

Assignment 11 - MA212M

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1 Answer 1

Given:

- $X_1, X_2, \dots, X_n \sim N(\mu, \sigma^2)$
- σ is known.

1.1 Answer 1.a

To Find: Most Powerful level α test for $H_0 : \mu = \mu_0$ against $H_1 : \mu = \mu_1$, where $\mu_1 < \mu_0$.

Since both $\Theta_0 = \mu_0$ and $\Theta_1 = \mu_1$ are singleton, therefore, we can use Neyman Pearson Lemma.

Hence, we first need to find $\frac{L(\mu_1)}{L(\mu_0)}$

$$\frac{L(\mu_1)}{L(\mu_0)} = \exp \left(\frac{1}{2\sigma^2} \{2n\bar{x}(\mu_1 - \mu_0) + n(\mu_0^2 - \mu_1^2)\} \right)$$

Therefore, if $\frac{L(\mu_1)}{L(\mu_0)} > k$, this implies that

$$\bar{x} < k_1 \quad \text{where } k_1 > 0, \text{ as } \mu_1 < \mu_0$$

Thus the M.P. level α test is

$$\varphi(x) = \begin{cases} 1 & \text{if } \bar{x} < k_1 \\ \gamma & \text{if } \bar{x} = k_1 \\ 0 & \text{if } \bar{x} > k_1 \end{cases}$$

this should be such that

$$\begin{aligned} \mathbb{E}_{\mu_0} [\varphi(x)] &= \alpha \\ \mathbb{E}_{\mu_0} [\varphi(x)] &= P(\bar{X} < k_1) + \gamma P(\bar{X} = k_1) \\ &= P(\bar{X} < k_1) + 0 \quad \text{as } \bar{X} \text{ follows a Normal distribution} \\ &= P(\bar{X} < k_1) \quad \text{where } \bar{X} \sim N\left(\mu_0, \frac{\sigma^2}{n}\right) \\ &\implies \frac{\sqrt{n}(\bar{X} - \mu_0)}{\sigma} \sim N(0, 1) \\ &\implies P(\bar{X} < k_1) = \Phi\left(\frac{\sqrt{n}(k_1 - \mu_0)}{\sigma}\right) = \alpha \\ &\implies k_1 = \frac{z_\alpha \sigma}{\sqrt{n}} + \mu_0 \end{aligned}$$

Also, since $P(\bar{X} = k_1) = 0$ therefore, $\gamma = 0$.

Hence,

$$\varphi(x) = \begin{cases} 1 & \text{if } \bar{x} - \mu_0 < \frac{z_\alpha \sigma}{\sqrt{n}} \\ 0 & \text{otherwise} \end{cases}$$

1.2 Answer 1.b

To Find: Uniformly Most Probable level α test for $H_0 : \mu = \mu_0$ against $H_1 : \mu < \mu_0$.

Note that the statement of this question is exactly same as that for that of part 1.a, the U.M.P. level α test is same as in 1.a

2 Answer 2

Given:

- $\phi(\cdot)$ be a M.P. level α test for testing $H_0 : \theta = \theta_0$ against $H_1 : \theta = \theta_1$

To Show: $\beta(\theta_0) \leq \beta(\theta_1)$ where $\beta(\cdot)$ is the power function of the Most Powerful test.

Consider

$$\phi(x) = \alpha \quad \text{for all } x$$

as a test.

Clearly, $\mathbb{E}_{\theta_0}[\phi(x)] = \alpha$

Hence, $\phi(x)$ is the most powerful level α test. Since $\phi(x)$ is the M.P. level α test, therefore,

$$\begin{aligned} \beta(\theta) &\geq \beta^*(\theta) \quad \text{where } \theta \in \Theta_1 \\ \implies \beta(\theta_1) &\geq \beta^*(\theta_1) \\ \implies \beta(\theta_1) &\geq \alpha \end{aligned}$$

where $\beta^*(\cdot)$ represents power function for all other level α tests.

Note that $\beta(\theta_0)$ represents the probability of rejecting H_0 when θ_0 is the true parameter, i.e. H_0 is correct. Which is nothing but Type-I Error.

Since

$$\begin{aligned} \beta(\theta_0) &= \mathbb{E}_{\theta_0}[\phi(x)] \leq \alpha \\ \beta(\theta_0) &\leq \alpha \end{aligned}$$

Therefore:

$$\beta(\theta_0) \leq \beta(\theta_1)$$

3 Answer 3

Given:

- X_1 and X_2 are two random samples drawn from a PDF $f(x)$, $x \in \mathbb{R}$.
- Consider

$$f_0(x) = \frac{3}{64}x^2 I_{(0,4)}(x)$$

$$f_1(x) = \frac{3}{16}\sqrt{x} I_{(0,4)}(x)$$

To Find: The most powerful level α test for testing $H_0 : f(x) = f_0(x)$ against $H_1 : f(x) = f_1(x)$

The Likelihood function is:

$$L(x_1, x_2) = f(x_1) f(x_2)$$

Since both $\Theta_0 = f_0$ and $\Theta_1 = f_1$ are singleton, thus, using Neyman-Pearson Lemma, we get the M.P. level α test function as

$$\varphi(x) = \begin{cases} 1 & \text{if } \frac{L(\theta_1)}{L(\theta_0)} > k \\ \gamma & \text{if } \frac{L(\theta_1)}{L(\theta_0)} = k \\ 0 & \text{if } \frac{L(\theta_1)}{L(\theta_0)} < k \end{cases}$$

Here, $\frac{L(\theta_1)}{L(\theta_0)}$ is:

$$\frac{L(f_1)}{L(f_0)} = 16 (x_1 x_2)^{\frac{3}{2}}$$

Therefore, if $\frac{L(f_1)}{L(f_0)} > k \implies x_1 x_2 > k_1$ for some $k_1 > 0$.

Consider now a new random variable under H_0 :

$$Y = -6 \ln \frac{X_1}{4}$$

Note that $\frac{dx_1}{dy} = -\frac{2}{3}e^{-\frac{y}{6}}$

This gives us the PDF of Y as

$$f_Y(y) = \frac{3}{64} \left(4e^{-\frac{y}{6}} \right) \frac{2}{3} e^{-\frac{y}{6}} \quad \text{if } y > 0$$

$$= \frac{1}{2} e^{-y} \quad \text{if } y > 0$$

Now, note that

$$Y \sim \chi_2^2$$

Also, if $Y_1, Y_2 \sim \chi_2^2$, then $Y_1 + Y_2 \sim \chi_4^2$.

Hence, we can now write

$$\begin{aligned} x_1, x_2 > k_1 &\implies \frac{x_1}{4} \frac{x_2}{4} > k_2 \\ &\implies \ln \frac{x_1}{4} + \ln \frac{x_2}{4} > k_3 \\ &\implies -6 \ln \frac{x_1}{4} - 6 \ln \frac{x_2}{4} < k_4 \end{aligned}$$

Now, since $\mathbb{E}_{f_0}[\varphi(x)] = \alpha$ Therefore (note that $\gamma = 0$ as in the previous question)

$$\begin{aligned} \mathbb{E}_{f_0}[\varphi(x)] &= P(Z < k_4) \quad \text{where } Z \sim \chi_4^2 \\ &\implies k_4 = \chi_{4;1-\alpha}^2 \end{aligned}$$

Hence,

$$\varphi(x) = \begin{cases} 1 & \text{if } -6 \ln \frac{x_1}{4} - 6 \ln \frac{x_2}{4} < \chi_{4;1-\alpha}^2 \\ 0 & \text{otherwise} \end{cases}$$

4 Answer 4

Given:

- $X_1, X_2, \dots, X_n \sim P(\lambda)$ where $\lambda > 0$.

TO Find: Most Powerful level α test for $H_0 : \lambda = \lambda_0$ against $H_1 : \lambda = \lambda_1 (> \lambda_0)$

To use Neyman Pearson Lemma, we first need the Likelihood:

$$L(\lambda) = \left(\frac{\lambda^{\sum_{i=1}^n x_i} e^{-n\lambda}}{\prod_{i=1}^n x_i!} \right)$$

Hence,

$$\frac{L(\lambda_1)}{L(\lambda_0)} = \left(\frac{\lambda_1}{\lambda_0} \right)^{\sum_{i=1}^n x_i} \times e^{-n(\lambda_1 - \lambda_0)}$$

This implies that,

$$\begin{aligned} \frac{L(\lambda_1)}{L(\lambda_0)} &= \left(\frac{\lambda_1}{\lambda_0} \right)^{\sum_{i=1}^n x_i} \times e^{-n(\lambda_1 - \lambda_0)} > k \\ &\implies \sum_{i=1}^n x_i > k_1 \quad \text{as } \lambda_1 > \lambda_0 \end{aligned}$$

Therefore, the M.P. level α test would be:

$$\varphi(x) = \begin{cases} 1 & \text{if } \sum_{i=1}^n x_i > k_1 \\ \gamma & \text{if } \sum_{i=1}^n x_i = k_1 \\ 0 & \text{if } \sum_{i=1}^n x_i < k_1 \end{cases}$$

such that $\mathbb{E}_{\lambda_0} [\varphi(x)] = \alpha$.

Now, remember that if $X_i \sim P(\lambda_i)$, then $\sum_{i=1}^n X_i \sim P(\sum_{i=1}^n \lambda_i)$

$$\mathbb{E}_{\lambda_0} [\varphi(x)] = P\left(\sum_{i=1}^n X_i > k_1\right) + \gamma P\left(\sum_{i=1}^n X_i = k_1\right) = \alpha$$

Note that $\sum_{i=1}^n X_i \sim P(n\lambda_0) = Y$ under H_0 , hence:

$$\mathbb{E}_{\lambda_0} [\varphi(x)] = P(Y > k_1) + \gamma P(Y = k_1) = \alpha$$

$$\text{Take } P(Y > k_1) \leq \alpha \leq P(Y \geq k_1)$$

$$\gamma = \frac{\alpha - P(Y > k_1)}{P(Y = k_1)}$$

5 Answer 5

Given:

- $X_1, X_2, \dots, X_n \sim f(x; \theta)$.

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$$f(x; \theta) = \theta^{-1} e^{-\frac{x}{\theta}} I_{(0, \infty)}(x).$$

- $\theta > 0$ and $\alpha \in (0, 1)$.

To Find: A Likelihood Ratio Test for $H_0 : \theta = \theta_0 (> 0)$ against $H_1 : \theta \neq \theta_0$.

Firstly, to find $\sup_{\theta \in \Theta_0} L(\theta, x)$:

$$\sup_{\theta \in \Theta_0} L(\theta) = L(x; \theta_0) = \theta_0^{-n} e^{-\frac{1}{\theta_0} \sum_{i=1}^n x_i} \text{ where } x_i > 0 \quad \forall i \in \{1, 2, \dots, n\}$$

Second, to find $\sup_{\theta \in \Theta_0 \cup \Theta_1} L(\theta, x)$.

$$\sup_{\theta \in \Theta_0 \cup \Theta_1} L(\theta, x) = L(x; \bar{x}) = \bar{x}^{-n} e^{-\frac{1}{\bar{x}} \sum_{i=1}^n x_i} \text{ where } x_i > 0 \quad \forall i \in \{1, 2, \dots, n\}$$

Therefore

$$\begin{aligned} \Lambda(x) &= \left(\frac{\theta_0}{\bar{x}}\right)^{-n} e^{-\frac{1}{\theta_0} n\bar{x} + n} \\ &= \frac{\bar{x}^n}{\theta_0^n} e^{-\frac{1}{\theta_0} \bar{x}n + n} \end{aligned}$$

Now, we need to analyze this function closely to draw a statistic from $\Lambda(x) < k$.

$$\begin{aligned} \ln \Lambda(x) &= n \ln \bar{x} - n \ln \theta_0 - \frac{1}{\theta_0} (\bar{x}n) + n \\ \frac{d}{d\bar{x}} (\ln \Lambda(x)) &= \frac{n}{\bar{x}} - \frac{n}{\theta_0} \\ \frac{d^2}{d\bar{x}^2} (\ln \Lambda(x)) &= -\frac{n}{\bar{x}^2} < 0 \end{aligned}$$

Hence, $\Lambda(x)$ has a maxima at $\bar{x} = \theta_0$.

Therefore, if $\Lambda(x) < k \implies$ either $\bar{x} < k_1$ or $\bar{x} > k_2$

Now, LRT level α can be found as:

$$\varphi(x) = \begin{cases} 1 & \text{if } \sum_{i=1}^n x_i < k_1 \text{ or } \sum_{i=1}^n x_i > k_2 \\ 0 & \text{otherwise} \end{cases}$$

where $E_{\theta_0}[\varphi(x)] = \alpha$, thus:

$$\begin{aligned} E_{\theta_0}[\varphi(x)] &= P\left(\sum_{i=1}^n X_i < k_1 \text{ or } \sum_{i=1}^n X_i > k_2\right) \\ &= P\left(\sum_{i=1}^n X_i < k_1\right) + P\left(\sum_{i=1}^n X_i > k_2\right) \end{aligned}$$

Now, note that $X_i \sim \text{Exp}\left(\frac{1}{\theta}\right)$, thus $\sum_{i=1}^n X_i = Y = \text{Gamma}\left(n, \frac{1}{\theta}\right)$

Which will translate to

$$P(Y < k_1) + P(Y > k_2) = \alpha$$

We can choose these two probabilities as simply:

$$\begin{aligned} P(Y < k_1) &= \frac{\alpha}{2} \\ P(Y > k_2) &= \frac{\alpha}{2} \end{aligned}$$

as there are no restrictions on each of them, the only constraint is their sum is $= \alpha$.

Hence,

$$\begin{aligned} k_1 &= G_{k_1; \frac{\alpha}{2}} \\ k_2 &= G_{k_2; 1 - \frac{\alpha}{2}} \end{aligned}$$