

Sur 11

1. 8.2.9 Soit $Y = \sum X_i$. Quand $EX = \theta$, $Y \approx N(n\theta, n\theta(1-\theta))$.
 (3 points) La fonction de puissance pour tester $H_0: \theta = \theta_0$ vs $H_1: \theta = \theta_1 > \theta_0$,
 $\gamma(\theta) = P_\theta(Y \geq c)$.

$$\gamma(\theta_0) = P\left(\frac{Y - n\theta_0}{\sqrt{n\theta_0(1-\theta_0)}} \geq \frac{c - n\theta_0}{\sqrt{n\theta_0(1-\theta_0)}}\right) = \alpha$$

$$\Rightarrow \frac{c - n\theta_0}{\sqrt{n\theta_0(1-\theta_0)}} = z_\alpha \quad (1)$$

Aussi

$$\gamma(\theta_1) = P\left(\frac{Y - n\theta_1}{\sqrt{n\theta_1(1-\theta_1)}} \geq \frac{c - n\theta_1}{\sqrt{n\theta_1(1-\theta_1)}}\right) = \beta$$

$$\Rightarrow \frac{c - n\theta_1}{\sqrt{n\theta_1(1-\theta_1)}} = z_\beta \quad (2)$$

$$(1) \quad c - n\theta_0 = \sqrt{n} \sqrt{\theta_0(1-\theta_0)} z_\alpha$$

$$(2) \quad c - n\theta_1 = \sqrt{n} \sqrt{\theta_1(1-\theta_1)} z_\beta$$

$$(1) - (2) \quad n(\theta_1 - \theta_0) = \sqrt{n} \left[z_\alpha \sqrt{\theta_0(1-\theta_0)} - z_\beta \sqrt{\theta_1(1-\theta_1)} \right]$$

$$\Rightarrow n = \frac{\left[z_\alpha \sqrt{\theta_0(1-\theta_0)} - z_\beta \sqrt{\theta_1(1-\theta_1)} \right]^2}{(\theta_1 - \theta_0)^2}$$

Pour $z_\alpha = 1.645$, $z_\beta = -1.282$, $\theta_0 = \frac{1}{20}$, $\theta_1 = \frac{1}{10}$,

$$n = 220.89 \approx 221$$

2. 8.2.11 C'est un membre de la famille exponentielle avec $p(\theta) = \theta$, $K(x) = \ln x$, $q(\theta) = \ln \theta$

Cette famille possède un mlr en $\sum K(x_i) = \sum \ln x_i = \ln(\prod x_i)$

(2 points) Donc le VMP rejette quand $\prod x_i \leq c$ puisque $\theta > 0$.

2. # 8.3.10

(3 points)

$$\Lambda = \frac{\max_{\theta} \frac{1}{\theta^n} \cdot I(\max \bar{x}_i < \theta)}{\max_{\theta} \frac{1}{\theta^n} e^{-\sum x_i / \theta}} = \frac{\left(\frac{1}{\hat{\theta}}\right)^n}{\frac{1}{\bar{x}^n} e^{-n}} \quad \hat{\theta} = \max x_i$$

$$\Rightarrow \text{Rej. if } \left(\frac{\hat{\theta}}{\bar{x}}\right)^n e^n \leq k$$

i.e. $\frac{\hat{\theta}}{\bar{x}} < k$

3. 8.3.12

$$H_0: \mu_1 = \mu_2 = 0$$

(3 points)

$$H_1: \mu_1 \neq 0, \mu_2 \neq 0$$

$$\max_{\mu_1, \mu_2=0} L(\mu_1, \mu_2) = \left(\frac{1}{2\pi}\right)^n \left(\frac{1}{\hat{\sigma}^2}\right)^n \exp - \frac{\left(\sum x_i^2 + \sum y_i^2\right)}{2\hat{\sigma}^2}$$

$$\text{or } \hat{\sigma}^2 = \frac{\sum x_i^2 + \sum y_i^2}{2n}$$

$$\max_{\mu_1, \mu_2} L(\mu_1, \mu_2) = \left(\frac{1}{2\pi}\right)^n \left(\frac{1}{\hat{\sigma}^2}\right)^n \exp - \frac{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2}{2\hat{\sigma}^2}$$

$$\text{or } \hat{\sigma}^2 = \frac{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2}{2n}$$

$$\therefore \Lambda = \left(\frac{1}{\hat{\sigma}^2}\right)^n \left(\frac{\hat{\sigma}^2}{1}\right)^n \leq k$$

$$\Rightarrow \frac{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2}{\sum x_i^2 + \sum y_i^2} \leq k$$

$$\frac{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2}{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2 + n(\bar{x}^2 + \bar{y}^2)} \leq k$$

Ref. when

$$\frac{n(\bar{x}^2 + \bar{y}^2)}{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2} > k$$

On sait que $\frac{\sqrt{n} \bar{X}}{\sigma} \sim N(0, 1)$, $\frac{\sqrt{n} \bar{Y}}{\sigma} \sim N(0, 1)$

$$\Rightarrow \frac{n \bar{X}^2 + n \bar{Y}^2}{\sigma^2} \sim \chi_2^2$$

Aussi

$$\frac{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2}{\sigma^2} \sim \chi_{2(n-1)}^2 \text{ indep.}$$

\Rightarrow

$$F = \frac{\frac{n(\bar{x}^2 + \bar{y}^2)}{2\sigma^2}}{S^2/\sigma^2} \sim F_{2, 2(n-1)} \text{ sous } H_0$$

c) Quand H_1 est vraie, $\frac{\sqrt{n}(\bar{x} - \mu_1)}{\sigma} \sim N(0, 1)$

$$\frac{\sqrt{n}(\bar{y} - \mu_2)}{\sigma} \sim N(0, 1)$$

$$\Rightarrow \frac{n}{\sigma^2} \left[(\bar{x} - \mu_1)^2 + (\bar{y} - \mu_2)^2 \right] \sim \chi_2^2$$