

Introduction to mathematical Statistics

The Likelihood Ratio Test

(Another approach to construct a test)

Example 1. Let X_1, X_2, \dots, X_n be a random sample from $N(\mu, \sigma^2)$ where σ^2 is known. We wish to test $H_0 : \mu = \mu_0$ versus $H_a : \mu \neq \mu_0$ at the significance level α . Please derive the test using the likelihood ratio method.

Solution.

1. Write down your parameter space under H_0

$$\omega = \{\mu : \mu = \mu_0\}$$

2. Write down the unrestricted/original parameter space.

$$\Omega = \{\mu : \mu \in R\}$$

3. Write down the likelihood (of the data)

$$L = f(x_1, x_2, \dots, x_n; \mu)$$

$$= \prod_{i=1}^n f(x_i; \mu) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}}$$

$$= (2\pi\sigma^2)^{-\frac{n}{2}} \cdot e^{-\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}}$$

4. Write down your log-likelihood.

$$l = \ln L = -\frac{n}{2} \ln(2\pi\sigma^2) - \frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}$$

5. Find your MLE under ω and plug it in to your L to obtain $\max_{\omega} L$

$$\max_{\omega} L = L(x_1, x_2, \dots, x_n; \mu_0) = (2\pi\sigma^2)^{-\frac{n}{2}} \cdot e^{-\frac{\sum_{i=1}^n (x_i - \mu_0)^2}{2\sigma^2}}$$

6. Find the MLE(s) under Ω and plug in to your L to obtain $\max_{\Omega} L$

$$\frac{d \ln L}{d \mu} = 0 \Rightarrow \frac{2 \sum_{i=1}^n (x_i - \mu)}{2\sigma^2} = 0 \Rightarrow \hat{\mu} = \bar{X}$$

$$\max_{\Omega} L = L(x_1, x_2, \dots, x_n; \hat{\mu}) = (2\pi\sigma^2)^{-\frac{n}{2}} \cdot e^{-\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{2\sigma^2}}$$

7. **Get the likelihood ratio**

$$LR = \frac{\max_{\omega} L}{\max_{\Omega} L} = \frac{(2\pi\sigma^2)^{-\frac{n}{2}} \cdot e^{-\frac{\sum_{i=1}^n (x_i - \mu_0)^2}{2\sigma^2}}}{(2\pi\sigma^2)^{-\frac{n}{2}} \cdot e^{-\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{2\sigma^2}}} = e^{\frac{\sum_{i=1}^n (x_i - \bar{x})^2 - \sum_{i=1}^n (x_i - \mu_0)^2}{2\sigma^2}}, \quad 0 < LR \leq 1 \quad (\because \omega \subseteq \Omega)$$

8. **Derive the decision rule for a given significance level α**

$$\begin{aligned} \alpha &= P(\text{Reject } H_0 \mid H_0 \text{ is true}) \\ &= P(LR \leq c \mid H_0; \mu = \mu_0) \end{aligned}$$

$$\begin{aligned} &= P\left(e^{\frac{\sum_{i=1}^n (x_i - \bar{x})^2 - \sum_{i=1}^n (x_i - \mu_0)^2}{2\sigma^2}} \leq c \mid H_0; \mu = \mu_0\right) \\ &= P\left(\sum_{i=1}^n (x_i - \bar{x})^2 - \sum_{i=1}^n (x_i - \mu_0)^2 \leq 2\sigma^2 \ln c \mid H_0; \mu = \mu_0\right) \end{aligned}$$

Recall the z-test we derived before using the Pivotal Quantity method.

$$\text{Test Statistic : } Z_0 = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}} \stackrel{H_0}{\sim} N(0,1)$$

$$H_0 : \mu = \mu_0 \text{ vs. } H_a : \mu \neq \mu_0$$

At α , we reject H_0 if $|Z_0| \geq Z_{\alpha/2}$

$$\begin{aligned} &= P\left(\sum_{i=1}^n (x_i^2 - 2\bar{x}x_i + \bar{x}^2) - \sum_{i=1}^n (x_i^2 - 2x_i\mu_0 + \mu_0^2) \leq 2\sigma^2 \ln c \mid H_0\right) \\ &= P(-2n\bar{x} + n\bar{x}^2 + 2n\bar{x}\mu_0 - n\mu_0^2 \leq 2\sigma^2 \ln c \mid H_0) \\ &= P(-n\bar{x}^2 + 2n\bar{x}\mu_0 - n\mu_0^2 \leq 2\sigma^2 \ln c \mid H_0) \\ &= P(\bar{x}^2 - 2\bar{x}\mu_0 + \mu_0^2 \geq \frac{-2\sigma^2 \ln c}{n} \mid H_0) \end{aligned}$$

$$\begin{aligned}
 &= P\left(\frac{(\bar{x} - \mu_0)^2}{n} \geq \frac{-2\sigma^2 \ln c}{n} \mid H_0: \mu = \mu_0\right) \\
 &= P\left(\frac{(\bar{x} - \mu_0)^2}{\frac{\sigma^2}{n}} \geq \frac{-2\sigma^2 \ln c}{\frac{\sigma^2}{n}} \mid H_0: \mu = \mu_0\right) \\
 &= P(Z_0^2 \geq c^* \mid H_0: \mu = \mu_0), \quad c^* = -2 \ln c \quad (c = e^{-\frac{c^*}{2}}) \\
 &= P(|Z_0| \geq \sqrt{c^*} \mid H_0: \mu = \mu_0) \\
 &\therefore \sqrt{c^*} = Z_{\alpha/2} \\
 &\therefore \text{At } \alpha, \text{ we reject } H_0 \text{ if } |Z_0| \geq Z_{\alpha/2}
 \end{aligned}$$

Example 2. Let X_1, X_2, \dots, X_n be a random sample from $N(\mu, \sigma^2)$ where σ^2 is **unknown**. Please derive a test for $H_0: \mu = \mu_0$ versus $H_a: \mu \neq \mu_0$ at the significance level α .

Solution.

- $\omega = \{(\mu, \sigma^2) : \mu = \mu_0, \sigma^2 > 0\}$

- $\Omega = \{(\mu, \sigma^2) : \mu \in R, \sigma^2 > 0\}$

- $L = f(x_1, x_2, \dots, x_n; \mu, \sigma^2)$

$$\begin{aligned}
 &= \prod_{i=1}^n f(x_i; \mu) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}} \\
 &= (2\pi\sigma^2)^{-\frac{n}{2}} \cdot e^{-\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}}
 \end{aligned}$$

- $l = \ln L = -\frac{n}{2} \ln(2\pi\sigma^2) - \frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}$

- Find MLEs under ω and plug in to get $\max_{\omega} L$

$$\frac{dl}{d\sigma^2} = -\frac{n}{2} \frac{1}{\sigma^2} + \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{2\sigma^4} = 0$$

$$\Rightarrow \hat{\sigma}_\omega^2 = \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{n}$$

$$\max_{\omega} L = L(x_1, x_2, \dots, x_n; \mu_0, \hat{\sigma}_\omega^2)$$

$$= \left(2\pi \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{n} \right)^{-\frac{n}{2}} \cdot e^{-\frac{\sum_{i=1}^n (x_i - \mu_0)^2}{2 \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{n}}}$$

$$= (2\pi)^{-\frac{n}{2}} \left(\frac{\sum_{i=1}^n (x_i - \mu_0)^2}{n} \right)^{-\frac{n}{2}} e^{-\frac{n}{2}}$$

6. Find MLEs under Ω and plug in to get $\max_{\Omega} L$

$$\begin{cases} \frac{\partial l}{\partial \mu} = \frac{\sum_{i=1}^n (x_i - \mu)}{\sigma^2} = 0 \\ \frac{\partial l}{\partial \sigma^2} = -\frac{n}{2\sigma^2} + \frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^4} = 0 \end{cases}$$

$$\Rightarrow \begin{cases} \hat{\mu}_{\Omega} = \bar{X} \\ \hat{\sigma}_{\Omega}^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n} \end{cases}$$

$$\max_{\Omega} L = L(x_1, x_2, \dots, x_n; \hat{\mu}_{\Omega}, \hat{\sigma}_{\Omega}^2)$$

$$= \left(2\pi \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n} \right)^{-\frac{n}{2}} \cdot e^{-\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{2 \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}}}$$

$$= (2\pi)^{-\frac{n}{2}} \left(\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n} \right)^{-\frac{n}{2}} \cdot e^{-\frac{n}{2}}$$

$$7. \quad LR = \frac{\max_{\omega} L}{\max_{\Omega} L} = \left(\frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \right)^{-\frac{n}{2}}$$

8. Derive the decision rule based on significance level α

$$\alpha = P(\text{Reject } H_0 \mid H_0 \text{ is true})$$

$$= P(LR \leq c \mid H_0 : \mu = \mu_0)$$

$$= P\left(\frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \leq c \mid H_0 : \mu = \mu_0 \right)$$

$$\text{Recall the } t\text{-test statistic : } T_0 = \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \stackrel{H_0}{\sim} t_{n-1}$$

At α , we reject H_0 in favor of H_a if $|T_0| \geq t_{n-1, \alpha/2}$

$$= P\left(\frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \geq \frac{1}{c} \mid H_0 : \mu = \mu_0 \right)$$

$$= P\left(\frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \geq \left(\frac{1}{c}\right)^2 \mid H_0 : \mu = \mu_0 \right)$$

$$= P\left(\frac{\sum_{i=1}^n (x_i - \bar{x} + \bar{x} - \mu_0)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \geq c^* \mid H_0 : \mu = \mu_0 \right)$$

$$\begin{aligned}
 &= P\left(\frac{\sum_{i=1}^n (x_i - \bar{x})^2 + 2(\bar{x} - \mu_0) \sum_{i=1}^n (x_i - \bar{x}) + n(\bar{x} - \mu_0)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \geq c^* \mid H_0: \mu = \mu_0\right) \\
 &= P\left(1 + \frac{n(\bar{x} - \mu_0)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \geq c^* \mid H_0: \mu = \mu_0\right) \\
 &= P(T_0^2 \geq c^{**} \mid H_0: \mu = \mu_0) \\
 &= P(|T_0| \geq \sqrt{c^{**}} \mid H_0: \mu = \mu_0)
 \end{aligned}$$

\therefore At α , we reject H_0 if $|T_0| \geq t_{n-1, \alpha/2}$

\therefore The LR test is equivalent to the t-test.

Example 3. If X_1, X_2, \dots, X_n are a random sample from the exponential distribution with parameter λ .

You can derive the LR test for $H_0: \lambda = \lambda_0$ vs $H_a: \lambda \neq \lambda_0$.

Example 4. If X_1, X_2, \dots, X_n are a random sample from the *Poisson*(θ). You can derive the LR test for $H_0: \theta = \theta_0$ vs $H_a: \theta \neq \theta_0$.