

1. Introduction

Welcome to the series of E learning modules on LRTP for testing equality of two means of two univariate Normal distributions. In this module we are going cover the Likelihood Ratio Test Procedure for testing the difference of means of two Normal populations when the variances are known and unknown and also a test criterion for pair wise testing of the independent samples drawn from the Normal population.

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

- Explain LRTP to test the difference between the means of two Normal populations when the variances are known and unknown
- Explain LRTP to test the difference between means in case of dependent or correlated observations.

In this paper let us discuss about the LRTP available for testing means of two independent Normal populations based on the fixed variance or an unknown variance and also for two dependent samples of a Normal population.

2. Application 1

Application one:

To test the null hypothesis H_0 : μ_1 is equal to μ_2 against the alternative hypothesis H_1 : μ_1 is not equal to μ_2 . Where μ_1 and μ_2 are the means of two Normal populations with a common variance σ^2 which is unknown.

Let x_1, x_2, \dots, x_n be a random sample of size 'n' from a Normal population with mean μ_1 and let y_1, y_2, \dots, y_m be a random sample of size 'm' from a Normal population with mean μ_2 . Then the likelihood ratio λ is given by:

λ is equal to Supremum of L of $(x_1, x_2, \dots, x_n, y_1, y_2, \dots, y_m)$ when μ_1 is equal to μ_2 is equal to μ and σ^2 divided by Supremum of L of $(x_1, x_2, \dots, x_n, y_1, y_2, \dots, y_m)$ under μ_1, μ_2, σ^2 .

λ is equal to Supremum of L of (x_1, x_2, \dots, x_n) into L of (y_1, y_2, \dots, y_m) when μ_1 is equal to μ_2 is equal to μ and σ^2 divided by Supremum of L of (x_1, x_2, \dots, x_n) into L of (y_1, y_2, \dots, y_m) under μ_1, μ_2, σ^2 .

Since all the observations are independent of each other, λ is equal to Supremum of $(1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu_1)^2 - \frac{1}{2\sigma^2} \sum_{j=1}^m (y_j - \mu_2)^2\right\}$ when μ_1 is equal to μ_2 is equal to μ and σ^2 .

Divided by Supremum of $(1/\sigma^2)^n \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu_1)^2\right\}$ to the power 'n' into 'e' to the power minus one by two into σ^2 into summation $(x_i - \mu_1)^2$ the whole square into $(1/\sigma^2)^m \exp\left\{-\frac{1}{2\sigma^2} \sum_{j=1}^m (y_j - \mu_2)^2\right\}$ to the power 'm' into 'e' to the power minus one by two into σ^2 into summation $(y_j - \mu_2)^2$ the whole square under μ_1, μ_2, σ^2 .

Under the null hypothesis the m.l.e's are obtained as $\hat{\mu}$ is equal to $\frac{1}{n+m} \sum_{i=1}^n x_i + \frac{1}{m} \sum_{j=1}^m y_j$ and $\hat{\sigma}^2$ is equal to $\frac{1}{n+m} \left(\sum_{i=1}^n (x_i - \hat{\mu})^2 + \sum_{j=1}^m (y_j - \hat{\mu})^2 \right)$.

Otherwise the m.l.e's are $\hat{\mu}_1$ is equal to \bar{x} , $\hat{\mu}_2$ is equal to \bar{y} and $\hat{\sigma}^2$ is equal to $\frac{1}{n+m} \left(\sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{j=1}^m (y_j - \bar{y})^2 \right)$.

Thus substituting the m.l.e's appropriately, we have λ is equal to $(\hat{\sigma}^2)^{-(n+m)/2} \exp\left\{-\frac{1}{2\hat{\sigma}^2} \sum_{i=1}^n (x_i - \hat{\mu})^2 - \frac{1}{2\hat{\sigma}^2} \sum_{j=1}^m (y_j - \hat{\mu})^2\right\}$ divided by $(\hat{\sigma}^2)^{-n/2} \exp\left\{-\frac{1}{2\hat{\sigma}^2} \sum_{i=1}^n (x_i - \bar{x})^2\right\}$ to the power (n plus m) by two into $(1/\hat{\sigma}^2)^{m/2} \exp\left\{-\frac{1}{2\hat{\sigma}^2} \sum_{j=1}^m (y_j - \bar{y})^2\right\}$ to the power (m plus n) into 'e' to the power minus one by two into $\hat{\sigma}^2$ into summation $(x_i - \bar{x})^2$ the whole square plus summation $(y_j - \bar{y})^2$ the whole square.

Divided by $(\hat{\sigma}^2)^{-(n+m)/2} \exp\left\{-\frac{1}{2\hat{\sigma}^2} \sum_{i=1}^n (x_i - \bar{x})^2 - \frac{1}{2\hat{\sigma}^2} \sum_{j=1}^m (y_j - \bar{y})^2\right\}$ to the power (n plus m) by two into $(1/\hat{\sigma}^2)^{m/2} \exp\left\{-\frac{1}{2\hat{\sigma}^2} \sum_{j=1}^m (y_j - \bar{y})^2\right\}$ to the power (m plus n) into 'e' to the power minus one by two into $\hat{\sigma}^2$ into summation $(x_i - \bar{x})^2$ the whole square plus summation $(y_j - \bar{y})^2$ the whole square.

On simplifying we get,

Λ is equal to $\frac{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2}{\sum (x_i - \mu)^2 + \sum (y_i - \mu)^2}$ to the power 'm' plus 'n' divided by two.

Consider $\sum (x_i - \mu)^2$ is equal to $\sum (x_i - \bar{x})^2 + n(\bar{x} - \mu)^2$.

$n(\bar{x} - \mu)^2$ is equal to $n[\bar{x}^2 - 2\bar{x}\mu + \mu^2]$ equal to $n\bar{x}^2 - 2n\bar{x}\mu + n\mu^2$.

$\sum (x_i - \mu)^2$ is equal to $\sum (x_i - \bar{x})^2 + n\bar{x}^2 - 2n\bar{x}\mu + n\mu^2$.

3. Application 1 Contd

Similarly,

$\sum (y_i - \mu)^2$ the whole square is equal to $\sum (y_i - \bar{y})^2$ the whole square plus $\sum (x_i - \bar{x})^2$ the whole square by $(m + n)$ the whole square.

$\sum (x_i - \mu)^2$ the whole square plus $\sum (y_i - \mu)^2$ the whole square is equal to $\sum (x_i - \bar{x})^2$ the whole square plus $\sum (y_i - \bar{y})^2$ the whole square plus $\sum (x_i - \bar{x})^2$ the whole square by $(m + n)$.

λ is equal to $\frac{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2}{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2}$ the whole square plus $\sum (x_i - \bar{x})^2$ the whole square plus $\sum (y_i - \bar{y})^2$ the whole square by $(m + n)$ to the power $m + n$ by two.

λ is equal to one by one plus $\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2$ the whole square by one plus $(m + n)$ by $\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2$ the whole square, the whole to the power $m + n$ by two

Which is equal to one by one plus t^2 square by $(m + n - 2)$ to the power $m + n$ by two.

Where t is equal to $\frac{(\bar{x} - \bar{y})}{\sqrt{\frac{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2}{m + n - 2}}}$ by square root of $(\frac{1}{m + n - 2})$ divided by square root of $\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2$ the whole square by $m + n - 2$.

Now $\lambda \leq \lambda_{\alpha}$ implies one by one plus t^2 square by $(m + n - 2)$ the whole to the power $m + n$ by two less than or equal to λ_{α} .

One plus t^2 square by $(m + n - 2)$ is greater than or equal to λ_{α} to the power minus two by $m + n$

t^2 square greater than or equal to λ_{α} to the power minus two by $(m + n - 2)$ into $(m + n - 2)$ which implies modulus of t is greater than or equal to λ_{α} one.

Now size of the test is equal to α implies Probability of reject H_0 when H_0 is true is equal to α .

This implies probability of modulus of t greater than or equal to λ_{α} one is equal to α .

When $\mu_1 = \mu_2 = \mu$, t is distributed as student's t variable with $(m + n - 2)$ degrees of freedom.

From the table of probabilities of Students t distribution we can read λ_{α} one as t_{α} into $(m + n - 2)$

A practical procedure for testing the hypothesis here is as follows:

To reject H_0 if modulus of $\frac{(\bar{x} - \bar{y})}{\sqrt{\frac{\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2}{m + n - 2}}}$ the whole divided by $\sum (x_i - \bar{x})^2 + \sum (y_i - \bar{y})^2$ the whole square by $m + n - 2$ is greater than t_{α} into $(m + n - 2)$

One sided tests

In case we have to test $H_0: \mu_1 = \mu_2$ against the alternative hypothesis $H_1: \mu_1 > \mu_2$.

Then we obtain the following test procedure.

To reject H_0 if the computed value of t exceeds the table value of $t_{\alpha/2, m+n-2}$.

Similarly, in case of testing $H_0: \mu_1 = \mu_2$ against the alternative hypothesis $H_1: \mu_1 < \mu_2$, then we obtain the following test procedure.

To reject H_0 if the computed value of t is less than the table value $-t_{\alpha/2, m+n-2}$.

4. Application 2

Application two

To test the null hypothesis $H_0: \mu_1 = \mu_2$ against the alternative hypothesis $H_1: \mu_1 \neq \mu_2$ where μ_1 and μ_2 are the means of two Normal populations with a known common variance σ^2 .

Let x_1, x_2, \dots, x_n be a random sample of size 'n' from a Normal population with mean μ_1 and let y_1, y_2, \dots, y_m be a random sample of size 'm' from a Normal population with mean μ_2 .

Then the likelihood ratio λ is given by:

λ is equal to $\frac{\text{Supremum of } (1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \mu_1)^2 + \sum_{j=1}^m (y_j - \mu_2)^2\right]\right\}}{\text{Supremum of } (1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \mu)^2 + \sum_{j=1}^m (y_j - \mu)^2\right]\right\}}$ when $\mu_1 = \mu_2 = \mu$.

Divided by $\frac{(1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \mu)^2 + \sum_{j=1}^m (y_j - \mu)^2\right]\right\}}{(1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{j=1}^m (y_j - \bar{y})^2\right]\right\}}$ under $\mu_1 = \mu_2 = \mu$.

Under the null hypothesis the m.l.e's of μ_1 and μ_2 are obtained as $\hat{\mu}$ is equal to $\frac{n\bar{x} + m\bar{y}}{m+n}$.

Otherwise the m. l. e's are $\mu_1 = \bar{x}$ and $\mu_2 = \bar{y}$.

Thus substituting the m.l.e's appropriately we have

λ is equal to $\frac{(1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \hat{\mu})^2 + \sum_{j=1}^m (y_j - \hat{\mu})^2\right]\right\}}{(1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{j=1}^m (y_j - \bar{y})^2\right]\right\}}$

Divided by $\frac{(1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{j=1}^m (y_j - \bar{y})^2\right]\right\}}{(1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{j=1}^m (y_j - \bar{y})^2\right]\right\}}$

Which is equal to $\frac{(1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \hat{\mu})^2 + \sum_{j=1}^m (y_j - \hat{\mu})^2\right]\right\}}{(1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{j=1}^m (y_j - \bar{y})^2\right]\right\}}$

On simplifying as in application one we get: $\sum_{i=1}^n (x_i - \hat{\mu})^2 + \sum_{j=1}^m (y_j - \hat{\mu})^2 = \sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{j=1}^m (y_j - \bar{y})^2 + \frac{n}{m+n}(\bar{x} - \bar{y})^2$.

$\lambda \leq \lambda_\alpha$ implies $\frac{(1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \hat{\mu})^2 + \sum_{j=1}^m (y_j - \hat{\mu})^2\right]\right\}}{(1/\sigma^2)^{n+m} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{j=1}^m (y_j - \bar{y})^2\right]\right\}} \leq \lambda_\alpha$.

Implies $|\bar{x} - \bar{y}| \geq \sigma \sqrt{\frac{1}{n} + \frac{1}{m}} \ln \frac{1}{\lambda_\alpha}$.

Which implies $|\bar{x} - \bar{y}| \geq \sigma \sqrt{\frac{1}{n} + \frac{1}{m}} \ln \frac{1}{\lambda_\alpha}$ which is equal to

lambda one, say.

Now size of the test is equal to alpha implies Probability of reject H_0 when H_0 is true is equal to alpha.

Which implies probability of lambda less than or equal to lambda alpha given μ_1 is equal to μ_2 is equal to alpha.

This implies probability of modulus of $\frac{\bar{x} - \bar{y}}{\sigma \sqrt{\frac{1}{m} + \frac{1}{n}}}$ is greater than lambda one is equal to alpha.

$\frac{\bar{x} - \bar{y}}{\sigma \sqrt{\frac{1}{m} + \frac{1}{n}}}$ follows Normal distribution with mean zero and variance one, under Null hypothesis.

Which implies probability of modulus of Normal (zero comma one) is greater than lambda one] which is equal to alpha.

Now from the table of Normal Probabilities we can read lambda one equal to $Z_{\alpha/2}$ divided by two. Using the relation among lambda alpha and lambda one, the test can be determined.

To test the null hypothesis $H_0: \mu_1 = \mu_2$ against the alternative hypothesis $H_1: \mu_1 > \mu_2$ when the variances are known.

Here from the above, we obtain the following test procedure:

To reject the null hypothesis, if the computed value of Z exceeds the table value of Z_{α} .

Similarly in case of testing the null hypothesis $H_0: \mu_1 = \mu_2$ against the alternative hypothesis $H_1: \mu_1 < \mu_2$, we obtain the following test procedure:

To reject the null hypothesis if the computed value of Z is less than the table value of minus Z_{α} .

5. Case of Paired Observations

Case of paired observations (Dependent observations)

Let us now consider two sample of equal sizes and the two samples are not independent but the sample observations are paired together

For example suppose we want to test the efficacy of a particular drug, say for inducing sleep.

Let X_i and y_i be the readings in the hours of sleep on the i th individual before and after the drug is given respectively. Here instead of applying the difference of the means test as discussed above we apply paired 'T' test as explained in the following slide.

Let (X_i, Y_i) be equal to one to n pairs of observations with x and y denoting observations from the Normal population. We assume here that the observations in each pair are dependent on each other.

To test the Hypothesis $H_0: \mu_1 = \mu_2$ against the alternative hypothesis $H_1: \mu_1 \neq \mu_2$, where μ_1 and μ_2 are the means of two Normal populations. Let d be a new variable defined by ' d_i ' is equal to $x_i - y_i$

The above testing of Hypothesis is same as $H_0: \mu_d = 0$ against the alternative hypothesis $H_1: \mu_d \neq 0$.

Where μ_d is the mean of the variable ' d ' and $\mu_d = \mu_1 - \mu_2$.

The above is a situation as that of application two of the last paper, that is, to test the mean of a Normal population with an unknown variance.

Therefore the test procedure is to reject H_0 if modulus of ' t ' is equal to modulus of ' D ' bar by ' SD ' divided by square root of ' n ' greater than or equal to $t_{\alpha/2}(n-1)$.

Where ' SD ' square is equal to summation $(d_i - \bar{d})^2$ the whole square by $(n-1)$

Assume that (D_i) follows Normal with mean $\mu_1 - \mu_2$ and variance σ_d^2 .

Then, ' D ' bar follows Normal with mean zero and variance σ_d^2/n under null hypothesis.

One sided tests:

Suppose we want to test the null hypothesis $H_0: \mu_1 = \mu_2$ against the alternative hypothesis : $\mu_1 > \mu_2$, for correlated or dependent variables with unknown variance, the critical region is given by C is equal to ' t ' greater than or equal to $t_{\alpha}(n-1)$

Suppose we want to test the null hypothesis $H_0: \mu_1 = \mu_2$ against the alternative hypothesis : $\mu_1 < \mu_2$, for correlated or dependent variables with unknown variance, the critical region is given by C is equal to ' t ' less than minus ' $t_{\alpha}(n-1)$

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

- LRTP for testing difference of means of two Normal populations when the variances are known and unknown
- LRTP for testing difference of means of two dependent samples