

Statistical Inference
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Lecture – 53
Likelihood Ratio Tests – III

In the last lecture, I have introduced the theory or you can say the concept of testing of hypothesis based on a heuristic consideration called Likelihood Ratio Tests. The idea was that we should consider that possibility are those that hypothesis to be more probable that gives a higher value of the maximum likelihood. Based on that, I derived the likelihood ratio test for parameters of a normal distribution. I was considering the testing for the mean and we had seen actually that the tests are almost same as the tests of derived using MN Pearson theory. For the variance testing, I derived a test for one sided null and one sided alternative hypothesis.

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Lecture - 32

For $H_4: \sigma^2 = \sigma_0^2$ vs $K_4: \sigma^2 \neq \sigma_0^2$ $\Omega_H = \{(\mu, \sigma^2): \mu \in \mathbb{R}, \sigma^2 > 0\}$

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

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

For Ω_H $\hat{\mu}_{\Omega_H} = \bar{x}$, $\hat{\sigma}_{\Omega_H}^2 = \sigma_0^2$

$$\hat{L}(\Omega_H) = \frac{1}{(2\pi \sigma_0^2)^{n/2}} e^{-\frac{1}{2\sigma_0^2} n \hat{\sigma}_\Omega^2}$$

The likelihood ratio is $\lambda(x) = \frac{\hat{L}(\Omega_H)}{\hat{L}(\Omega)}$

$$= y^{n/2} e^{\frac{n}{2}(1-y)}$$

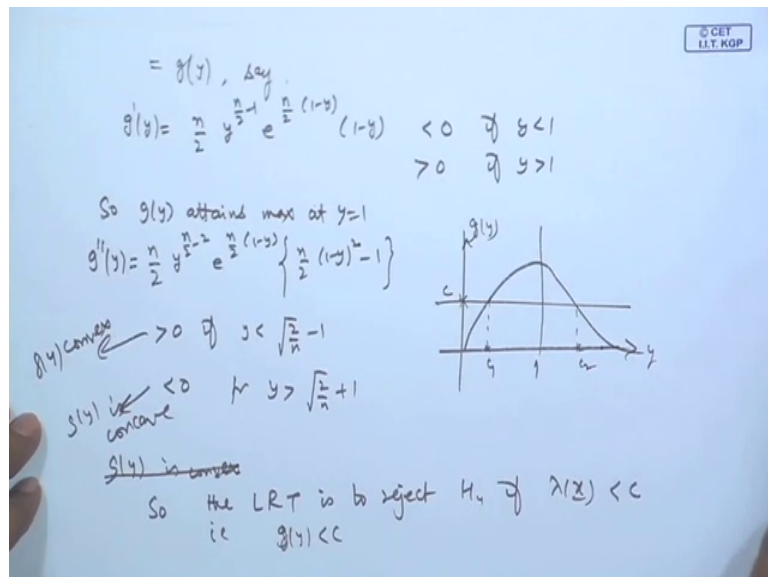
where $y = \frac{\hat{\sigma}_\Omega^2}{\sigma_0^2}$

Let me also consider for H 4 that a sigma square is equal to sigma naught square against K for sigma square is not equal to sigma naught square. So, I do not have to derive L hat omega. This is derived earlier that is 1 by 2 pi sigma omega hat square to the power n by 2 e to the power minus n by 2 where sigma omega hat square is equal to 1 by n sigma xi minus x bar square. Now when we are considering omega H, then mu hat omega H remains same; however, sigma omega H hat square that is actually equal to sigma naught

square because only this is the point null hypothesis. So, at this point only one value will come your omega H is actually mu sigma square mu is real and sigma square is equal to sigma naught square here.

So, L hat omega H, then this will be equal to 1 by 2 pi sigma naught square to the power n by 2 e to the power minus 1 by 2 sigma naught square and n sigma omega hat square. So, if I take the ratio the likelihood ratio is lambda x that is equal to L hat omega H by L hat omega. I can write it as same thing that is y to the power n by 2 e to the power n by 2 into 1 minus y, where y is equal to sigma omega hat square by sigma naught square. So, we have seen the behavior of this function; this is equal to say g y.

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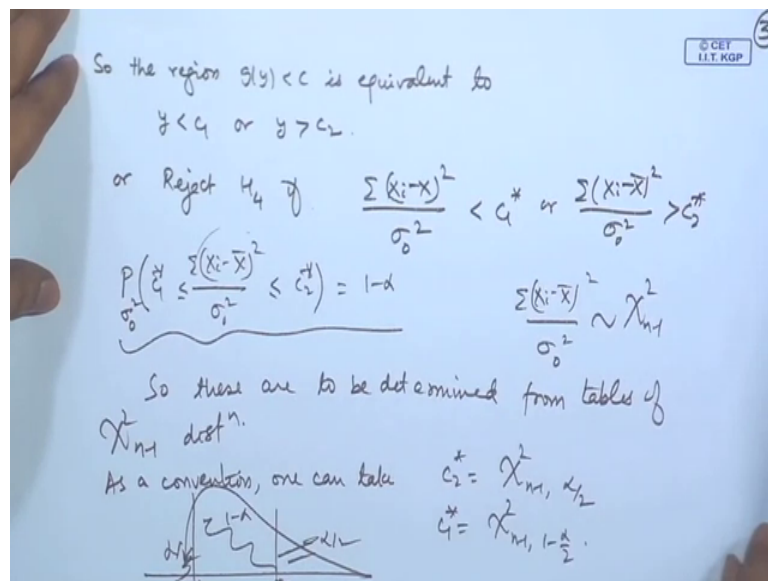


However, in the previous case y was always less than 1, but here y can take any value. And therefore, we need to look at the proper full behavior that is g prime y is actually equal to n by 2 y to the power n by 2 minus 1 e to the power n by 2 into 1 minus y into 1 minus y. So; obviously, this is less than 0; if y is less than 1, it is greater than 0 if y is greater than 1.

So, g y attains maximum at y is equal to 1. And the behavior actually we can also see what is g prime y g double prime, y g double prime y is n by 2 y to the power n by 2 minus 2 e to power n by 2 1 minus y n by 2 1 minus y square minus 1. That is greater than 0 if y is less than root 2 by n minus 1. It is less than 0 for y greater than root 2 by n plus 1.

So, it is actually that is $g(y)$ is convex in this region and in this region $g(y)$ is concave. So, the shape is something like this. This is one ok. So, the region LRT is to reject H_0 if λx is less than c . Now λx have written as $g(y)$. Now $g(y)$ less than c and g is a function of this nature. So now, you see here. So, suppose this is the point c and this is the curve $g(y)$ against y here. So, this could be some value say c_1 , this is some value c_2 . So, if I say $g(y)$ is less than c this is equivalent to y being less than c_1 or y being greater than c_2 .

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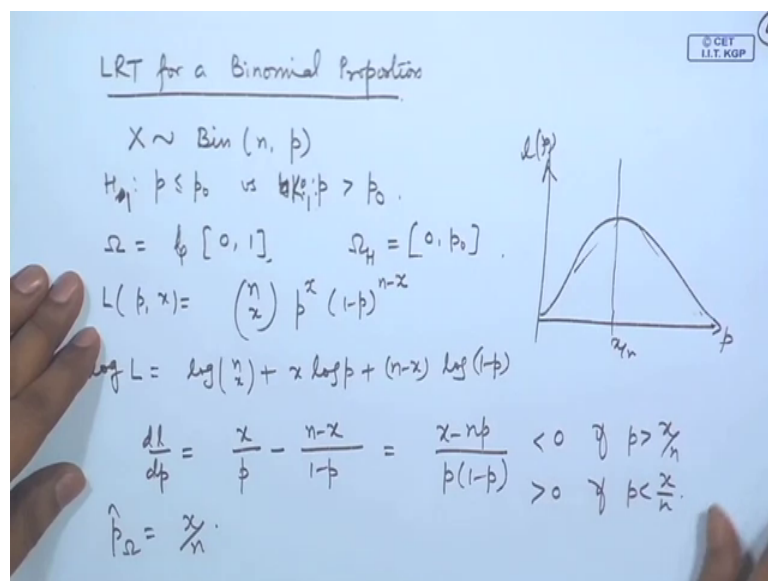


So, the region $g(y)$ less than c is equivalent to y less than c_1 or y greater than c_2 . So, y is defined as. So, we can say reject H_0 if $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}$ is less than say c_1 or $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}$ is greater than c_2 . And probability of $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}$ between c_1 and c_2 should be equal to $1 - \alpha$ when σ_0^2 is the true value.

Now, $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}$ follows chi square distribution on $n - 1$ degrees of freedom. So, these are to be determined from tables of chi square $n - 1$ distribution. As a convention one can take c_2 is equal to $\chi_{n-1, \alpha/2}^2$ and c_1 as $\chi_{n-1, 1-\alpha/2}^2$. Because the probability of between this suppose this is $\alpha/2$ probability this is $\alpha/2$ probability then this is $1 - \alpha$.

So, this is c1 star this is c 2 star that we can take here. You can see that the form is similar to the test which is derived in the ump unbiased test. Except that in the unp and bias test we got 2 conditions there one of the conditions is the same, but one more condition was there. Here we are getting only one condition. So, there is a similarity here and. In fact, one solution corresponds to that. Before we move to two sample problems let me give an application to the distributions either which are discrete or which are not in the exponential family. So, let us consider likelihood ratio test for a binomial proportion.

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So, we have the data x following normal a binomial n p distribution. And we are considering the hypothesis testing problem say p is less than or equal to p naught against say p is greater than p naught. Let me write it as $H_0: p \leq p_0$ vs $H_1: p > p_0$ following our usual convention for one sided testing problem H_0 and this is H_1 . Now your full parameter space is the interval 0 to 1 and Ω_H is 0 to p_0 . Now let us write down the likelihood function. So, $L(p, x)$ that is the $\binom{n}{x} p^x (1-p)^{n-x}$. we have actually discussed in detail the maximum likelihood estimator for this problem.

So, derivative and putting equal to 0 all those things are the standard; however, when we consider the parameter space under the null hypothesis. Then we have to see carefully. So, I will write down the expression for that part. So, log of the likelihood is log of $\binom{n}{x} p^x (1-p)^{n-x}$

plus $x \log p$ plus n minus $x \log(1-p)$. So, let me write it as small l . So, l by d p that is equal to $x \log p$ minus $n \log(1-p)$ that is equal to $x \log p$ minus $n \log(1-p)$ divided by p into $1-p$. This is less than 0 if p is greater than x/n and it is greater than 0 if p is less than x/n .

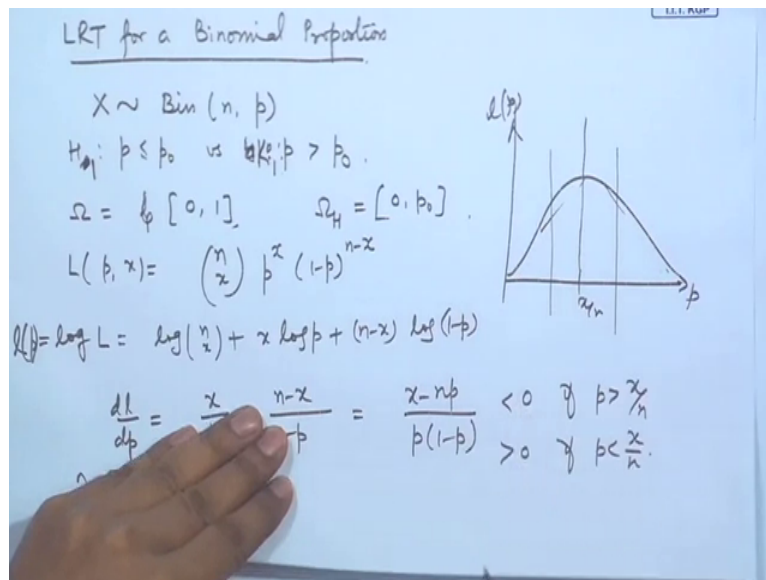
. So, if you look at the behavior of $l(p)$ this side we are having $l(p)$. So, up to x/n this is increasing and thereafter it is decreasing. So, \hat{p}_{Ω_H} is equal to actually x/n .

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The image shows a whiteboard with handwritten mathematical work. At the top right, there is a small logo for 'CET I.I.T. KGP'. The main work starts with the likelihood function $L(\Omega) = \binom{n}{x} \left(\frac{x}{n}\right)^x \left(1 - \frac{x}{n}\right)^{n-x}$. Below this, it states 'On $\Omega_H : p \leq p_0$ '. Then, two cases are listed: if $\frac{x}{n} \leq p_0$, then $\hat{p}_{\Omega_H} = \frac{x}{n}$; and if $\frac{x}{n} > p_0$, then $\hat{p}_{\Omega_H} = p_0$. A bracket groups these two cases, leading to the conclusion $\hat{p}_{\Omega_H} = \min(p_0, \frac{x}{n})$. Finally, the likelihood function $L(\Omega_H)$ is defined piecewise: $\binom{n}{x} \left(\frac{x}{n}\right)^x \left(1 - \frac{x}{n}\right)^{n-x}$ for $\frac{x}{n} \leq p_0$, and $\binom{n}{x} p_0^x (1-p_0)^{n-x}$ for $\frac{x}{n} > p_0$.

And therefore, the $L(\hat{\Omega}_H)$ that is equal to $\binom{n}{x} \left(\frac{x}{n}\right)^x \left(1 - \frac{x}{n}\right)^{n-x}$ to the power x $1-p$ to the power $n-x$. Now on Ω_H you are having $p \leq p_0$. If I have that then there will be 2 cases.

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I may have p naught here and I may have p naught here. So, if x by n is less than or equal to p naught then p hat ω_H that is equal to x by n ; however, if x by n is greater than p naught.

In that case if this is p naught then the maximum value is attained at p naught because this is outside the region. So, then p hat ω_H is actually equal to p naught; that means, we can say p hat ω_H is actually equal to minimum of p naught and x by n . So, L hat ω_H is equal to n c x p hat. So, x by n to the power x 1 minus x by n to the power n minus x if x by n is less than or equal to p naught and it is equal to n c x p naught to the power x 1 minus p naught to the power n minus x if x by n is greater than p naught.

So, if you compare L hat ω and L hat 1 hat ω_H then for the case x by n less than or equal to p naught. They are the same. In that case you always accept because both are the same. So, you accept H_1 .

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So $\lambda(x) = \frac{\hat{L}(\Omega_H)}{\hat{L}(\Omega_0)} = 1$ if $\frac{x}{n} \leq p_0$
 So always accept H_1 .

When $\frac{x}{n} > p_0$
 Then $\lambda(x) = \frac{p_0^x (1-p_0)^{n-x}}{\left(\frac{x}{n}\right)^x \left(1-\frac{x}{n}\right)^{n-x}}$ (LRT is Rej H_0 if $\lambda(x) < c$)

$\lambda^*(x) = \log \lambda(x) = x \log p_0 + (n-x) \log (1-p_0) - x \log \frac{x}{n} - (n-x) \log \left(1-\frac{x}{n}\right)$

$\frac{d}{dx} \lambda^*(x) = \log p_0 - \log (1-p_0) - \log \frac{x}{n} - \frac{x \cdot \frac{1}{n}}{\frac{x^2}{n^2}} + \log \left(1-\frac{x}{n}\right) + \frac{n-x}{1-x/n} \cdot \frac{-1}{n}$

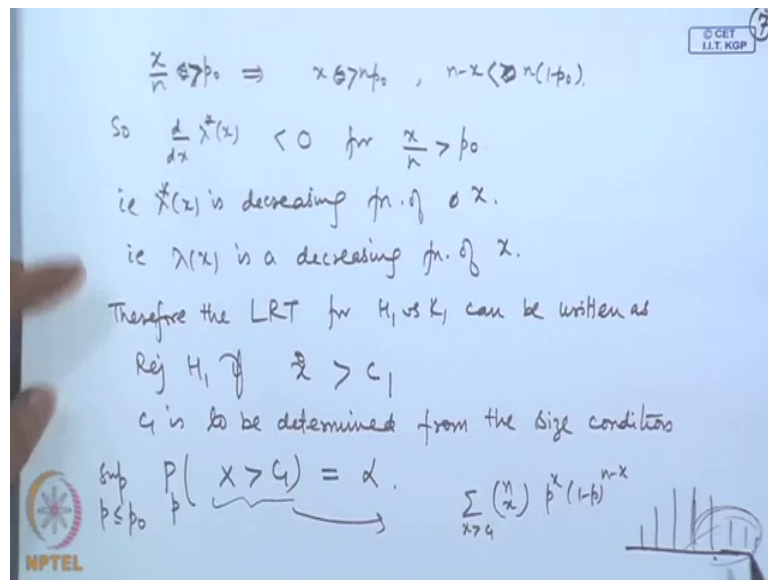
$= \log \frac{(n-x)p_0}{x(1-p_0)}$

So, $\lambda(x)$ that is $\frac{\hat{L}(\Omega_H)}{\hat{L}(\Omega_0)}$, that is equal to 1 if $\frac{x}{n}$ is less than or equal to p_0 . So, always accept H_1 . Now when $\frac{x}{n}$ is greater than p_0 in that case this $\lambda(x)$ will become equal to $p_0^x (1-p_0)^{n-x}$ divided by $\left(\frac{x}{n}\right)^x \left(1-\frac{x}{n}\right)^{n-x}$.

So, if I look at say $\lambda^*(x)$ that is equal to \log of $\lambda(x)$, that is equal to $x \log$ of p_0 plus $(n-x) \log$ of $1-p_0$ minus $x \log$ of $\frac{x}{n}$ minus $(n-x) \log$ of $1-\frac{x}{n}$. So, what is the behavior of this? Because LRT is reject H_0 if $\lambda(x) < c$ ok. Now if I write that in terms of x , what happens? So, we need to analyze the behavior of this. If I consider the derivative of this with respect to x get \log of p_0 minus \log of $1-p_0$ minus \log of $\frac{x}{n}$ minus $(n-x) \cdot \frac{1}{1-x/n} \cdot \frac{-1}{n}$ plus \log of $1-\frac{x}{n}$ plus $\frac{n-x}{1-x/n} \cdot \frac{-1}{n}$. So, you can see this term gets cancelled out and this whole thing cancels out.

So, we are getting \log of $\frac{(n-x)p_0}{x(1-p_0)}$.

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Now, we have chosen that x by n is less than or equal to p naught. This implies x is less than or equal to $n p$ naught. And n minus x will be n minus x will be greater than or equal to n into 1 minus p naught. So, d by $d x$ λ star x ; this will be less than 0 sorry. This is greater actually I made a mistake here x by n is greater than p naught region we are considering. So, x is greater than $n p$ naught n minus x is less than n into 1 minus p naught.

So, what will happen that if we consider this term \log of n minus $x p$ naught divided by x into 1 minus p naught this term becomes less than one therefore, \log of this becomes less than 0 . So, this is less than 0 for x by n greater than p naught. That is λ star is a decreasing function of x . That is λx is a decreasing function of x . So, note here I am considering the likelihood ratio that is λx , the region is λx less than c now λ is turning out to be a decreasing function of x . Therefore, this region is equivalent to therefore, the likelihood ratio test for H_1 versus K_1 can be written as reject H_1 if x is greater than some c_1 .

Now, c_1 is to be determined from the size condition. That is probability of x greater than c_1 for p supremum of p less than or equal to p naught. This should be equal to α . Now as a function of p what is this term this is actually $\sum_{x > c_1} \binom{n}{x} p^x (1-p)^{n-x}$ x is greater than c_1 . If you plot the binomial

probabilities the behavior is like this. Now we are looking at the right tail. Now right tail corresponds to a higher number of successes.

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This probability is the right tail of the binomial distⁿ. corresponds to the higher number of successes. So it is ↑ in p.

So sup is attained at $p = p_0$

So c_1 is determined from $P_{p_0}(X > c_1) = \alpha$

$X \sim \text{Bin}(n, p_0) \rightarrow$ tables of binomial probabilities

It may be that no value of c_1 gives an exact α .

So we choose $c_1 \rightarrow$

$$P_{p_0}(X > c_1) \leq \alpha \quad \& \quad P_{p_0}(X > c_1 - 1) > \alpha$$

So, this probability that is the right tail of the binomial distribution corresponds to the higher number of success. So, it is increasing in p. So, supremum is attained at p equal to p naught. So, c1 is determined from probability x greater than c1 equal to alpha for p is equal to p naught, where x follows binomial n p naught; that means, you have to see the tables of binomial probabilities. Now this being a discrete distribution, it is quite possible that there may not be any c1 for which this is equal to alpha. It may be that no value of c1 gives an exact alpha. So, we may choose c1 such that probability x greater than c1 at p naught is less than or equal to alpha, but probability of x greater than c 1 minus 1 at p naught is greater than alpha. So, this is the likelihood ratio test for the proportion of a binomial distribution.