

Stat511(Section001): Homework #10

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Problem 1

(a)

We know under H_0 or H_1 , $\hat{\mu} = \bar{X}$. And under H_1 , we also know the the MLE of σ^2 is:

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$$

Then we can get the log LR for this test is:

$$\log L = \max L_{H_0}(x) - \max L_{H_1}(x) = -\frac{n}{2} \log(\sigma_0^2) + \frac{n}{2} \log(\hat{\sigma}^2) - \frac{n}{2} \frac{\hat{\sigma}^2}{\sigma_0^2} + \frac{n}{2} = \frac{n}{2} \log\left(\frac{\hat{\sigma}^2}{\sigma_0^2}\right) - \frac{n}{2} \frac{\hat{\sigma}^2}{\sigma_0^2} + \frac{n}{2}$$

We also know that, under H_0 :

$$\frac{n\hat{\sigma}^2}{\sigma_0^2} \sim \chi^2(n-1)$$

Then choose $\frac{n\hat{\sigma}^2}{\sigma_0^2} = T$, we have:

$$\log L = \frac{n}{2} \log\left(\frac{T}{n}\right) - \frac{1}{2}T + \frac{n}{2}$$

We will reject H_0 , when $\log L < k$. And we can see that:

$$\frac{d \log L}{dT} = \frac{n}{2T} - \frac{1}{2}$$

Thus, when $T < n$, $\log L$ is a increasing function of T , and when $T > n$ it is a decreasing function of T . Hence:

$$\log L < k \rightarrow T > k_1 \text{ or } T < k_2$$

Then we can know:

$$k_1 = \chi^2(n-1)_{1-\alpha/2}, k_2 = \chi^2(n-1)_{\alpha/2}$$

where $\chi^2(n-1)_{\alpha/2}$ is the $\frac{\alpha}{2}$ percentile of $\chi^2(n-1)$.

(b)

We know the $1 - \alpha$ confidence interval for T is:

$$k_2 < T < k_1 \rightarrow k_2 < \frac{n\hat{\sigma}^2}{\sigma^2} < k_1$$

Thus we can get:

$$\frac{n\hat{\sigma}^2}{k_1} < \sigma^2 < \frac{n\hat{\sigma}^2}{k_2} \rightarrow \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{k_1} < \sigma^2 < \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{k_2}$$

$\left[\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{k_1}, \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{k_2} \right]$ is the $1 - \alpha$ confidence interval of σ^2 , where $k_1 = \chi^2(n-1)_{1-\alpha/2}$, $k_2 = \chi^2(n-1)_{\alpha/2}$.

Problem 2

(a)

We know:

$$E(X_i) = \lambda$$

$$Var(X_i) = \lambda$$

Thus, by central limit theorem, we have:

$$\sqrt{n}(\bar{X} - \lambda) \sim N(0, \lambda) \rightarrow \frac{T - n\lambda}{\sqrt{n\lambda}} \sim N(0, 1)$$

And we can get:

$$\frac{T - n\lambda}{\sqrt{2n\lambda}} \sim N(0, \frac{1}{2})$$

Thus it is asymptotically pivotal.

(b)

From (a), we know the $1 - \alpha$ confidence level of $\frac{T - n\lambda}{\sqrt{n\lambda}}$ is:

$$z_{\alpha/2} < \frac{T - n\lambda}{\sqrt{n\lambda}} < z_{1-\alpha/2}$$

where $z_{\alpha/2}$ is $\frac{\alpha}{2}$ percentile of standard normal. $z_{1-\alpha/2}$ is $1 - \frac{\alpha}{2}$ percentile of standard normal. Then we have:

$$z_{\alpha/2} < \frac{T - n\lambda}{\sqrt{n\lambda}} < -z_{\alpha/2}$$

Solving to get:

$$\frac{2T + z_{\alpha/2}^2 - \sqrt{4Tz_{\alpha/2}^2 + z_{\alpha/2}^4}}{2n} < \lambda < \frac{2T + z_{\alpha/2}^2 + \sqrt{4Tz_{\alpha/2}^2 + z_{\alpha/2}^4}}{2n}$$

And that is the confidence interval for λ . (c)

By (b), we can get the 95% interval is [1.094, 2.888]

Problem 3

It easy to know if X is the number of success in 5 independent missile trials. Then we know $X \sim \text{Bin}(5, p)$. Now to seek lower confidence bound. We consider $H_0 : p = p_0, H_1 : p > p_0$ with $\alpha = 0.1$. Then under H_0 , we have:

$$P(X \geq 4) = 5p_0^4(1 - p_0) + p_0^5 = 5p_0^4 - 4p_0^5 > 0.1$$

Then we can have $p_0 = 0.416$. And we can get 90% lower confidence bound is 0.416.

Problem 4

(a)

We know the likelihood function for one X_i can be written as:

$$f(X_i) = (1 - 2\theta)^{I(X_i=0)} \theta^{I(X_i=1)+I(X_i=-1)} = (1 - 2\theta)^{I(X_i=0)} \theta^{1-I(X_i=0)}$$

Thus, take $T = \sum_{i=1}^n I(X_i = 0)$, then we can get the likelihood function of X_1, \dots, X_n is:

$$L(\theta) = \theta^{n-T} (1 - 2\theta)^T$$

$$\log L(\theta) = (n - T)\log(\theta) + T\log(1 - 2\theta)$$

Then, we have the MLE of θ is:

$$\hat{\theta} = \frac{n - T}{2n}$$

Hence, under H_1 , if $\frac{n-T}{2n} > \theta_0$ $\theta_{H_1} = \frac{n-T}{2n}$. else we get $\theta_{H_1} = \theta_0$. Thus we can get the Likelihood Ratio is:

$$L = \begin{cases} 1 & \theta_0 > \frac{n-T}{2n} \\ \frac{\theta_0^{n-T} (1 - 2\theta_0)^T}{(\frac{n-T}{2n})^{n-T} (\frac{T}{n})^T} & \text{else} \end{cases}$$

This is a function of T . We will reject H_0 when this function is less than k_1 . Then we have:

$$\frac{d \log L}{dT} = \log\left(\frac{n-T}{T}\right) + \log\left(\frac{1-2\theta_0}{\theta_0}\right) - \log 2 \geq 0$$

Thus $L < k_1$ is equivalent to $T < k$. That is end of our proof.

(b)

We have the reject region $T < k(\alpha)$. Thus $T \geq k(\alpha)$ is the acceptance region. Then we can get $1 - \alpha$ lower confidence bound for θ is just $k(\alpha)$.

(c)

We know under H_0 $T \sim \text{Bin}(10, \frac{1}{3})$. Then we need to find the biggest k . $P(T < k) \leq 0.05$. And By python, we get $k = 0$.