

TD 4

- intervalles de confiance sur la moyenne:

→ si σ^2 est connue :

$$IC_{1-\alpha}(\mu) = \left[\bar{X}_n - z_{1-\frac{\alpha}{2}} \times \frac{\sigma}{\sqrt{n}} ; \bar{X}_n + z_{1-\frac{\alpha}{2}} \times \frac{\sigma}{\sqrt{n}} \right]$$

← normale

→ si σ^2 est estimée :

$$IC_{1-\alpha}(\mu) = \left[\bar{X}_n - t_{n-1, 1-\frac{\alpha}{2}} \times \frac{S_n}{\sqrt{n}} ; \bar{X}_n + t_{n-1, 1-\frac{\alpha}{2}} \times \frac{S_n}{\sqrt{n}} \right]$$

← student

- intervalles de confiance
sur la variance :

$$IC_{1-\alpha}(\sigma^2) = \left[\frac{(n-1)S_n^2}{\chi_{n-1, 1-\frac{\alpha}{2}}^2} ; \frac{(n-1)S_n^2}{\chi_{n-1, \frac{\alpha}{2}}^2} \right]$$

↙
les deux

$$S_n^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$$

TD 6

• méthode des moments

$X_1, \dots, X_n$ iid

• $m_k = E[X_i^k] = \varphi(\theta)$

• $\hat{m}_{n,k} = \frac{1}{n} \sum_{i=1}^n X_i^k$

$\Rightarrow$ on pose $\hat{\theta}_n = \varphi^{-1}(\hat{m}_{n,k})$

exemple: $X_1, \dots, X_n$ iid $E(\theta)$

• $m_1 = E[X_1] = \frac{1}{\theta} = \varphi(\theta)$

• $\hat{m}_{n,1} = \frac{1}{n} \sum_{i=1}^n X_i =: \bar{X}_n$

on pose $\varphi : x \mapsto \frac{1}{x}$

et $\varphi^{-1} : x \mapsto \frac{1}{x}$

on pose $\hat{\theta}_n = \varphi^{-1}(\bar{r}_{n,1})$

$$= \frac{1}{\bar{x}_n}$$

• maximum de vraisemblance

$X_1, \dots, X_n$ iid.

$$\Rightarrow L_X(\theta) = \prod_{i=1}^n \left\{ \begin{array}{l} P_{\theta}(X=X_i) \\ f_{\theta}(X_i) \end{array} \right.$$

$\Rightarrow$ Pe log-vraisemblance

$$\begin{aligned} P_X(\theta) &= P_n(L_X(\theta)) \\ &= \sum_{i=1}^n P_n(f_{\theta}(X_i)) \end{aligned}$$

$\Rightarrow$ Pe but est de trouver
Pe maximum de $P_X(\theta)$

example :

$X_1, \dots, X_n$ iid $\text{Poi}(\theta)$.

$$\begin{aligned} \bullet \quad f_{\theta}(x_i) &= \mathbb{P}_{\theta}(X = x_i) \\ &= \theta^{x_i} (1 - \theta)^{1 - x_i} \end{aligned}$$

$$\begin{aligned} \bullet \quad L_X(\theta) &= \prod_{i=1}^n f_{\theta}(x_i) \\ &= \prod_{i=1}^n \theta^{x_i} (1 - \theta)^{1 - x_i} \\ &= \theta^{\sum x_i} (1 - \theta)^{\sum (1 - x_i)} \\ &= \theta^{\sum x_i} (1 - \theta)^{n - \sum x_i} \\ &= \theta^{n\bar{x}_n} (1 - \theta)^{n - n\bar{x}_n} \end{aligned}$$

$$\cdot P_x(\theta) = P_{\text{eg}}(L_x(\theta))$$

$$= P_n \left(e^{n\bar{x}_n} (1-\theta)^{n-n\bar{x}_n} \right)$$

$$= P_n(\theta^{n\bar{x}_n}) + P_n((1-\theta)^{n-n\bar{x}_n})$$

$$= n\bar{x}_n P_n(\theta) + (n-n\bar{x}_n) P_n(1-\theta)$$

$$\cdot P'_x(\theta) = \frac{n\bar{x}_n}{\theta} + (n-n\bar{x}_n) \frac{-1}{1-\theta}$$

$$P'_x(\theta) = 0$$

$$\Leftrightarrow \frac{n\bar{x}_n}{\theta} - \frac{(n-n\bar{x}_n)}{1-\theta} = 0$$

$$\Leftrightarrow \frac{n\bar{x}_n}{\theta} = \frac{n - n\bar{x}_n}{1 - \theta}$$

$$\Leftrightarrow \theta = \bar{x}_n \quad \leftarrow \text{résoudre}$$

$$\bullet P_x''(\theta) = -\frac{n\bar{x}_n}{\theta^2} - \frac{(n - n\bar{x}_n)}{(1 - \theta)^2}$$

$$< 0$$

$$\text{d'où } P_x''(\bar{x}_n) < 0$$

donc $\theta = \bar{x}_n$ est un maximum global.

$$\text{Donc } \hat{\theta}_n^{\text{ML}} = \bar{x}_n.$$

TD 8

- exprimer des données y_i en fonction d'autres données x_i .

$$\hat{y} = \hat{a}x + \hat{b}$$

$$\hat{a} = \frac{\sum_{i=1}^n (y_i - \bar{y})(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$\hat{b} = \bar{y}_n - \hat{a} \bar{x}_n$$

• coefficient de corrélation

$$\rho = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y}$$

• coefficient de détermination

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y}_n)^2}$$