

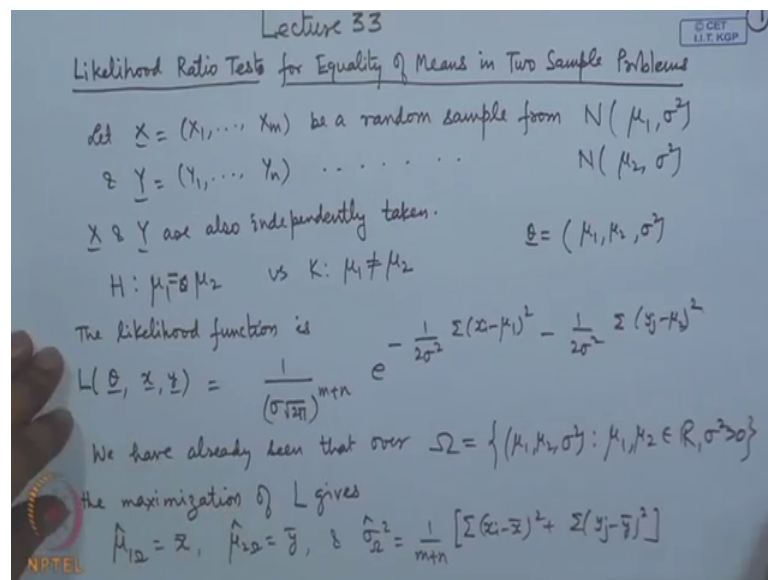
Statistical Inference
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Lecture - 55
Likelihood Ratio Tests -V

In the last two lectures, I have introduced the concept of Likelihood Ratio Tests. We consider derivation of the likelihood ratio test for some one sample problems and especially for the parameters of normal distribution when we have a sample from one normal distribution. Then later on I introduced two normal populations and we had some independent random samples from both of them.

We considered the test for comparing the means and in that I had given the test for μ_1 less than or equal to μ_2 the null hypothesis. Now, today I will firstly derive the test when we are having the null hypothesis as equality and the alternative hypothesis as the inequality.

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So, here let us consider, so let me reintroduce the model here let X_1, X_2, \dots, X_m be a random sample from normal μ_1 sigma square distribution and Y is equal to Y_1, Y_2, \dots, Y_n is a random sample from normal μ_2 sigma square. And X and Y are also independently taken. This is the model I had introduced yesterday. Yesterday we had considered the hypothesis μ_1 less than or equal to μ_2 . Now, today I will consider μ_1

$\mu_1 < \mu_2$ against $\mu_1 \neq \mu_2$. Another important point to notice here is that in the likelihood ratio test the alternative hypothesis does not play a role. Whereas, in the Neyman Pearson Theory the alternative hypothesis has to be specified in order to discuss the power, because we are talking about the most powerful, uniformly most powerful are the UMP unbiased tests. So, all the time power is a consideration.

In the likelihood ratio test we are only looking at the null hypothesis parameter set and the full parameter set. Of course, by elimination what is happening is that, when we are taking the full parameter space the complimentary space of the null hypothesis space is the alternative hypothesis parameter space. Therefore, indirectly it is playing a role and you have already seen yesterday that the tests which we are deriving using the likelihood ratio method is they are actually the same as the UMP unbiased tests for the parameters of normal distributions. Now we consider this particular hypothesis. Now as before let me write down the likelihood function here.

So, μ_1, μ_2, σ^2 these are the parameters here and ah. So, the likelihood function $L(\theta, x, y)$ that is equal to one by $\sigma \sqrt{2\pi}$ to the power $m+n$ $e^{-\frac{1}{2\sigma^2} \sum_{i=1}^m (x_i - \mu_1)^2 - \frac{1}{2\sigma^2} \sum_{j=1}^n (y_j - \mu_2)^2}$. So, we have already seen that over the full parameter space ω that is μ_1, μ_2, σ^2 where μ_1, μ_2 are real and σ^2 is positive. Over this the maximization of L gives $\hat{\mu}_1 = \bar{x}$, $\hat{\mu}_2 = \bar{y}$ and $\hat{\sigma}^2 = \frac{1}{m+n} \sum_{i=1}^m (x_i - \bar{x})^2 + \sum_{j=1}^n (y_j - \bar{y})^2$.

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and so $\hat{L}(\Omega) = \frac{1}{(2\pi \hat{\sigma}^2)^{\frac{m+n}{2}}} e^{-\frac{(m+n)}{2}}$

Now we consider maximization of L over $\Omega_H = \{\mu_1, \mu_2, \sigma^2 : \mu_1, \mu_2 \in \mathbb{R}, \sigma^2 > 0\}$

So $L = \frac{1}{(2\pi \sigma^2)^{\frac{m+n}{2}}} e^{-\frac{1}{2\sigma^2} [\sum (x_i - \mu)^2 + \sum (y_j - \mu)^2]}$ ($\mu_1 = \mu_2 = \mu$)

$\log L = -\frac{m+n}{2} \log 2\pi - \frac{m+n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} [\sum (x_i - \mu)^2 + \sum (y_j - \mu)^2]$

$\frac{\partial \log L}{\partial \mu} = + \frac{2}{2\sigma^2} [m(\bar{x} - \mu) + n(\bar{y} - \mu)]$

$= \frac{1}{\sigma^2} [m\bar{x} + n\bar{y} - (m+n)\mu] > 0$ for $\mu < \frac{m\bar{x} + n\bar{y}}{m+n}$

< 0 for $\mu > \frac{m\bar{x} + n\bar{y}}{m+n}$

So L is maximized with respect to μ when $\hat{\mu}_{\Omega_H} = \frac{m\bar{x} + n\bar{y}}{m+n}$

So, if we use this \hat{L} that is turning out to be $\frac{1}{(2\pi \hat{\sigma}^2)^{\frac{m+n}{2}}} e^{-\frac{(m+n)}{2}}$. Now, we consider maximization of L over Ω_H that is μ_1, μ_2, σ^2 : μ_1 is equal to μ_2 and σ^2 is positive. So, now let us write down the likelihood function in the modified form because here now μ_1 is equal to μ_2 . So, L is now $\frac{1}{(2\pi \sigma^2)^{\frac{m+n}{2}}} e^{-\frac{1}{2\sigma^2} [\sum (x_i - \mu)^2 + \sum (y_j - \mu)^2]}$.

That means, I have taken here μ_1 is equal to μ_2 is equal to μ . So, $\log L$ that is equal to $-\frac{m+n}{2} \log 2\pi - \frac{m+n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} [\sum (x_i - \mu)^2 + \sum (y_j - \mu)^2]$. So, let us consider the maximization of this with respect to μ and σ^2 . So, derivative with respect to μ that will give me $-\frac{1}{\sigma^2}$; then here if I differentiate this and this term I will get $-\frac{2}{\sigma^2}$. So, this will become plus and I will get $m\bar{x} - \mu + n\bar{y} - \mu$. That we can say $m\bar{x} + n\bar{y} - (m+n)\mu$ and this $\frac{1}{\sigma^2}$ will be outside.

So, easily you can see this is greater than 0 for $\mu < \frac{m\bar{x} + n\bar{y}}{m+n}$ and less than 0 for $\mu > \frac{m\bar{x} + n\bar{y}}{m+n}$. So, L is maximized with respect to μ when μ is, so we call it $\hat{\mu}_{\Omega_H}$ is

equal to $m\bar{x} + n\bar{y}$ divided by $m+n$. So, this is the maximization of l with respect to μ . When the null hypothesis $\mu_1 = \mu_2$ is true.

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For maximization w.r.t σ^2 , we consider

$$\frac{\partial l}{\partial \sigma^2} = -\frac{m+n}{2\sigma^2} + \frac{1}{2\sigma^4} \left[\sum (x_i - \mu)^2 + \sum (y_j - \mu)^2 \right]$$

$$= \frac{m+n}{\sigma^4} \left[\frac{1}{m+n} \left\{ \sum (x_i - \mu)^2 + \sum (y_j - \mu)^2 \right\} - \sigma^2 \right]$$

> 0 for $\sigma^2 < \frac{1}{m+n} \left\{ \sum (x_i - \mu)^2 + \sum (y_j - \mu)^2 \right\}$

< 0 for $\sigma^2 > \frac{1}{m+n} \left\{ \sum (x_i - \mu)^2 + \sum (y_j - \mu)^2 \right\}$

So max w.r.t σ^2 occurs at $\frac{1}{m+n} \left\{ \sum (x_i - \mu)^2 + \sum (y_j - \mu)^2 \right\}$

So $\hat{\sigma}_{\Omega H}^2 = \frac{1}{m+n} \left\{ \sum (x_i - \hat{\mu}_{\Omega H})^2 + \sum (y_j - \hat{\mu}_{\Omega H})^2 \right\}$

Now, based on this I can consider the maximization with respect to sigma square for maximization with respect to sigma square we consider $\frac{\partial l}{\partial \sigma^2}$ that is equal to $-\frac{m+n}{2\sigma^2} + \frac{1}{2\sigma^4} \left[\sum (x_i - \mu)^2 + \sum (y_j - \mu)^2 \right]$. And this you can follow from looking at this term here, that if I have differentiated this term with respect to sigma square. So, this term gives me $-\frac{m+n}{2\sigma^2}$ and this term gives me $\frac{1}{2\sigma^4} \left[\sum (x_i - \mu)^2 + \sum (y_j - \mu)^2 \right]$. So, once again we can write down this as $\frac{m+n}{\sigma^4} \left[\frac{1}{m+n} \left\{ \sum (x_i - \mu)^2 + \sum (y_j - \mu)^2 \right\} - \sigma^2 \right]$. So, we can say that $\hat{\sigma}_{\Omega H}^2$ that is equal to $\frac{1}{m+n} \left\{ \sum (x_i - \hat{\mu}_{\Omega H})^2 + \sum (y_j - \hat{\mu}_{\Omega H})^2 \right\}$. Now $\hat{\mu}_{\Omega H}$ that we evaluated just now, that is equal to $\frac{m\bar{x} + n\bar{y}}{m+n}$. So, this value we substitute here.

So, naturally you can see this is greater than 0 for sigma square less than $\frac{1}{m+n} \left\{ \sum (x_i - \mu)^2 + \sum (y_j - \mu)^2 \right\}$ and it is less than 0 for sigma square greater than this value. So, maximization with respect to sigma square occurs at this quantity, that is $\frac{1}{m+n} \left\{ \sum (x_i - \mu)^2 + \sum (y_j - \mu)^2 \right\}$. So, we can say that $\hat{\sigma}_{\Omega H}^2$ that is equal to $\frac{1}{m+n} \left\{ \sum (x_i - \hat{\mu}_{\Omega H})^2 + \sum (y_j - \hat{\mu}_{\Omega H})^2 \right\}$. Now $\hat{\mu}_{\Omega H}$ that we evaluated just now, that is equal to $\frac{m\bar{x} + n\bar{y}}{m+n}$. So, this value we substitute here.

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We can simplify $\hat{\sigma}_H^2$ as

$$\frac{1}{m+n} \left[\sum \left(x_i - \frac{m\bar{x} + n\bar{y}}{m+n} \right)^2 + \sum \left(y_j - \frac{m\bar{x} + n\bar{y}}{m+n} \right)^2 \right]$$

$$= \frac{1}{m+n} \left[\sum \left(x_i - \bar{x} + \bar{x} - \frac{m\bar{x} + n\bar{y}}{m+n} \right)^2 + \sum \left(y_j - \bar{y} + \bar{y} - \frac{m\bar{x} + n\bar{y}}{m+n} \right)^2 \right]$$

$$= \frac{1}{m+n} \left[\sum (x_i - \bar{x})^2 + \frac{n^2}{(m+n)^2} (\bar{x} - \bar{y})^2 + 2 \sum (x_i - \bar{x}) \left(\bar{x} - \frac{m\bar{x} + n\bar{y}}{m+n} \right) \right]$$

$$+ \sum (y_j - \bar{y})^2 + \frac{m^2}{(m+n)^2} (\bar{y} - \bar{x})^2 + 2 \sum (y_j - \bar{y}) \left(\bar{y} - \frac{m\bar{x} + n\bar{y}}{m+n} \right)$$

$$\hat{\sigma}_H^2 = \frac{1}{m+n} \left[\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2 + \frac{mn}{m+n} (\bar{x} - \bar{y})^2 \right]$$

$\frac{n}{m+n} (\bar{x} - \bar{y})$
 $m\bar{y} + n\bar{x} - m\bar{x} - n\bar{y}$

We can simplify sigma omega H hat square as 1 by m plus n sigma x i minus m x bar divided by n y bar divided by m plus n y j minus m x bar plus ny bar divided by m plus n square. In this first term I add and subtract x bar here and in the second one I add and subtract y bar. So, this becomes 1 by m plus n sigma x i minus x bar plus x bar minus m x bar plus ny bar divided by m plus n; y j minus y bar plus y bar minus m x bar plus n y bar divided by m plus n square. So, that is equal to 1 by m plus n. And this term now I expand. So, I will get sigma x i minus x bar square plus now this second term if I simplify I get m x bar plus n x bar minus m x bar minus n y bar divided by m plus n.

So, m x bar gets cancelled out and I get n divided by m plus n x bar minus y bar and this will be squared. So, I get n square by m plus n square x bar minus y bar square. Then there is a cross product term twice sigma x i minus x bar into x bar minus that is the same term n by m plus n x bar minus y bar. Now, this term is nothing but 0. Because sigma x i minus x bar is 0. Similarly, I expand the second term. If I expand the second term I will get sigma y j minus y bar square plus now if I look at this second term I can write my bar plus ny bar minus m x bar minus ny bar. So, this gets cancelled out. So, this becomes m square divided by m plus n whole square y bar minus x bar whole square. And, once again this cross product term sigma y j minus y bar into m by m plus n x bar minus y bar gets this gets cancelled out.

Now, the term that is remaining I can actually simplify this. This I can write as 1 by m plus n sigma x_i minus \bar{x} whole square plus sigma y_j minus \bar{y} whole square, plus m n by m plus n , \bar{x} minus \bar{y} whole square. That is the term that I will be getting after simplification of this term here. So, if I substitute this value so this is my sigma omega H hat square. So, in the likelihood function if I substitute this value that is 1 by sigma omega H hat square and here I substitute this value. So, here this is obtained after substituting μ_1 μ_2 is equal to μ I will get.

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So we will get

$$\hat{L}(\Omega_H) = \frac{1}{(2\pi \hat{\sigma}_{\Omega_H}^2)^{\frac{m+n}{2}}} e^{-\frac{m+n}{2}}$$

The likelihood ratio is

$$\lambda(x, y) = \frac{\hat{L}(\Omega_H)}{\hat{L}(\Omega)} = \left(\frac{\hat{\sigma}_{\Omega}^2}{\hat{\sigma}_{\Omega_H}^2} \right)^{\frac{m+n}{2}}$$

LRT is Reject H_0 if $\lambda(x, y) < C$

$$\frac{\hat{\sigma}_{\Omega}^2}{\hat{\sigma}_{\Omega_H}^2} < C \quad \text{or} \quad \frac{\sum(x_i - \bar{x})^2 + \sum(y_j - \bar{y})^2}{\sum(x_i - \bar{x})^2 + \sum(y_j - \bar{y})^2 + \frac{mn}{m+n}(\bar{x} - \bar{y})^2} < C$$

Taking reciprocal and further simplifying we can write the rejection region as

So, we will get L hat omega h as equal to 1 by 2 pi sigma omega H hat square to the power m plus n by 2 e to the power minus m plus n by 2 . now we have obtained the maximization over the null hypothesis parameter set. We have also derived L hat omega that is the maximization over the full parameter set. So, the likelihood ratio that is $\lambda(x, y)$ here that is L hat omega H by L hat omega that will become sigma omega hat square divided by sigma omega H hat square to the power m plus n by 2 .

So, the likelihood ratio test is reject H_0 if $\lambda(x, y)$ is less than C . Now, that will be equivalent to that sigma omega hat square divided by sigma omega H hat square is less than some C . And, then we can substitute this values here sigma omega hat square was obtained as it was 1 by m plus n sigma x_i minus \bar{x} whole square plus sigma y_j minus \bar{y} whole square.

So, this term is $\sum x_i^2 - n\bar{x}^2 + \sum y_j^2 - n\bar{y}^2$ divided by $\sum \omega_H$ and this we calculated just now. So, that is again equal to $\sum x_i^2 - n\bar{x}^2 + \sum y_j^2 - n\bar{y}^2$ divided by $m+n-2$. I am saying it is less than C_1 . So, I can take a reciprocal of this inequality taking reciprocal and further simplifying we can write the rejection region as, so when I take reciprocal this comes in the numerator and I divide by this full term I get 1 then I take it to the other side.

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$$\frac{mn}{m+n} \frac{(\bar{x} - \bar{y})^2}{S_p^2} > C_2 \quad \text{where } S_p^2 = \frac{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2}{m+n-2}$$

$$\text{or } |T| = \sqrt{\frac{mn}{m+n}} \frac{|\bar{x} - \bar{y}|}{S_p} > C_3$$

$$P(|T| > C_3) = \alpha$$

$$\text{So } C_3 = t_{m+n-2, \frac{\alpha}{2}}$$

$$T = \sqrt{\frac{mn}{m+n}} \frac{|\bar{x} - \bar{y}|}{S_p} \sim t_{m+n-2} \text{ when } \mu_1 = \mu_2$$

So LRT is
 Reject H_0 if $|T| \geq t_{m+n-2, \frac{\alpha}{2}}$
 (this is the same as the UMP unbiased test)

So, I get the term as $\frac{mn}{m+n} \frac{(\bar{x} - \bar{y})^2}{S_p^2} > C_2$ where, S_p^2 is the pooled sample variance. That is $\sum x_i^2 - n\bar{x}^2 + \sum y_j^2 - n\bar{y}^2$ divided by $m+n-2$. So, so if I take the square root I get, square root $\frac{mn}{m+n}$ modulus of $\bar{x} - \bar{y}$ divided by S_p greater than say C_3 . Now, we will require let me give this term as T . Probability P of T greater than C_3 . When $\mu_1 = \mu_2$, it should be equal to α .

Now in yesterday's lecture I have given the distribution of this that is t . So, this is modulus T . This term is T that is $\sqrt{\frac{mn}{m+n}} \frac{|\bar{x} - \bar{y}|}{S_p}$. So, this follows t distribution on $m+n-2$ degrees of freedom, when $\mu_1 = \mu_2$. So, C_3 we can take to be $t_{m+n-2, \frac{\alpha}{2}}$. That is the upper 100α by 2 percent point.

So, this is $t_{m+n-2, \alpha/2}$ point. This probability is $\alpha/2$ if this is the curve of t distribution on $m+n-2$ degrees of freedom that is the density function of this. So, you can see here likelihood ratio test is reject H_0 if modulus of T is greater than or equal to $t_{m+n-2, \alpha/2}$. And this is same as the UMP unbiased test for this problem. So, once again this likelihood ratio procedure leads to excellent tests or you can say optimal tests as we have derived using the Neyman Pearson Theory.