

Statistical Inference
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Lecture – 52
Likelihood Ratio Tests- II

Fortunately, for the Likelihood Ratio Test the asymptotic properties do hold; that means, asymptotic distinction of the test statistic is nice, it becomes actually the chi square. But before that let me also consider the other alternative here; what is the other alternative? That is H_4 . So, I have considered here the testing problem which is specified by H_1 that is $\mu \leq 0$ and $\mu > 0$.

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Case II: $H_4: \mu=0$ vs $K_4: \mu \neq 0$

$\Omega_H = \{(\mu, \sigma^2): \mu=0, \sigma^2 > 0\}$

First we have $\hat{L}(\Omega) = \frac{1}{(2\pi\hat{\sigma}^2)^{n/2}} e^{-ny/2}$, $\hat{\sigma}^2 = \frac{1}{n} \sum (x_i - \bar{x})^2$

On Ω_H $\mu=0$ so $\hat{\mu}_{\Omega_H} = 0$

$\Rightarrow \hat{\sigma}_{\Omega_H}^2 = \frac{1}{n} \sum (x_i - \hat{\mu}_{\Omega_H})^2$

$= \frac{1}{n} \sum x_i^2$

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

Now, let me modify and I will consider second case of the μ is equal to 0 against μ not equal to 0 that two sided alternative. In this situation we had seen the UMP unbiased test was based on the t statistic. In fact, the same thing modulus of its square root and \bar{x} by s was greater than or equal to $t_{n-1, \alpha/2}$. So, here what is happening? The Ω_H becomes μ is equal to 0 and σ^2 is greater than 0; if that happens. So, now, let us see first we have $\hat{L}(\Omega_H)$.

So, this will be as before because am not doing fresh calculations it is $2\pi\hat{\sigma}_{\Omega_H}^2$ to the power $n/2$ $e^{-n/2}$, where $\hat{\sigma}_{\Omega_H}^2$ was $1/n \sum (x_i - \bar{x})^2$. Now, on Ω_H μ is equal to

0; so there is only one point here there is no question of further maximization; so this is equal to 0. If that happens then sigma omega H hat square which I calculated in the previous case what was happening that the value was dependent upon mu only.

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So maximum for σ^2 is attained when $\sigma^2 = \frac{1}{n} \sum (x_i - \mu)^2$.

So when we consider maximization of $L(\mu, \sigma^2, x)$ over Ω , we get at $\hat{\mu}_\Omega = \bar{x}$, $\hat{\sigma}_\Omega^2 = \frac{1}{n} \sum (x_i - \bar{x})^2$

So $\hat{L}(\Omega) = \frac{1}{(2\pi \hat{\sigma}_\Omega^2)^{n/2}} e^{-\frac{1}{2\hat{\sigma}_\Omega^2} \sum (x_i - \bar{x})^2}$

$= \frac{1}{(2\pi \hat{\sigma}_\Omega^2)^{n/2}} e^{-\frac{n}{2}}$

In order to evaluate $\hat{L}(\Omega_H)$, we consider maximization

The value was dependent upon the mu; it was 1 by n sigma xi minus mu hat mu square. So, if I put mu is equal to 0; I will get the sigma omega H hat square. So, this becomes 1 by n sigma xi minus mu omega H hat square that is equal to 1 by n sigma xi square. So, if we substitute this we get L hat omega H is equal to 1 by 2 pi sigma omega H hat square to the power n by 2; e to the power minus n by 2.

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So LRT is to Reject H_0 if $\lambda(x) = \frac{\hat{L}(\Omega_H)}{\hat{L}(\Omega_0)} < C$

or $\left(\frac{\hat{\sigma}_{\Omega_H}^2}{\hat{\sigma}_{\Omega_0}^2} \right)^{n/2} < C$ or $\frac{\hat{\sigma}_{\Omega_H}^2}{\hat{\sigma}_{\Omega_0}^2} < C_1$

or $\frac{\sum (x_i - \bar{x})^2}{\sum x_i^2} < C_1$ or $\frac{\sum x_i^2}{\sum (x_i - \bar{x})^2} > C_2$

or $\frac{\sum (x_i - \bar{x})^2 + n\bar{x}^2}{\sum (x_i - \bar{x})^2} > C_2$ or $\frac{n\bar{x}^2}{\sum (x_i - \bar{x})^2 / n-1} > C_3$

or $\left| \frac{\sqrt{n} \bar{x}}{S} \right| > C_4$ (taking square roots)

So, if I take the likelihood ratio test this is to reject H_0 if $\lambda(x)$ that is equal to $L(\Omega_H)$ by $L(\Omega_0)$ is greater than sorry. It is less than C . So, this is equivalent to $\sigma_{\Omega_H}^2$ by $\sigma_{\Omega_0}^2$ to the power $n/2$ less than C or $\sigma_{\Omega_H}^2$ by $\sigma_{\Omega_0}^2$ less than say C_1 . Or if I substitute the values here I get $\sum (x_i - \bar{x})^2$ by $\sum x_i^2$ less than C_1 or if I take the reciprocal is greater than say C_2 .

And as before this I can write as $\sum (x_i - \bar{x})^2 + n\bar{x}^2$ divided by $\sum (x_i - \bar{x})^2$ greater than C_2 or $n\bar{x}^2$ divided by $\sum (x_i - \bar{x})^2 / n-1$ greater than some C_3 or square root $n \bar{x}$ divided by S modulus greater than say C_4 that is I have taken the square roots.

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where c_4 is given by

$$P_{\mu=0} \left(\left| \frac{\sqrt{n} \bar{X}}{S} \right| > c_4 \right) = \alpha$$

$\Rightarrow c_4 = t_{n-1, \alpha/2}$ as $\frac{\sqrt{n} \bar{X}}{S} \sim t_{n-1}$ when $\mu=0$.

LRT is Reject H_0 if $\left| \frac{\sqrt{n} \bar{X}}{S} \right| \geq t_{n-1, \alpha/2}$

Note that this test is the same as UMP unbiased test.

Consider testing for the variance

$$H_1: \sigma^2 \leq \sigma_0^2 \text{ vs } K_1: \sigma^2 > \sigma_0^2$$
$$\Omega_H = \left\{ (\mu, \sigma^2): -\infty < \mu < \infty, \sigma^2 \leq \sigma_0^2 \right\}$$

Now, to determine C_4 where C_4 is given by probability of modulus root $n \bar{x}$ by s greater than C_4 at μ equal to 0 is equal to α . This means C_4 is nothing, but $t_{n-1, \alpha/2}$ because root $n \bar{X}$ by S follows t distribution on $n-1$ degrees of freedom when μ is equal to 0.

Now, so the test has become; so likelihood ratio test is reject H_0 if root $n \bar{X}$ by S modulus is greater than or equal to $t_{n-1, \alpha/2}$; which is actually the UMP unbiased test for. Note that this test is the same as UMP unbiased test. So, which the point which I mentioned, that in many situations the likelihood ratio test leads to the same theory as in the UMP unbiased tests.

Now let us consider testing for the variance; let us consider say H_1 sigma square say less than or equal to sigma naught square versus K_1 sigma square greater than sigma naught square. What will be required is the behavior of the likelihood function that I wrote. So, once again let us go back to the behavior of the likelihood function which I wrote in the sheet number 5 yeah this was the behavior.

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$$\frac{\partial \log L}{\partial \mu} = \frac{1}{\sigma^2} \sum (x_i - \mu) = \frac{n(\bar{x} - \mu)}{\sigma^2} < 0 \text{ if } \mu > \bar{x}$$

$$> 0 \text{ if } \mu < \bar{x}$$

So $\log L \uparrow$ for $\mu < \bar{x}$
 \downarrow for $\mu > \bar{x}$
 So maximum over μ is attained for $\mu = \bar{x}$ (on Ω)

$$\frac{\partial \log L}{\partial \sigma^2} = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum (x_i - \mu)^2$$

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

> 0 if $\sigma^2 < \frac{\sum (x_i - \mu)^2}{n}$
 < 0 if $\sigma^2 > \frac{\sum (x_i - \mu)^2}{n}$

So $\log L \uparrow$ for $\sigma^2 < \frac{\sum (x_i - \mu)^2}{n}$
 \downarrow for $\sigma^2 > \frac{\sum (x_i - \mu)^2}{n}$

We had written the derivative with respect to mu and derivative with respect to sigma square in the equations 1 and 2. So, here you see if I am considering the omega H; in the omega H mu is on the whole real line and sigma square is less than or equal to sigma naught square.

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As before $\hat{L}(\Omega) = \frac{1}{(2\pi \hat{\sigma}_\Omega^2)^{n/2}} e^{-\frac{n}{2}}$

where $\hat{\sigma}_\Omega^2 = \frac{1}{n} \sum (x_i - \bar{x})^2$

Over Ω_H

(i) $\frac{1}{n} \sum (x_i - \bar{x})^2 \leq \sigma_0^2$
 then $\hat{\sigma}_{\Omega_H}^2 = \frac{1}{n} \sum (x_i - \bar{x})^2$

(ii) $\frac{1}{n} \sum (x_i - \bar{x})^2 > \sigma_0^2$
 then $\hat{\sigma}_{\Omega_H}^2 = \sigma_0^2$

So, as before if I consider L hat omega that does not change 2 pi sigma omega hat square to the power n by 2 e to the power minus n by 2; where this sigma omega hat square was 1 by n sigma xi minus x bar square.

However, if I am considering over ω_H then we look at this behavior here that that is the behavior of $\log L$ with respect to σ^2 . We have seen it that; so this is 0 this point is $\frac{1}{n} \sum (x_i - \bar{x})^2$. So, this is increasing up to this point and decreasing there after.

So, there can be two cases if $\frac{1}{n} \sum (x_i - \bar{x})^2$ is less than or equal to σ_0^2 ; that means, σ_0^2 is say here. Then the maximum will be as before at this point; then $\hat{\sigma}^2$ will be $\frac{1}{n} \sum (x_i - \bar{x})^2$. Whereas, the other case can be that $\frac{1}{n} \sum (x_i - \bar{x})^2$ is greater than σ_0^2 ; that means, this value is coming here.

So, if am looking at this likelihood function with respect to σ^2 ; then it is increasing and thereafter we do not consider because the maximization ranges from 0 to σ_0^2 ; so this value is the maximum. Then $\hat{\sigma}^2$ that is equal to σ_0^2 .

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So $\hat{\sigma}_{\Omega_H}^2 = \min \left\{ \sigma_0^2, \frac{1}{n} \sum (x_i - \bar{x})^2 \right\} = \min \left\{ \sigma_0^2, \hat{\sigma}^2 \right\}$

So $\hat{L}(\Omega_H) = \frac{1}{(\sigma_{\Omega_H}^2)^{n/2} \cdot 2\pi} e^{-\frac{1}{2\sigma_{\Omega_H}^2} \sum (x_i - \bar{x})^2}$

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

So $\lambda(\mathbf{z}) = \frac{\hat{L}(\Omega_H)}{\hat{L}(\Omega_0)} = \left(\frac{\hat{\sigma}^2}{\sigma_0^2} \right)^{n/2} e^{-\frac{n}{2} \left\{ 1 - \frac{\hat{\sigma}^2}{\sigma_0^2} \right\}}$

When $\hat{\sigma}^2 \leq \sigma_0^2$, $\lambda(\mathbf{z}) = 1$, we always accept H_0 ($K=0$)

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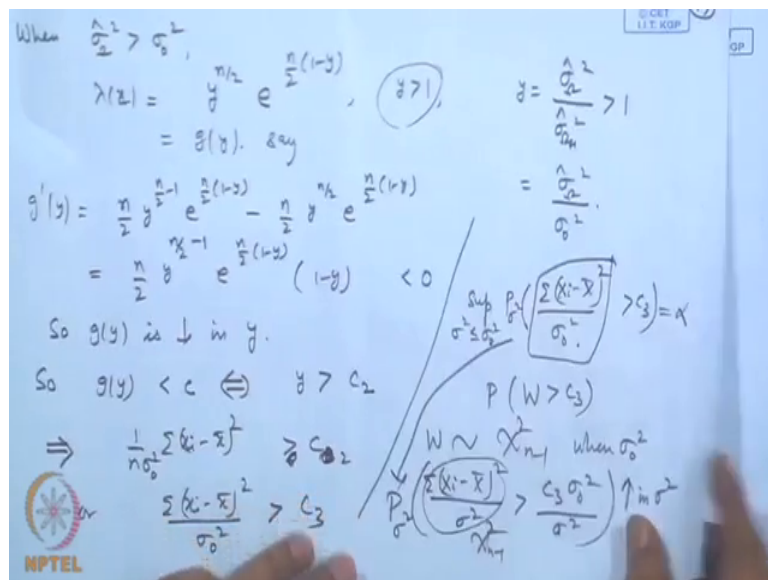
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So, what we have got that $\hat{\sigma}^2$ is actually minimum of σ_0^2 and $\frac{1}{n} \sum (x_i - \bar{x})^2$; that is minimum of σ_0^2 and $\hat{\sigma}^2$. So, $\hat{L}(\Omega_H)$; that is $\frac{1}{(2\pi \hat{\sigma}_{\Omega_H}^2)^{n/2}} e^{-\frac{n \hat{\sigma}^2}{2 \hat{\sigma}_{\Omega_H}^2}}$; $\frac{1}{2\pi \hat{\sigma}_{\Omega_H}^2}$; that is equal to $\frac{1}{2\pi \hat{\sigma}_{\Omega_H}^2}$

hat square to the power n by 2 e to the power minus sigma n sigma omega hat square divided by twice sigma omega H hat square.

So, L hat omega H divided by L hat omega; if I take this ratio it is becoming sigma omega hat square divided by sigma omega H hat square to the power n by 2; e to the power n by 2, 1 minus sigma omega hat square divided by sigma omega H hat square. Now there will be two cases if sigma omega hat square is less than sigma naught square then sigma omega H and sigma omega is equal. So, this will become 0 this will become 1. So, when sigma omega hat square is less than or equal to sigma naught square; this lambda x this ratio is 1. So, we always accept H 4 sorry this is H 1; we always accept H 1 that is alpha is equal to 0.

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When sigma omega hat square is greater than sigma naught square then lambda x is equal to this value I write it in the form y to the power n by 2 e to the power n by 2 into 1 minus y where y is greater than 1; y is sigma omega hat square divided by sigma omega H square that is equal to actually; in this particular case when sigma square is greater than sigma naught square in that case this value is turning out to be sigma omega hat square divided by sigma naught square.

Let us look at this function I call it say g of y then what is g prime y? If I look at the derivative of this the derivative of this is n by 2 y to the power n by 2 minus 1 e to the power n by 2 into 1 minus y minus n by 2 y to the power n by 2; e to the power n by 2

into $1 - y$, that is equal to $n \cdot 2^y$ to the power $n \cdot 2 - 1$; e to the power $n \cdot 2$ into $1 - y$.

So, this is less than 0 because y is greater than 1 what I have taken this to be y . And I have considered the case when σ^2 is greater than sorry σ^2 is less than $\hat{\sigma}^2$; so this quantity is greater than one. So,; so this is always less than 0; so, what we are saying is that $g(y)$ is decreasing in y . If it is decreasing in y then the region $g(y) < C$; this is equivalent to saying y is greater than C^2 .

Now y is $1 - n \frac{\sum (x_i - \bar{x})^2}{\sigma^2}$ greater than or equal to C or $\sum (x_i - \bar{x})^2$ by σ^2 greater than say sorry C^3 ; I may say this is equal to C^3 here. Now we should have supremum of probability $\sum (x_i - \bar{x})^2$ by σ^2 greater than C^3 ; this is for σ^2 less than or equal to σ^2 , this should be equal to α .

I want this probability to be equal to α . Now let us look at this follows this is probability of W greater than C^3 where W follows chi square distribution on $n - 1$ degrees of freedom; when σ^2 is (Refer Time: 16:52). So, if I write here $\sum (x_i - \bar{x})^2$ by σ^2 greater than C^3 σ^2 by σ^2 , this probability is equal to this.

Now this is a chi square $n - 1$ variable; since I am considering the region σ^2 less than or equal to σ^2 ; this value is greater than 1. So, if I increase σ^2 ; if I increase σ^2 this value will increase ah, this value will decrease why? Right now σ^2 is less than σ^2 σ^2 is less than σ^2 . So, if I increase σ^2 this value will decrease; if this value decreases the probability of the whole region will increase; so, this is increasing in σ^2 .

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So $P\left(\frac{\sum (x_i - \bar{x})^2}{\sigma^2} > c_3\right)$ is increasing in σ^2 , so it will attain a maximum value at $\sigma^2 = \sigma_0^2$ (for $\sigma^2 \leq \sigma_0^2$)

So the size condition is

$$P\left(\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} > c_3\right) = \alpha$$

But $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} \sim \chi^2_{n-1}$ when $\sigma^2 = \sigma_0^2$

So $c_3 = \chi^2_{n-1, \alpha}$

LRT is $\text{Rej } H_1 \text{ if } \frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} > \chi^2_{n-1, \alpha}$ else accept H_1

So, this probability $\frac{\sum (x_i - \bar{x})^2}{\sigma^2} > c_3$ is increasing in σ^2 . So, it will attain a maximum value at $\sigma^2 = \sigma_0^2$ for $\sigma^2 \leq \sigma_0^2$.

So, the size condition is probability of $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} > c_3$, when σ_0^2 is the true parameter value is α . But $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}$ follows chi square distribution on $n - 1$ degrees of freedom when $\sigma^2 = \sigma_0^2$.

So, c_3 is equal to $\chi^2_{n-1, \alpha}$ that is the upper 100α percent point of chi square distribution on $n - 1$ degree of freedom. So, likelihood ratio test is reject H_1 if $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} > \chi^2_{n-1, \alpha}$. This is when $\sigma^2 > \sigma_0^2$ and if it is greater then always accept H_1 ; always accept H_1 .

As again you can see this is similar to the UMP unbiased test which we derived in the previous lecture. In the next lecture I will continue derivation of the likelihood ratio test for various problems related to normal populations and also some other discrete and continuous distributions.