=1}^n (d_i - \hat{d}_0)^2$$

$$S = \left(\frac{d_0}{2} \right)^2 \pi ;$$

$$\hat{S} = \frac{\pi}{4} \cdot \left[\hat{d}_0^2 + \hat{\sigma}_0^2 - \frac{1}{n-1} \sum (d_i - d_0) \right]$$

$$E(\hat{S}) = \frac{\pi}{4} \left[E\left(\frac{\hat{d}_0^2}{n^2}\right) + E(\hat{\sigma}_0^2) - E(S^2) \right] \text{ with } S^2 = \frac{\sum (d_i - d_0)^2}{n}$$

$$= \frac{\pi}{4} \left[\frac{\text{Var}(\sum d_i)}{n^2} + \left(E(\sum d_i) \right)^2 + \frac{(n-1)}{n} E(S^2) - E(S^2) \right]$$

$$= \frac{\pi}{4} \left[\frac{\sigma^2}{n} + n \frac{d_0^2}{n^2} + \frac{n-1}{n} \sigma^2 - \sigma^2 \right]$$

$$= \frac{\pi}{4} d_0^2$$

Ex 6

$$f_{\theta}(x) = \frac{1}{2} \exp(-|\theta - x|)$$

$$E(X) = \int_{-\infty}^{\theta} \frac{x}{2} \exp(-\theta + x) dx + \int_{\theta}^{+\infty} \frac{x}{2} \exp(\theta - x) dx$$

$$\begin{aligned} &= \left[\frac{x}{2} \exp(-\theta + x) \right]_{-\infty}^{\theta} \\ &\quad - \frac{1}{2} \int_{-\infty}^{\theta} \exp(-\theta + x) dx \\ &\quad + \left[-\frac{x}{2} \exp(\theta - x) \right]_{\theta}^{+\infty} \\ &\quad + \frac{1}{2} \int_{\theta}^{+\infty} \exp(\theta - x) dx \end{aligned}$$

$$\begin{aligned} &= \frac{\theta}{2} - \frac{1}{2} \left[\exp(-\theta + x) \right]_{-\infty}^{\theta} \\ &\quad + \frac{\theta}{2} - \frac{1}{2} \left[\exp(\theta - x) \right]_{\theta}^{+\infty} \\ &= \theta - \frac{1}{2} (1 - 1) \\ &= \theta \end{aligned}$$

$$\hat{\theta}^{\text{ENV}} = \bar{x}$$

$$E(\hat{\theta}) = E(\bar{x})$$

$$= \frac{1}{n} \{E(x_i)\} = \frac{1}{n} n\theta = \theta$$

$$\text{Var}(\hat{\theta}) = \text{Var}(\bar{x})$$

$$= \text{Var}(\bar{x})$$

$$= \frac{\text{Var}(\sum x_i)}{n^2}$$

$$= \frac{\sum \text{Var}(x_i)}{n^2}$$

$$= \frac{1}{n^2} \sum_i \left(E(X_i^2) - (E(X_i))^2 \right)$$

$$= \frac{1}{n^2} \sum_i \left(\int_{-\infty}^{\infty} \frac{x^2}{2} \exp(-|\theta - x|) dx - \theta^2 \right)$$

$$= \frac{1}{n^2} \sum_{i=1}^n \left(\int_{-\infty}^{\theta} \frac{x^2}{2} \exp(x - \theta) dx + \int_{\theta}^{+\infty} \frac{x^2}{2} \exp(\theta - x) dx - \theta^2 \right)$$

$$= \frac{1}{n^2} \sum_{i=1}^n \left(\left[\frac{x^2}{2} \exp(x - \theta) \right]_{-\infty}^{\theta} - \int_{-\infty}^{\theta} x \exp(x - \theta) dx \right. \\ \left. + \left[-\frac{x^2}{2} \exp(\theta - x) \right]_{\theta}^{+\infty} - \int_{\theta}^{+\infty} x(-1) \exp(\theta - x) dx \right)$$

$$= \frac{1}{n^2} \sum_{i=1}^n \left(\left(\frac{\theta^2}{2} - \int_{-\infty}^{\theta} x \exp(x - \theta) dx \right) + \frac{\theta^2}{2} + \int_{\theta}^{+\infty} x \exp(\theta - x) dx \right) - \theta^2$$

$$= \frac{1}{n^2} \left(\sum_i \theta^2 - \left[\left[x \exp(x - \theta) \right]_{-\infty}^{\theta} - \int_{-\infty}^{\theta} \exp(x - \theta) dx \right] + \left[(-x) \exp(\theta - x) \right]_{\theta}^{+\infty} + \int_{\theta}^{+\infty} \exp(\theta - x) dx - \theta^2 \right)$$

$$= \frac{1}{n^2} \left(\sum_i (-\theta) + 1 + \theta + 1 \right)$$

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

$$3) f_{\theta}(x) = \frac{1}{2} \exp(-|\theta - x|)$$

$$\mathcal{L}(x_1, \dots, x_n, \theta) = \frac{1}{2^n} \exp(-\sum |\theta - x_i|)$$

$$\log \mathcal{L}(x_1, \dots, x_n, \theta) = n \ln(2) - \sum_{i=1}^n |\theta - x_i|$$

$$= -n \ln(2) - \sum \sqrt{(\theta - x_i)^2}$$

$$\frac{\partial \mathcal{L}}{\partial \theta} = - \sum \frac{\partial \sqrt{(\theta - x_i)^2}}{\partial \theta}$$

$$= - \sum \frac{\partial ((\theta - x_i)^2)^{\frac{1}{2}}}{\partial \theta}$$

$$= - \sum \frac{1}{2} ((\theta - x_i)^2)^{-\frac{1}{2}} ((\theta - x_i)^2)$$

$$= - \sum \frac{1}{2} \frac{1}{\sqrt{(\theta - x_i)^2}} \cdot 2(\theta - x_i)$$

$$= - \sum \frac{1}{2} \frac{\theta - x_i}{|\theta - x_i|} = 0$$

$$= - \sum_{i=1}^n \frac{1}{2} \left(+1(x_i)_{[-\infty, \theta]} - 1(x_i)_{[\theta, +\infty]} \right)$$

$$= 0$$

$$\text{Si } \sum_{i=1}^n (1[x_i < \theta] - 1[\theta < x_i])$$

$$\Rightarrow \sum_{i=1}^n 1(x_i < \theta) = \sum_{i=1}^n 1(\theta < x_i)$$

$$\hat{\theta} = \text{median}(X)$$

Ex 7

$$f_{\mu}(x) = \frac{1}{x \sigma \sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$$

$$\mathcal{L} = \prod_{i=1}^n f_{\mu}(x_i) = \frac{1}{\sigma^n (\sqrt{2\pi})^n} \cdot \frac{1}{\prod_{i=1}^n x_i} \exp\left(-\sum_{i=1}^n \frac{(\ln x_i - \mu)^2}{2\sigma^2}\right)$$

$$\ln \mathcal{L} = -n \ln(\sigma) - n \ln(\sqrt{2\pi}) - \sum_{i=1}^n \ln x_i - \frac{1}{2\sigma^2} \sum_{i=1}^n (\ln x_i - \mu)^2$$

$$\frac{\partial}{\partial \mu} \mathcal{L} = + \frac{\mathcal{L}}{2\sigma^2} \left(\sum_{i=1}^n \ln x_i - n\mu \right) = 0$$

$$\Rightarrow \hat{\mu} = \frac{\sum \ln(x_i)}{n}$$

$$\Rightarrow E(\hat{\mu}) = \frac{\sum E(\ln(x_i))}{n}$$

$$= \frac{n\mu}{n} = \mu$$

Ex 9.

$$F_{\theta}(x) = \left(1 + \frac{1}{x^2}\right)^{-\theta} \mathbb{1}(x > 0)$$
$$= \begin{cases} \left(1 + \frac{1}{x^2}\right)^{-\theta} & x > 0 \\ 0 & x < 0 \end{cases}$$

$$f_{\theta}(x) = \begin{cases} (\theta) \left(1 + \frac{1}{x^2}\right)^{-\theta-1} \left(\frac{2}{x^3}\right) & x > 0 \\ 0 & x < 0 \end{cases}$$

$$\prod_{i=1}^n f_{\theta}(x_i) = (\theta)^n \left(\frac{2}{x^3}\right) \left(\prod_{i=1}^n \left(1 + \frac{1}{x_i^2}\right)\right)^{-(\theta+1)}$$
$$\ell = n \ln(\theta) + \sum \ln\left(\frac{2}{(x_i)^3}\right) - (\theta+1) \sum \ln\left(1 + \frac{1}{x_i^2}\right)$$

$\hat{\theta}^{ENV}$ est solution of $\frac{\partial \ell}{\partial \theta} \Big|_{\hat{\theta}^{ENV}} = 0$

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

for $\theta = \hat{\theta}^{ENV}$, $\frac{\partial \ell}{\partial \theta} \Big|_{\theta = \hat{\theta}^{ENV}} = 0$

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

$$I(\theta) = E \left(\left(\frac{\partial \log f(x, \theta)}{\partial \theta} \right)^2 \middle| \theta \right)$$
$$= -n E \left(\frac{\partial^2 \log f(x, \theta)}{\partial \theta^2} \right)$$

$$\log f(x, \theta) = \ln(\theta) - (\theta+1) \ln\left(1 + \frac{1}{x^2}\right) + \ln\left(\frac{2}{x^3}\right)$$

$$\log f(x, \theta) = \ln(\theta) - (\theta+1) \ln\left(1 + \frac{1}{x^2}\right) + \ln\left(\frac{2}{x^3}\right)$$

$$\frac{\partial \log f(x, \theta)}{\partial \theta} = \frac{1}{\theta} - \ln\left(1 + \frac{1}{x^2}\right)$$

$$\frac{\partial^2 \log f(x, \theta)}{\partial \theta^2} = -\frac{1}{\theta^2}$$

$$I(\theta) = \frac{n}{\theta^2}$$

Ex 11:

$$U \sim U[-\theta, +\theta]$$

$$1) E(U_{1:n}) = E[\min(U_i)]$$

$$F_{U_{1:n}}(x) = P(\min(U_i) \leq x)$$

$$\begin{aligned} &= P(\cup \{U_k \leq x\}) \\ &= 1 - P(\cap \{U_k > x\}) \\ &= 1 - \prod P(U_k > x) \\ &= 1 - \left(\frac{\theta - x}{2\theta}\right)^n \end{aligned}$$

$$f_{U_{1:n}}(x) = +n \frac{(\theta - x)^{n-1}}{(2\theta)^n}$$

$$\begin{aligned} E[U_{1:n}] &= \int_{-\theta}^{\theta} n x \frac{(\theta - x)^{n-1}}{(2\theta)^n} dx \\ &= - \left[\frac{n x (\theta - x)^n}{(2\theta)^n n} \right]_{-\theta}^{\theta} + \int_{-\theta}^{\theta} \frac{n}{(2\theta)^n} \frac{(\theta - x)^n}{n} dx \\ &= - \left[\frac{n \theta}{(2\theta)^n} \cdot \frac{(2\theta)^n}{n} \right] - \left[\frac{(\theta - x)^{n+1}}{(2\theta)^n (n+1)} \right]_{-\theta}^{\theta} \\ &= - (\theta) + \frac{(2\theta)^{n+1}}{(2\theta)^n (n+1)} \\ &= -\theta + \frac{2\theta}{n+1} \end{aligned}$$

$$U_{n:n}:$$

$$P(U_{n:n} < x) = \left(P(U_1 < x) \right)^n$$

$$= \left(\int_{-\theta}^x \frac{1}{2\theta} dz \right)^n = \left(\frac{x+\theta}{2\theta} \right)^n$$

$$f_{U_{n:n}}(x) = n \frac{(x+\theta)^{n-1}}{(2\theta)^n}$$

$$E_{U_{n:n}} = \int_{-\theta}^{\infty} n x \frac{(x+\theta)^{n-1}}{(2\theta)^n} dx$$

$$= \left[\frac{x}{(2\theta)^n} (x+\theta)^n \right]_{-\theta}^{\theta} - \int_{-\theta}^{\theta} \frac{1}{(2\theta)^n} (x+\theta)^n dx$$

$$= \frac{\theta(2\theta)^n}{(2\theta)^n} - \left[\frac{(x+\theta)^{n+1}}{(2\theta)^n(n+1)} \right]_{-\theta}^{\theta}$$

$$= \theta - \frac{2\theta}{n+1} = \frac{(n+1)\theta - 2\theta}{n+1} = \frac{(n-1)\theta}{n+1}$$

$$2) P(|U_i| < x) = P(-x < U_i < x) \text{ si } x > 0$$

$$= \int_{-x}^x \frac{1}{2\theta} dz = \frac{x}{\theta} \text{ si } x > 0$$

$$P(|U_i| < x) = 0 \text{ si } x < 0$$

$$f_{|U_i|}(x) = \frac{1}{\theta} \mathbb{1}_{(0 < x < \theta)}$$

$$P(\max |U_i| < x) = \prod P(|U_i| < x)$$

$$= \left(P(|U_i| < x) \right)^n$$

$$= \left(\int_0^x \frac{1}{\theta} d\theta \right)^n = \left(\frac{x}{\theta} \right)^n$$

$$f_{\max |U_i|}(x) = n \frac{x^{n-1}}{\theta^n}$$

$$E(\max |U_i|) = \int_0^\theta \frac{n x^n}{\theta^n} dx$$

$$= \frac{1}{\theta^n} \theta^{n+1} \cdot \frac{n}{n+1} = \frac{\theta n}{n+1}$$

$$4) \mathcal{L}(u_1, \dots, u_n, \theta) = \prod_{i=1}^n p_{\theta}(x_i)$$

$$= \prod_{i=1}^n \frac{1}{2\theta} \mathbb{1}_{[-\theta, \theta]}(x_i)$$

$$= \begin{cases} 0 & \text{sinon} \\ \frac{1}{(2\theta)^n} & ; \max(|x_i|) < \theta \end{cases}$$

La fct $\theta \rightarrow \left(\frac{1}{2\theta}\right)^n$ est décroissante en θ pour $\theta > 0$; donc \mathcal{L} prend son maximum en $\theta = \max |x_i|$, donc l'estimateur de vraisemblance s'écrit:

$$\hat{\theta}^{MV} = \max |X_i|$$

$$5) E(\hat{\theta}^{MV}) = \theta \cdot \frac{n}{n+1} \neq \theta$$

$$6) \text{Var}(U_{[-\theta, \theta]}) = E(U^2) - (E(U))^2$$

$$= \int_{-\theta}^{\theta} \frac{u^2}{2\theta} du$$

$$= \left[\frac{u^3}{3 \cdot 2\theta} \right]_{-\theta}^{\theta}$$

$$= \left(\frac{\theta^3}{6\theta} + \frac{\theta^3}{6\theta} \right)$$

$$= \frac{\theta^3}{3}$$