

1. Introduction

Welcome to the series of E-learning modules on Likelihood Ratio Test Procedure for testing the mean and variance of Univariate Normal distribution. In this module we are going to cover the Likelihood Ratio Test Procedure for testing mean of a Normal population when variance is known and unknown and also test criteria for testing variance of a Normal population when the mean is known and unknown.

By the end of this session, you will be able to:

- Apply Likelihood Ratio Test Procedure or LRTP to test the mean when the variance is known and unknown in case of a Normal population
- Apply Likelihood Ratio Test Procedure to test the variance of a Normal population when the mean is known and unknown

A test introduced by Neyman and Pearson for testing a hypothesis, simple or composite against a simple or composite alternative hypothesis is related to the maximum likelihood estimates.

Before deriving the Likelihood ratio test statistic for mean and variance of Univariate Normal population let us just recollect the Likelihood Ratio test procedure.

Suppose a composite null hypothesis, H_0 : θ belongs to the parameter space under the null hypothesis H_0 , is to be tested against a composite alternative hypothesis H_1 , θ belongs to parameter space under the alternative hypothesis H_1 .

Let a random sample x_1, x_2, \dots, x_n of size n be drawn from the given population with probability density function $f(x, \theta)$.

Let λ be equal to $\frac{\sup_{\theta \in \Omega_0} L(\theta, x_1, x_2, \dots, x_n)}{\sup_{\theta \in \Omega} L(\theta, x_1, x_2, \dots, x_n)}$ when θ belongs to the parameter space under the null hypothesis H_0 divided by $\sup_{\theta \in \Omega} L(\theta, x_1, x_2, \dots, x_n)$ when θ belongs to the entire parameter space Ω .

The test procedure is as follows: If λ is very large, that is, λ is greater than or equal to λ_α , the null hypothesis is accepted.

If λ is very small, that is, λ is less than λ_α ; the null hypothesis is to be rejected.

The constant λ_α is so chosen that the size of the test is α .

2. Application 1

Application:1

Now let us look into some applications of LRTP

Let x follow Normal (μ , σ^2) with a known variance σ^2 . To test the null hypothesis $H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu \neq \mu_0$.

Let x_1, x_2, \dots, x_n be a random sample of size n drawn from a Normal population with parameters μ and σ^2 .

λ is equal to $\sup_{\mu} L(\mu, x_1, x_2, \dots, x_n)$ when $\mu = \mu_0$ divided by $\sup_{\mu} L(\mu, x_1, x_2, \dots, x_n)$ when μ lies between $-\infty$ and ∞ .

Where λ_α is such that the size of the test is equal to α .

λ is equal to $\sup_{\mu} \left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum (x_i - \mu)^2}$ when $\mu = \mu_0$.

Divided by $\sup_{\mu} \left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum (x_i - \mu)^2}$ when μ is between $-\infty$ and ∞ .

The denominator attains the maximum value when the unknown parameter is substituted with its maximum likelihood estimate.

Thus by substituting μ with \bar{x} , a sample mean in the denominator, we can make it attain its maximum value.

λ is equal to $\left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum (x_i - \mu_0)^2}$.

Divided by $\left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum (x_i - \bar{x})^2}$.

This is equal to $e^{-\frac{1}{2\sigma^2} \left[\sum (x_i - \mu_0)^2 - \sum (x_i - \bar{x})^2 \right]}$.

which implies $e^{-\frac{n}{2\sigma^2} [\mu_0^2 - \bar{x}^2]}$

Which implies $e^{-\frac{n}{2\sigma^2} (\bar{x} - \mu_0)^2}$ the whole square.

Now $\lambda \leq \lambda_\alpha$ implies $e^{-\frac{n}{2\sigma^2} (\bar{x} - \mu_0)^2} \leq \lambda_\alpha$.

This implies $-\frac{n}{2\sigma^2} (\bar{x} - \mu_0)^2 \leq \ln \lambda_\alpha$.

Which implies $[\bar{x} - \mu_0]^2 \geq \frac{2\sigma^2}{n} \ln \lambda_\alpha$.

Which implies modulus of $[\bar{x} - \mu_0] / (\sigma / \sqrt{n})$ is greater than square root of minus two Ln $\lambda \alpha$ is equal to λ_1 (say).

Now size of the test is equal to α implies, probability of $[\lambda \leq \lambda \alpha]$, given μ is equal to μ_0 is equal to α .

This implies, probability of modulus of $[\bar{x} - \mu_0] / (\sigma / \sqrt{n})$ is greater than λ_1 is equal to α .

When x_i follows Normal with parameters μ and σ^2 a sample mean follows Normal with mean μ and variance σ^2 / n .

Then $[\bar{x} - \mu_0] / (\sigma / \sqrt{n})$ follows Normal with mean zero and variance one under Null hypothesis.

Now from the table of Normal Probabilities we can read λ_1 equal to $Z_{\alpha/2}$.

Using the relation between $\lambda \alpha$ and λ_1 equal to $Z_{\alpha/2}$, $\lambda \alpha$ and the test can be determined.

3. One Sided Tests: Cases 1 and 2

One sided test case 1:

To test the null hypothesis H_0 : μ is equal to μ_0 against the alternative hypothesis H_1 : μ is greater than μ_0 .

Here from the above we have, if μ_0 is greater than the sample mean, estimate of μ is μ_0 in the denominator then λ equal to one.

In which case the null hypothesis should surely be accepted.

If μ_0 is *less than* the sample mean, then the maximum likelihood estimate of μ is \bar{x} .

Thus substituting μ with \bar{x} , a sample mean in the denominator we can make it to attain its maximum value as above.

Then, we get, λ is equal to $(1/\sigma \sqrt{2\pi})^n e^{-\frac{1}{2\sigma^2} \sum (x_i - \mu_0)^2}$.

Divided by $(1/\sigma \sqrt{2\pi})^n e^{-\frac{1}{2\sigma^2} \sum (x_i - \bar{x})^2}$

Now, $\lambda \leq \lambda_\alpha$ implies $[\bar{x} - \mu_0] \geq \sigma \sqrt{n} \sqrt{-2 \ln \lambda_\alpha}$.

Which implies $[\bar{x} - \mu_0] \geq \sigma \sqrt{n} \sqrt{-2 \ln \lambda_\alpha}$ is greater than square root of $-2 \ln \lambda_\alpha$ is equal to λ_1

Now size of the test is equal to α implies probability of $[\bar{x} - \mu_0] \geq \sigma \sqrt{n} \sqrt{-2 \ln \lambda_1}$ is equal to α .

Now from the table of Normal Probabilities we can read λ_1 equal to Z_α .

Using the relation among λ_α , and λ_1 equal to Z_α , λ_α and hence the test can be determined.

Case 2:

To test the null hypothesis H_0 : μ equal to μ_0 against the alternative hypothesis H_1 : μ less than μ_0

Here from the above we have:

If μ_0 is less than the sample mean, estimate of μ is μ_0 in the denominator then λ is equal to one, in which case the null hypothesis should surely be accepted.

If μ_0 is greater than the sample mean, then the maximum likelihood estimate of μ is \bar{x} .

Thus substituting μ with \bar{x} , a sample mean in the denominator, we can make it to attain its maximum value as above.

Now we get, λ is equal to $(1/\sigma \sqrt{2\pi})^n e^{-\frac{1}{2\sigma^2} \sum (x_i - \mu_0)^2}$ the whole square.

Divided by $(1/\sigma \sqrt{2\pi})^n e^{-\frac{1}{2\sigma^2} \sum (x_i - \bar{x})^2}$

Now $\lambda \leq \lambda_\alpha$ implies, $[\bar{x} - \mu_0] / [\sigma / \sqrt{n}]$ the whole square is greater than $-2 \ln \lambda_\alpha$.

Which implies $[\mu_0 - \bar{x}] / [\sigma / \sqrt{n}]$ is greater than $\sqrt{-2 \ln \lambda_\alpha}$

Which implies $[\bar{x} - \mu_0] / [\sigma / \sqrt{n}]$ is less than or equal to $-\sqrt{-2 \ln \lambda_\alpha}$ is equal to $-\lambda_1$.

Now size of the test is equal to α implies probability of $[\bar{x} - \mu_0] / [\sigma / \sqrt{n}]$ is less than or equal to $-\lambda_1$ is equal to α .

Now from the table of Normal Probabilities we can read λ_1 is equal to $-Z_\alpha$.

Using the relation between λ_α , and λ_1 equal to $-Z_\alpha$, λ_α and hence the test can be determined.

4. Application 2

Let x follow Normal (μ , σ^2) with an unknown variance.

To test the null hypothesis H_0 : μ is equal to μ_0 against the alternative hypothesis H_1 : μ is not equal to μ_0 .

λ is equal to Supremum of L of (x_1, x_2, \dots, x_n) when μ is equal to μ_0 , σ^2

Divided by Supremum of L of (x_1, x_2, \dots, x_n) under μ comma σ^2 .

Where λ_α is such that the size of the test is equal to α .

λ is equal to Supremum of $(1/\sigma^2)^{n/2} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2\right)$ under $\mu = \mu_0$ comma μ equal to μ_0 .

Divided by Supremum of $(1/\sigma^2)^{n/2} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2\right)$ under μ comma μ .

Under the null hypothesis the m.l.e of σ^2 is $\sum_{i=1}^n (x_i - \mu_0)^2 / n$ otherwise the m.l.e's of μ and σ^2 are \bar{x} and $\sum_{i=1}^n (x_i - \bar{x})^2 / (n-1)$.

In the expression of λ by substituting the above and simplifying we get,

λ is equal to $\sum_{i=1}^n (x_i - \bar{x})^2$ by $\sum_{i=1}^n (x_i - \mu_0)^2$ to the power $n/2$.

Consider $\sum_{i=1}^n (x_i - \mu_0)^2$ is equal to $\sum_{i=1}^n (x_i - \bar{x} + \bar{x} - \mu_0)^2$ which is equal to $\sum_{i=1}^n (x_i - \bar{x})^2 + n(\bar{x} - \mu_0)^2$, because $\sum_{i=1}^n (x_i - \bar{x}) = 0$.

By substituting and simplifying we get λ is equal to $1 + n(\bar{x} - \mu_0)^2 / \sum_{i=1}^n (x_i - \bar{x})^2$ to the power $n/2$.

Now $\lambda \leq \lambda_\alpha$ implies modulus of t greater than $t_{\alpha/2, n-1}$ where t is equal to $(\bar{x} - \mu_0) / (s / \sqrt{n})$.

Now size of the test is equal to α implies Probability of modulus of t is greater than $t_{\alpha/2, n-1}$ is equal to α .

The quantity $t_{\alpha/2, n-1}$ can be read from the table of probabilities of Student's t distribution for $(n-1)$ degrees of freedom as $t_{\alpha/2, n-1}$ is equal to $t_{\alpha/2, n-1}$.

One sided tests: Case 1:

To test H_0 : μ is equal to μ_0 against the alternative hypothesis H_1 : μ is greater than μ_0 , with unknown variance.

$\lambda \leq \lambda_\alpha$ and size of the test equal to α implies

Probability of t is greater than $t_{1-\alpha}$ is equal to α .

From the table of Probabilities of t distribution we can read $t_{1-\alpha}$ as $t_{2\alpha}$ into $n-1$.

To test $H_0: \mu = \mu_0$ against the alternative $H_1: \mu < \mu_0$, the variance unknown.

$t \leq t_{1-\alpha}$ and size of the test is equal to α implies Probability of $t \leq t_{1-\alpha}$ is equal to α .

From the table of Probabilities of t distribution we can read $t_{1-\alpha}$ as $t_{2\alpha}$ into $n-1$.

That is, we reject the null hypothesis if $\bar{x} - \mu_0$ by s/\sqrt{n} is less than $-t_{1-\alpha}$ ($n-1$)

5. Applications 3 and 4

Application :3

To test the null hypothesis H_0 : σ^2 is equal to σ_0^2 against the alternative, H_1 : σ^2 is not equal to σ_0^2 , for a known mean μ .

Λ is equal to supremum of $(1/\sigma^2)^{n/2} \exp(-\sum (x_i - \mu)^2 / (2\sigma^2))$ to the power 'n' by two into $(1/\sigma_0^2)^{n/2} \exp(-\sum (x_i - \mu)^2 / (2\sigma_0^2))$ when σ^2 is equal to σ_0^2 .

Divided by supremum of $(1/\sigma^2)^{n/2} \exp(-\sum (x_i - \mu)^2 / (2\sigma^2))$ to the power 'n' by two into $(1/\sigma^2)^{n/2} \exp(-\sum (x_i - \mu)^2 / (2\sigma^2))$ when σ^2 is greater than or equal to zero.

By substituting σ^2 with $\sum (x_i - \mu)^2 / n$ in the denominator we can make it to attain its maximum value and then on simplifying we get:

$\Lambda \leq \Lambda_\alpha$ implies ' U ' less than or equal to ' C_1 ' or ' U ' greater than or equal to ' C_2 '

Where ' U ' is equal to $\sum (x_i - \mu)^2 / \sigma_0^2$ follows chi square with ' n ' degrees of freedom.

Which implies probability of chi square less than or equal to ' C_1 ' plus probability of chi square greater than or equal to ' C_2 ' is equal to α

where ' C_1 ' equal to chi square $(1 - \alpha/2)$ with ' n ' degrees of freedom and ' C_2 ' is equal to chi square $(\alpha/2)$ with ' n ' degrees of freedom.

One sided tests:

To test the null hypothesis H_0 : σ^2 is equal to σ_0^2 against the alternative H_1 : σ^2 is greater than σ_0^2 , for a known mean

We reject the null hypothesis if $\sum (x_i - \mu)^2 / \sigma_0^2$ exceeds chi square α with ' n ' degrees of freedom.

To test the null hypothesis H_0 : σ^2 is equal to σ_0^2 against the alternative H_1 : σ^2 is less than σ_0^2 , for a known mean

We reject the null hypothesis if $\sum (x_i - \mu)^2 / \sigma_0^2$ is less than chi square $1 - \alpha$ with ' n ' degrees of freedom.

Application :4

To test the null hypothesis H_0 : σ^2 is equal to σ_0^2 against the null hypothesis H_1 : σ^2 is not equal to σ_0^2 , for an unknown mean.

This procedure is same as application three.

Under the null hypothesis the m.l.e of μ is equal to \bar{x} .

Otherwise the m.l.e's of μ and σ^2 are \bar{x} and $\sum (x_i - \bar{x})^2 / n$.

In the expression of Λ , by substituting the parameters with the m.l.e's and then simplifying we get,

$\Lambda \leq \Lambda_\alpha$ implies ' U ' less than or equal to ' C_1 ' or ' U ' greater than or equal to ' C_2 ' where ' U ' is equal to $\sum (x_i - \bar{x})^2 / \sigma_0^2$

square by sigma naught square follows chi square with 'n' minus one degrees of freedom.

Size of the test is equal to alpha which implies probability of chi square less than or equal to 'C' one plus probability of chi square greater than or equal to 'C' two is equal to alpha.

where 'C' one equal to chi square (one minus alpha by two) with (n minus one)degrees of freedom and 'C' two is equal to chi square (alpha by two) with (n minus one)degrees of freedom.

One sided tests:

To test the null hypothesis H_0 : sigma is equal to sigma naught against H_1 : sigma is greater than sigma naught, for an unknown mean,

We reject the null hypothesis if summation $(x_i - \bar{x})^2$ by sigma naught square exceeds chi square alpha with (n minus 1) degrees of freedom.

To test the null hypothesis H_0 : sigma is equal to sigma naught against H_1 : sigma is less than sigma naught, for an unknown mean

We reject the null hypothesis if summation $(x_i - \bar{x})^2$ by sigma naught square is less than chi square (one minus alpha) with (n minus one)degrees of freedom.

Here's a summary of our learning in this session where we have understood the following:

- Likelihood Ratio Test Procedure or LRTP for testing mean of a Normal population when the variance is known
- LRTP for testing mean when the variance is unknown
- LRTP for testing variance of a Normal population when the variance is known and unknown