

Example

Let X_1, \dots, X_n r.v.s. of $N(\theta, 1)$. Prove that there exist no u.m.q.t. for $H_0: \theta = \theta_0$ vs $H_1: \theta \neq \theta_0$ with error α .

Solution

Let $\theta_1 \neq \theta_0$, from the N-P lemma we have:

$$\frac{L_0}{L_1} \leq k \Leftrightarrow \frac{(2\pi)^{-n/2} \cdot \exp\left\{-\frac{1}{2} \sum_{i=1}^n (x_i - \theta_0)^2\right\}}{(2\pi)^{-n/2} \cdot \exp\left\{-\frac{1}{2} \sum_{i=1}^n (x_i - \theta_1)^2\right\}} \leq k \Leftrightarrow$$

$$\Leftrightarrow \exp\left\{-\frac{\sum x_i^2}{2} - \frac{n\theta_0^2}{2} + \theta_0 \sum_{i=1}^n x_i + \frac{\sum x_i^2}{2} + \frac{n\theta_1^2}{2} - \theta_1 \sum_{i=1}^n x_i\right\} \leq k \Leftrightarrow$$

$$\Leftrightarrow -(\theta_1 - \theta_0) \sum_{i=1}^n x_i + \frac{n}{2} (\theta_1^2 - \theta_0^2) \leq \log k \Leftrightarrow$$

$$\Leftrightarrow (\theta_1 - \theta_0) \sum_{i=1}^n x_i \geq -\log k + \frac{n}{2} (\theta_1^2 - \theta_0^2)$$

$$\begin{aligned} \bullet \text{ If } \theta_1 > \theta_0, \text{ then } \sum_{i=1}^n x_i &\geq \frac{\frac{n}{2} (\theta_1^2 - \theta_0^2) - \log k}{\theta_1 - \theta_0} = W \Leftrightarrow \dots \Leftrightarrow \\ \Leftrightarrow \frac{\sum x_i - \theta_0}{\sqrt{1/n}} &\geq \frac{W - \theta_0}{\sqrt{1/n}} \Rightarrow W = \theta_0 + 2\alpha/2 \cdot \sqrt{1/n} \end{aligned}$$

$$\begin{aligned} \bullet \text{ If } \theta_1 < \theta_0, \text{ then } \sum_{i=1}^n x_i &\leq \frac{\frac{n}{2} (\theta_1^2 - \theta_0^2) - \log k}{\theta_1 - \theta_0} = W \Leftrightarrow \dots \Leftrightarrow \\ \Leftrightarrow W &= \theta_0 - 2\alpha/2 \cdot \sqrt{1/n} \end{aligned}$$

The first case determines a u.q.c.r. for $H_0: \theta = \theta_0$ vs $H_1: \theta = \theta_1$ with $\theta_1 > \theta_0$ and the second for $\theta_1 < \theta_0$.

Hence, according to the definition, there exists no u.m.q.t.

Complex vs Complex

The N-P lemma cannot be used with complex hypotheses.

Let $H_0: \theta \in \Theta_0$ vs $H_1: \theta \in \Theta_1$, with $\Theta = \Theta_0 \cup \Theta_1$

Generalized likelihood ratio

$$L_0 = \sup_{\theta \in \Theta_0} L(\theta) \quad \text{and} \quad L_1 = \sup_{\theta \in \Theta_1} L(\theta)$$

Instead of calculating $\frac{L_0}{L_1} = \frac{\sup_{\theta \in \Theta_0} L(\theta)}{\sup_{\theta \in \Theta_1} L(\theta)}$, we calculate $\frac{L_0}{L} = \frac{\sup_{\theta \in \Theta_0} L(\theta)}{\sup_{\theta \in \Theta_0 \cup \Theta_1} L(\theta)} \leq k$ and define the critical range C :

i) $\frac{L_0}{L} \leq k$ if $(x_1, \dots, x_n) \in C$

ii) $\frac{L_0}{L} > k$ if $(x_1, \dots, x_n) \in C$

iii) $P((x_1, \dots, x_n) \in C \mid H_0) = \alpha$

Notes

→ The tests that are created via the generalized likelihood ratio are not necessarily u.m.p.t

→ If we have more than one parameters, then it is not obvious if a hypothesis is simple, e.g. if $H_0: \mu = \mu_0$ for $N(\mu, \sigma^2)$ is simple if σ^2 is known, but complex if not.

→ Since $\Theta = \Theta_0 \cup \Theta_1$, $L = \sup_{\theta \in \Theta_0 \cup \Theta_1} L(\theta) = \sup_{\theta \in \Theta} L(\theta) = L(\hat{\theta})$, where $\hat{\theta}$ the MLE.

Example

Let x_1, \dots, x_n r.s. of $N(\mu, \sigma^2)$, where σ^2 is known.

We want to find a critical range with error α for

$$H_0: \mu = \mu_0 \quad \text{vs} \quad H_1: \mu \neq \mu_0$$

Solution

$$L_0 = L(\mu_0) = (2\pi\sigma^2)^{-v/2} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^v (X_i - \mu_0)^2\right\}$$

$$L = \sup_{\mu \in \mathbb{R}} L(\mu) = L(\hat{\mu}) = L(\bar{X}) = (2\pi\sigma^2)^{-v/2} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^v (X_i - \bar{X})^2\right\}$$

$$\text{So } \frac{L_0}{L} \leq k \Leftrightarrow \frac{(2\pi\sigma^2)^{-v/2} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^v (X_i - \mu_0)^2\right\}}{(2\pi\sigma^2)^{-v/2} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^v (X_i - \bar{X})^2\right\}} \leq k \Leftrightarrow$$

$$\Leftrightarrow \exp\left\{-\frac{1}{2\sigma^2} \left(\sum_{i=1}^v (X_i - \mu_0)^2 - \sum_{i=1}^v (X_i - \bar{X})^2\right)\right\} \leq k \Leftrightarrow$$

$$\Leftrightarrow -\frac{1}{2\sigma^2} \left(\sum_{i=1}^v X_i^2 + v\mu_0^2 - 2\mu_0 \sum_{i=1}^v X_i - \sum_{i=1}^v X_i^2 - v\bar{X}^2 + 2\bar{X} \sum_{i=1}^v X_i\right) \leq \log k$$

$$\Leftrightarrow v(\mu_0^2 - \bar{X}^2) - 2\sum_{i=1}^v X_i(\mu_0 - \bar{X}) \geq -2\sigma^2 \log k \Leftrightarrow$$

$$\Leftrightarrow (\mu_0 - \bar{X})(v\mu_0 - v\bar{X} - 2\sum_{i=1}^v X_i) \geq -2\sigma^2 \log k \Leftrightarrow$$

$$\Leftrightarrow (\mu_0 - \bar{X})^2 \geq -\frac{2\sigma^2 \log k}{v} \Leftrightarrow |\mu_0 - \bar{X}| \geq \sqrt{\frac{2\sigma^2 \log k}{v}} = w$$

$$\text{so } G = \{(X_1, \dots, X_v) : |\bar{X} - \mu_0| \geq w\}$$

$$\text{and we want } P(G | H_0) = \alpha \Rightarrow P(|\bar{X} - \mu_0| \geq w) = \alpha \quad (1),$$

$$\text{but } \bar{X} \sim N(\mu_0, \sigma^2/v), \text{ so } (1) \Rightarrow P\left(\left|\frac{\bar{X} - \mu_0}{\sigma/\sqrt{v}}\right| \geq \frac{w}{\sigma/\sqrt{v}}\right) = \alpha \Rightarrow$$

$$\Rightarrow P(|Z| \geq w/\sigma/\sqrt{v}) = \alpha$$

We know that $Z \geq Z_{\alpha/2}$ or $Z \leq -Z_{\alpha/2}$, so we reject H_0

$$\text{if } \left|\frac{\bar{X} - \mu_0}{\sigma/\sqrt{v}}\right| = |Z| \geq Z_{\alpha/2} \Rightarrow \bar{X} \geq \mu_0 + Z_{\alpha/2} \frac{\sigma}{\sqrt{v}} \text{ or } \bar{X} \leq \mu_0 - Z_{\alpha/2} \frac{\sigma}{\sqrt{v}}$$

