

2003 Spring Part 1

1. Fisher Information

$$\log f(x) = -\frac{1}{2} \log 2\pi - \frac{1}{2} \log \theta_2 - \frac{(x - \theta_1)^2}{2\theta_2}$$
$$\frac{\partial \log f(x)}{\partial \theta} = \begin{pmatrix} \frac{1}{\theta_2}(x - \theta_1) \\ -\frac{1}{2\theta_2} + \frac{1}{2\theta_2^2}(x - \theta_1)^2 \end{pmatrix}$$

Fisher Information is

$$I(\theta) = E \left[\frac{\partial \log f(x)}{\partial \theta} \frac{\partial \log f(x)}{\partial \theta'} \right] \equiv \begin{pmatrix} A & B \\ C & D \end{pmatrix}$$

where

$$A = E \left[\frac{(X - \theta_1)^2}{\theta_2^2} \right] = \frac{\theta_2}{\theta_2^2} = \frac{1}{\theta_2}$$
$$B = C = E \left[-\frac{1}{2\theta_2^2}(X - \theta_1) + \frac{1}{2\theta_2^3}(X - \theta_1)^3 \right] = 0$$
$$D = E \left[\frac{1}{4\theta_2^2} - \frac{1}{2\theta_2^3}(X - \theta_1)^2 + \frac{1}{4\theta_2^4}(X - \theta_1)^4 \right] = \frac{1}{4\theta_2^2} - \frac{\theta_2}{2\theta_2^3} + \frac{3\theta_2^2}{4\theta_2^4} = \frac{1}{2\theta_2^2}$$

2. Asymptotic variance of MLE (a)

Apply the asymptotic efficiency theorem of MLE $\sqrt{n}(\hat{\theta}_{MLE} - \theta) \xrightarrow{d} N(0, I(\theta)^{-1})$

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

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

Fisher Information is

$$I(\theta) = -E \left[\frac{\partial^2 \log f(X, \theta)}{\partial \theta^2} \right] = \frac{1}{\theta^2}$$

The asymptotic variance of $\hat{\theta}_{MLE}$ is $I(\theta)^{-1} = \theta^2$.

(b)

$$\log f(x, \theta) = -\log \theta + \frac{x}{\theta}$$

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

Fisher Information is

$$I(\theta) = -E \left[\frac{\partial^2 \log f(X, \theta)}{\partial \theta^2} \right] = -\frac{1}{\theta^2} + \frac{2E[X]}{\theta^3} = \frac{1}{\theta^2}$$

where we used $E[X] = \theta$ since $X \sim \Gamma(1, \theta)$. The asymptotic variance of $\hat{\theta}_{MLE}$ is $I(\theta)^{-1} = \theta^2$.

3. Optimal test

From Neyman-Pearson theorem, the optimal critical region is given by

$$C = \left\{ x = (x_1, \dots, x_n) \left| \frac{\prod_{i=1}^{25} f(x, \mu_1)}{\prod_{i=1}^{25} f(x, \mu_0)} \geq k \right. \right\} = \left\{ x \left| \frac{1}{25} \sum_{i=1}^{25} x_i \geq c \right. \right\}$$

Find c such that $\Pr(X \in C) = 0.05$ under H_0 . Since $\frac{1}{25} \sum_{i=1}^{25} X_i \sim N\left(\mu_0, \frac{1}{25}\right)$,

$$0.05 = \Pr\left(\frac{\left[\frac{1}{25} \sum_{i=1}^{25} X_i - \mu_0\right]}{\sqrt{1/25}} \geq 1.645\right) = \Pr\left(\frac{1}{25} \sum_{i=1}^{25} X_i \geq \mu_0 + 0.329\right)$$

Therefore, the optimal critical region is

$$C = \left\{ x \left| \frac{1}{25} \sum_{i=1}^{25} x_i \geq \mu_0 + 0.329 \right. \right\}$$

4. Asyptotic distriubtion

When $n = 4$,

$$S \geq \frac{1.96}{\sqrt{n}} \cdot \frac{1}{2} \iff \frac{1}{4} \sum_{i=1}^4 1(X_i \geq 0) \geq 0.99 \iff X_i \geq 0 \quad \forall i = 1, 2, 3, 4$$

Under H_0 ,

$$\Pr(X_i \geq 0 \quad \forall i) = \prod_{i=1}^4 \Pr(X_i \geq 0) = \frac{1}{16} \quad \because iid$$

When $n \rightarrow \infty$,

$$S \geq \frac{1.96}{\sqrt{n}} \cdot \frac{1}{2} \iff \sqrt{n} \left[\frac{1}{n} \sum_{i=1}^n 1(X_i \geq 0) - \frac{1}{2} \right] \geq \frac{1}{2} \times 1.96$$

Under H_0 , $1(X_i \geq 0)$ has a Bernoulli distribution $B\left(\frac{1}{2}\right)$. Thus

$$\begin{aligned} E[1(X_i \geq 0)] &= \frac{1}{2} \\ \text{var}[1(X_i \geq 0)] &= \frac{1}{4} \end{aligned}$$

Apply CLT,

$$\sqrt{n} \left[\frac{1}{n} \sum_{i=1}^n 1(X_i \geq 0) - \frac{1}{2} \right] \xrightarrow{d} N\left(0, \frac{1}{4}\right)$$

Therefore,

$$\lim_{n \rightarrow \infty} \Pr\left(S \geq \frac{1.96}{\sqrt{n}} \cdot \frac{1}{2}\right) = \lim_{n \rightarrow \infty} \Pr\left(\frac{\sqrt{n} \left[\frac{1}{n} \sum_{i=1}^n 1(X_i \geq 0) - \frac{1}{2} \right]}{\frac{1}{2}} \geq 1.96\right) = 0.025$$