

Statistical Inference
Prof. Somesh Kumar
Department of Mathematics
Indian Institute of Technology, Kharagpur

Lecture - 54
Likelihood Ratio Tests _ IV

Suppose I ask for H_4 hypothesis that is if I consider p is equal to p_0 , against p is not equal to p_0 .

(Refer Slide Time: 00:27)

The image shows a whiteboard with handwritten mathematical work. At the top right, there is a small logo for 'IIT KGP' and a circled number '5'. The main text is as follows:

$$\hat{L}(\Omega) = \binom{n}{x} \left(\frac{x}{n}\right)^x \left(1 - \frac{x}{n}\right)^{n-x}$$

On $\Omega_{H_4} : \underline{p \leq p_0}$

$$\left. \begin{array}{l} \text{If } \frac{x}{n} \leq p_0, \quad \hat{p}_{\Omega_{H_4}} = \frac{x}{n} \\ \text{If } \frac{x}{n} > p_0, \quad \hat{p}_{\Omega_{H_4}} = p_0 \end{array} \right\} \hat{p}_{\Omega_{H_4}} = \min(p_0, \frac{x}{n})$$

$$\hat{L}(\Omega_{H_4}) = \begin{cases} \binom{n}{x} \left(\frac{x}{n}\right)^x \left(1 - \frac{x}{n}\right)^{n-x} & \text{if } \frac{x}{n} \leq p_0 \\ \binom{n}{x} p_0^x (1-p_0)^{n-x} & \text{if } \frac{x}{n} > p_0 \end{cases}$$

At the bottom left, there is a logo for 'IIT KGP'.

In place of p less than or equal to p_0 if I modify that, then we can this region will not come only this portion will come and we will analyze the behavior of this function in a more appropriate fashion. Because there will be 2 regions; one will be corresponding to x by n greater than p_0 . We have already seen that in this region we are getting the function to be a decreasing function.

(Refer Slide Time: 00:49)

So $\lambda(z) = \frac{\hat{L}(\Omega_1)}{\hat{L}(\Omega_0)} = 1$ if $\frac{x}{n} \leq p_0$
 So always accept H_1 .

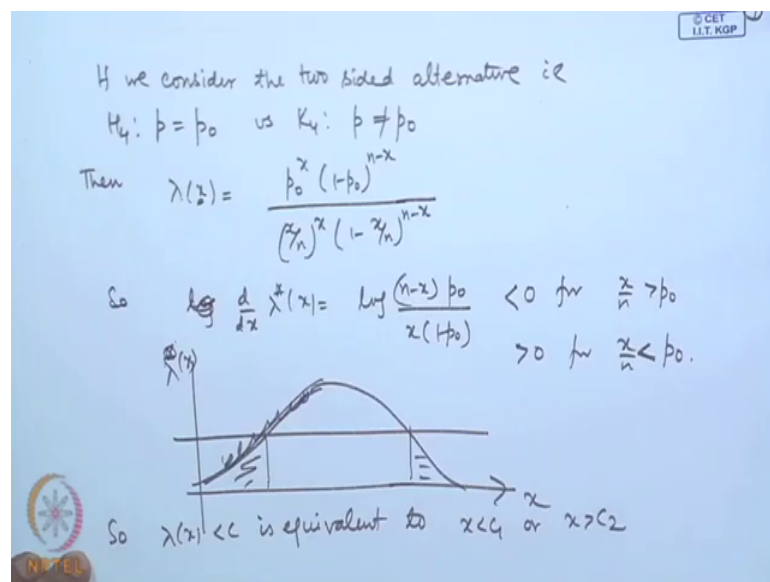
When $\frac{x}{n} > p_0$
 Then $\lambda(z) = \frac{p_0^x (1-p_0)^{n-x}}{\left(\frac{x}{n}\right)^x (1-\frac{x}{n})^{n-x}}$ (LRT is $\lambda(x) < c$)

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

$\frac{d}{dz} \lambda^*(z) = \log p_0 - \log (1-p_0) - \log \frac{x}{n} - \frac{x \cdot \frac{1}{n}}{\frac{x}{n}} + \log (1-\frac{x}{n}) + \frac{n-x}{1-\frac{x}{n}} \cdot \frac{-1}{n}$
 $= \log \frac{(n-x) p_0}{x(1-p_0)}$

However, if I consider x by n less than or equal to p naught this value will become positive. And therefore, $\lambda^* x$ will become an increasing function. So, let me just give the complete analysis for the two sided testing problem.

(Refer Slide Time: 01:25)

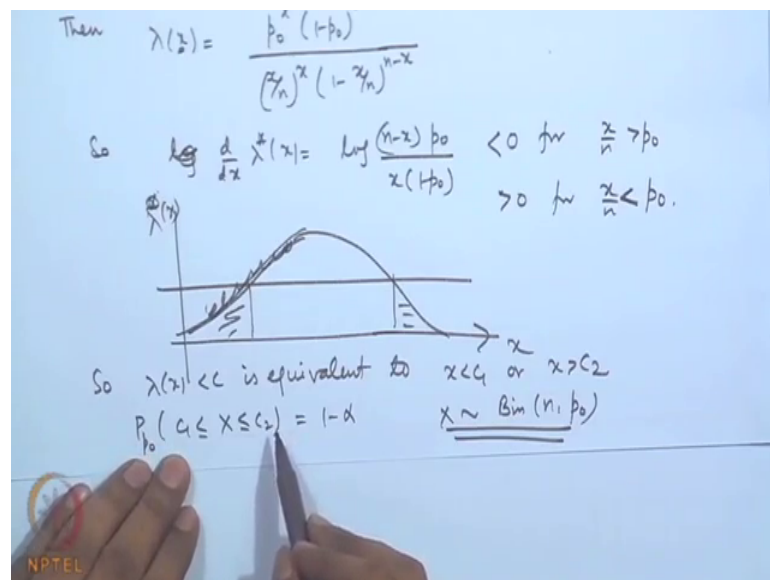


If we consider the two sided alternative that is $H_0: p$ is equal to p naught against $H_1: p$ is not equal p naught. In that case $\lambda^* x$ that is equal to simply p naught to the power x 1 minus p naught to the power n minus x divided by x by n to the power x 1 minus x by n to the power n minus x . So, lambda the behavior of lambda star we have seen that

derivative of a d by dx of lambda star x that is equal to log of n minus x into p naught divided by x into 1 minus p naught. So, this is less than 0 for x by n greater than p naught and it is greater than 0 for x by n less than p naught.

So, the nature of the function is then that it is increasing and then for x by n less than p naught it is increasing. So, if I am treating it as a function of x then it is firstly, for x by n yeah it is increasing and then it is decreasing on this side I have x on this side I have lambda x or lambda star x. So now, the region lambda x less than or equal to c, that is equal to this 2 regions. So, lambda x less than C is equivalent to x less than C 1 or x is greater than C 2.

(Refer Slide Time: 03:47)



And we should have probability of C 1 less than or equal to x less than or equal to C 2 is equal to 1 minus alpha where x follows binomial n p naught. So, this C 1 and C 2 can measurement from the tables of binomial distribution. I have shown you that, even in the case of discrete case the likelihood ratio test can give a nice and elegant solution. However, if the distribution is not in an exponential family let us consider one example.

(Refer Slide Time: 04:21)

Let X_1, \dots, X_n be a random sample from an exponential popⁿ. with location parameter e^{-x} , $x > \theta$.

$H_0: \theta \leq \theta_0$ vs $K_1: \theta > \theta_0$.

$$L(\theta, x) = e^{n\theta - \sum x_i} = \begin{cases} e^{n(\theta - \bar{x})} & x_{(1)} > \theta \\ 0 & \text{ew} \end{cases}$$

L is \uparrow in θ . $\hat{\theta}_{\Omega} = x_{(1)}$.

$$\hat{L}(\Omega) = e^{n(x_{(1)} - \bar{x})}$$

For Ω_{H_0} $\hat{\theta}_{\Omega_{H_0}} = \begin{cases} x_{(1)} & \text{if } x_{(1)} \leq \theta_0 \\ \theta_0 & \text{if } x_{(1)} > \theta_0. \end{cases}$

Let X_1, X_2, \dots, X_n be a random sample from an exponential population with location parameter that is e^{-x} is the density function. So, the likelihood ratio function is $e^{n\theta - \sum x_i}$ which I can write as $e^{n\theta - n\bar{x}}$. This is for $x_{(1)} > \theta$ it is equal to 0, if $x_{(1)} \leq \theta$. So, naturally you can see that L is increasing in θ . So, $\hat{\theta}$ is equal to $x_{(1)}$ this is over Ω .

So, $\hat{L}(\Omega)$ is nothing but $e^{n(x_{(1)} - \bar{x})}$. Let us consider Ω_{H_0} . For Ω_{H_0} if I am considering, now this is an increasing function. In fact, you can see that $\hat{\theta}$ is equal to $x_{(1)}$ this will be this value, but it is going like that. So, for Ω_{H_0} $\hat{\theta}_{\Omega_{H_0}}$ that will be equal to $x_{(1)}$, if $x_{(1)} \leq \theta_0$ and it is equal to θ_0 if $x_{(1)} > \theta_0$.

(Refer Slide Time: 06:35)

$$\hat{L}(\Omega_H) = \begin{cases} e^{n(x_1 - \bar{x})} & , x_1 \leq \theta_0 \\ e^{n(\theta_0 - x_1)} & , x_1 > \theta_0 \end{cases}$$

$$\lambda(z) = \frac{\hat{L}(\Omega_H)}{\hat{L}(\Omega_0)} = \begin{cases} 1 & \text{if } x_1 \leq \theta_0 \\ e^{n(\theta_0 - x_1)} & \text{if } x_1 > \theta_0 \end{cases}$$

Accept H_1 if $e^{n(\theta_0 - x_1)} < c \Rightarrow x_1 > c$

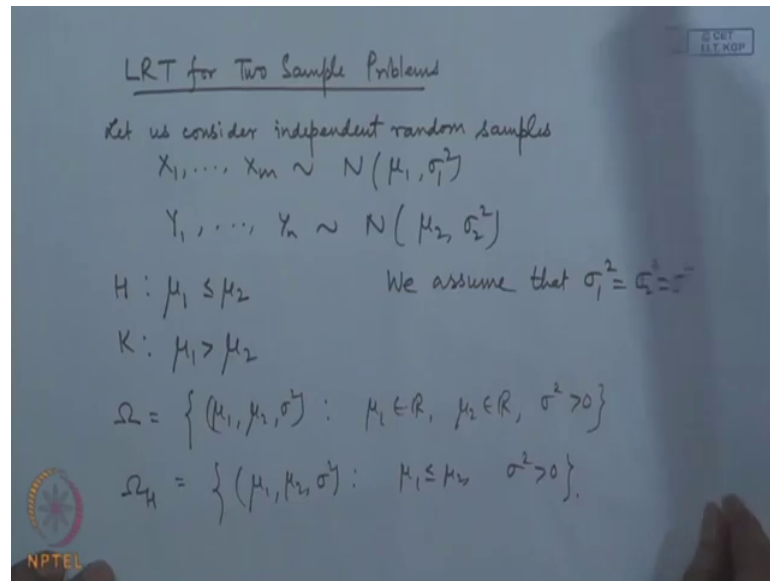
$P_{\theta_0}(x_1 > c) = \alpha$
 $\Rightarrow \int_c^{\infty} n e^{n(\theta_0 - x)} dx = \alpha$
 $\Rightarrow e^{-n(\theta_0 - c)} = \alpha \Rightarrow c = \theta_0 - \frac{\log \alpha}{n}$

So, $\hat{L}(\Omega_H)$ that is equal to e to the power $n \times x_1$ minus x bar, if x_1 is less than or equal to θ_0 it is equal to e to the power $n \theta_0$ minus x bar if x_1 is greater than θ_0 . So, the ratio that is $\hat{L}(\Omega_H)$ by $\hat{L}(\Omega_0)$ that is equal to 1, if x_1 is less than or equal to θ_0 and it is equal to e to the power $n \theta_0$ minus x_1 .

If x_1 is greater than θ_0 so, here in this case we will accept H_1 and in this particular case, if I am considering e to the power $n \theta_0$ minus x_1 less than C then this is equivalent to x_1 greater than C . So, this C will be determined from the size condition probability of x_1 greater than C . When θ_0 we are taking maximum for θ_0 less than or equal to θ_0 this should be equal to α . Now, what is the distribution of x_1 ? That is equal to $n e$ to the power $n \theta_0$ minus x for x greater than θ_0 .

So, if I consider the probability of x_1 greater than C that is equal to e to the power $n \theta_0$ minus C . So, this value is actually e to the power $n \theta_0$ minus C . So, if I take supremum θ_0 less than or equal to θ_0 that is equal to e to the power $n \theta_0$ minus C , that is equal to α . That means C is equal to θ_0 minus \log of α by n .

(Refer Slide Time: 08:41)



So, the likelihood ratio test is so, when x_1 is greater than θ naught reject H_1 if x_1 is greater than θ naught minus \log of α by n . Now, we take up the likelihood ratio test for two sample problems. So, likelihood ratio test for two sample problems. To start with I consider random samples from 2 normal populations. Let us consider, let us consider independent random samples X_1, X_2, \dots, X_m from normal μ_1, σ_1^2 , Y_1, Y_2, \dots, Y_n from normal μ_2, σ_2^2 . Let us consider the hypothesis say, for testing of $\mu_1 \leq \mu_2$ against $\mu_1 > \mu_2$.

We assume here that σ_1^2 is equal to σ_2^2 . this case we have derived the UMP unbiased tests, when this is not equal that is $\sigma_1^2 \neq \sigma_2^2$ it was known as a Byron's Fisher situation. So, our parameter space is μ_1, μ_2, σ^2 : μ_1 is real, μ_2 is real and σ^2 is positive and Ω_H that is μ_1, μ_2, σ^2 : $\mu_1 \leq \mu_2$ and $\sigma^2 > 0$.

(Refer Slide Time: 11:33)

The likelihood function is

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

$$\ell = \log L = -\frac{m+n}{2} \log 2\pi - \frac{m+n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \left\{ \sum (x_i - \mu_1)^2 + \sum (y_j - \mu_2)^2 \right\}$$

$$\frac{\partial \ell}{\partial \mu_1} = \frac{\sum (x_i - \mu_1)}{\sigma^2} = \frac{n(\bar{x} - \mu_1)}{\sigma^2} < 0 \text{ for } \mu_1 > \bar{x}$$

$$> 0 \text{ if } \mu_1 < \bar{x}$$

(So max is attained at \bar{x}) i.e. $\hat{\mu}_{1\Omega} = \bar{x}$

$$\frac{\partial \ell}{\partial \mu_2} = \frac{n(\bar{y} - \mu_2)}{\sigma^2} < 0 \text{ if } \bar{y} < \mu_2$$

$$> 0 \text{ if } \bar{y} < \mu_2$$

(So max is attained at \bar{y}) i.e. $\hat{\mu}_{2\Omega} = \bar{y}$

Let us write down the likelihood function. The likelihood function is given by $L(\mu_1, \mu_2, \sigma^2, \underline{x}, \underline{y})$. So, that is equal to $\frac{1}{(2\pi\sigma^2)^{\frac{m+n}{2}}} e^{-\frac{1}{2\sigma^2} [\sum (x_i - \mu_1)^2 + \sum (y_j - \mu_2)^2]}$. Log of ℓ is equal to $-\frac{m+n}{2} \log 2\pi - \frac{m+n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} [\sum (x_i - \mu_1)^2 + \sum (y_j - \mu_2)^2]$.

So, if I consider the maximization over the full parameter space. So, let me write this as ℓ . So, $\frac{\partial \ell}{\partial \mu_1}$ that will give me $\frac{\sum (x_i - \mu_1)}{\sigma^2}$, that is $\frac{n(\bar{x} - \mu_1)}{\sigma^2}$. So, once again less than 0; if μ_1 is greater than \bar{x} it is greater than 0. If μ_1 is less than \bar{x} so, maximum is attained at \bar{x} , that is $\hat{\mu}_{1\Omega} = \bar{x}$. Similarly, if I take $\frac{\partial \ell}{\partial \mu_2}$ that is equal to $\frac{n(\bar{y} - \mu_2)}{\sigma^2}$ that is less than 0 if \bar{y} is less than μ_2 it is greater than 0, if \bar{y} is less than μ_2 . So, maximum is attained at \bar{y} . That is $\hat{\mu}_{2\Omega} = \bar{y}$.

(Refer Slide Time: 14:25)

$$\begin{aligned} \frac{\partial^2 \ell}{\partial \sigma^2} &= -\frac{(m+n)}{2\sigma^2} + \frac{1}{2\sigma^4} \left\{ \sum (x_i - \mu_1)^2 + \sum (y_j - \mu_2)^2 \right\} \\ &= \frac{m+n}{2\sigma^4} \left[\frac{1}{m+n} \left\{ \sum (x_i - \mu_1)^2 + \sum (y_j - \mu_2)^2 \right\} - \sigma^2 \right] \\ &< 0 \quad \text{if } \sigma^2 > \frac{1}{m+n} \left\{ \sum (x_i - \mu_1)^2 + \sum (y_j - \mu_2)^2 \right\} \\ &> 0 \quad \text{if } \sigma^2 < \frac{1}{m+n} \left\{ \sum (x_i - \mu_1)^2 + \sum (y_j - \mu_2)^2 \right\} \\ \text{So } \hat{\sigma}_2^2 &= \frac{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2}{(m+n)} \end{aligned}$$

Let us also consider the maximization with respect to sigma square, so we get minus m plus n by 2 sigma square plus 1 by 2 sigma to the power 4 sigma x i minus mu 1 square plus sigma y j minus mu 2 square. So, that is equal to if I take m plus n by 2 sigma to the power 4 out then I get 1 by m plus n sigma x i minus mu 1 square plus sigma y j minus mu 2 square minus sigma square. Once, again it is less than 0 if sigma square is greater than 1 by m plus n sigma x i minus mu 1 square plus sigma y j minus mu 2 square, it is greater than 0 if sigma square is less than 1 by m plus n sigma x i minus mu 1 square plus sigma y j minus mu 2 square.

So, sigma omega hat square that is attained at this value where mu 1 and mu 2 are replaced by their respective maximum likelihood estimators. That means, it is attained at sigma x i minus x bar square plus sigma y j minus y bar square divided by m plus n. So, if we consider l hat omega.

(Refer Slide Time: 16:23)

So $\hat{L}(\Omega) = \frac{1}{(2\pi\hat{\sigma}^2)^{\frac{m+n}{2}}} e^{-\frac{(m+n)}{2} \frac{(\bar{x} - \bar{y})^2}{\hat{\sigma}^2}}$

Now over Ω_H : When $\bar{x} \leq \bar{y}$, we take

$\hat{\mu}_{1\Omega_H} = \bar{x}$, $\hat{\mu}_{2\Omega_H} = \bar{y}$, $\hat{\sigma}_{\Omega_H}^2 = \frac{1}{m+n} [\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2]$

In this case $\lambda(\bar{x}) = \frac{\hat{L}(\Omega_H)}{\hat{L}(\Omega)} = 1$. Always accept H_1 . ($\alpha=0$)

When $\bar{x} > \bar{y}$.

Fix μ_2 , and then the max w.r.t μ_1 is $\hat{\mu}_1 = \min(\mu_2, \bar{x})$

If $\bar{x} < \mu_2$ then $\hat{\mu}_1 = \max(\bar{x}, \bar{y})$ (by finding max w.r.t μ_1) (and we always accept H_1)

So, $\hat{L}(\Omega)$ is equal to $\frac{1}{(2\pi\hat{\sigma}^2)^{\frac{m+n}{2}}} e^{-\frac{(m+n)}{2} \frac{(\bar{x} - \bar{y})^2}{\hat{\sigma}^2}}$. Now let us consider over Ω_H . Over Ω_H what is happening? That let us look at the derivatives here the maximization were occurring at \bar{x} and \bar{y} for μ_1 and μ_2 . Now, we are saying μ_1 is less than or equal to μ_2 over Ω_H . So, when \bar{x} is less than or equal to \bar{y} we can treat them as such.

So, when \bar{x} is less than or equal to \bar{y} we take, μ_1 $\hat{L}(\Omega_H)$ is equal to \bar{x} , μ_2 $\hat{L}(\Omega_H)$ is equal to \bar{y} and $\hat{\sigma}^2$ that is equal to $\frac{1}{m+n} [\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2]$. There is no change. In this case the ratio that is $\hat{L}(\Omega_H)$ by $\hat{L}(\Omega)$ that is equal to 1.

So, we always accept H_1 the hypothesis that I mentioned here, μ_1 less than or equal to μ_2 , against μ_1 greater than μ_2 . So, we always accept H_1 . So, that is α is equal to 0. Now the other possibility is when \bar{x} is greater than \bar{y} . Now when \bar{x} is greater than \bar{y} then we analyze. Firstly, you look at the behavior with respect to μ_1 .

Now with respect to μ_1 you see it is initially increasing up to \bar{x} and then decreasing. So, now if \bar{y} is less than \bar{x} then, we will have to modify this thing. What we do? Fix μ_2 first say ok. And then the maximum with respect to μ_1 is μ_1 hat is equal to minimum of μ_2 and \bar{x} . Now if \bar{x} is less than μ_2 . Then μ_2 hat

will be equal to maximum of \bar{x} , \bar{y} that is by finding the maximum with respect to μ_2 . And we always accept H_0 .

(Refer Slide Time: 20:03)

$$\text{If } \bar{x} > \mu_2, \quad \frac{\partial L}{\partial \mu_1} = \frac{m(\bar{x} - \mu_1)}{\sigma^2} > 0 \quad (\text{on } \Omega_{H_0} \text{ as } \mu_1 \leq \mu_2)$$

So with μ_1 , the maximum is attained at the line $\mu_1 = \mu_2$.

In this case

$$l = \log \hat{L} = -\frac{m+n}{2} \log 2\pi - \frac{m+n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \left\{ \sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2 \right\}$$

$$- \left\{ \frac{m}{2\sigma^2} (\bar{x} - \mu_0)^2 + \frac{n}{2\sigma^2} (\bar{y} - \mu_1)^2 \right\}$$

$$\frac{\partial l}{\partial \mu} = 0 \Rightarrow \hat{\mu} = \frac{m\bar{x} + n\bar{y}}{m+n} = \hat{\mu}_{1, \Omega_{H_0}} = \hat{\mu}_{2, \Omega_{H_0}}$$

$$\hat{\sigma}_{\Omega_{H_0}}^2 = \frac{1}{m+n} \left[\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2 + \frac{m}{m+n} (\bar{x} - \bar{y})^2 \right]$$

So $\hat{L}(\Omega_{H_0}) = \left(\frac{1}{2\pi \hat{\sigma}_{\Omega_{H_0}}^2} \right)^{\frac{m+n}{2}} \cdot e^{-\frac{m+n}{2}}$

However, another case occurs when, if \bar{x} is greater than μ_2 . In this case the $\frac{\partial l}{\partial \mu_1}$ that is equal to $m\bar{x} - m\mu_1$ by σ^2 . I think I wrote a little bit wrongly in the first place this was m times not n times. So, this one will become greater than 0 on Ω_{H_0} because, we are having $\mu_1 \leq \mu_2$ ok. So, with respect to μ_1 the maximum is attained at the line $\mu_2 = \mu_1$. So, in this case the log likelihood that is L , I can write as $-\frac{m+n}{2} \log 2\pi$, minus m plus n by 2 log of σ^2 , minus $\frac{1}{2\sigma^2} \left\{ \sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2 \right\}$ plus $\frac{m}{2\sigma^2} (\bar{x} - \mu_1)^2 + \frac{n}{2\sigma^2} (\bar{y} - \mu_1)^2$.

So, if I consider $\frac{\partial l}{\partial \mu}$ then I will get $\hat{\mu}$ is equal to $m\bar{x} + n\bar{y}$ divided by $m+n$. That is the grand mean; that is $\mu_{1, \Omega_{H_0}} = \mu_{2, \Omega_{H_0}}$ because, I have assumed them to be equal here. And $\hat{\sigma}_{\Omega_{H_0}}^2$ we will also get because there we were getting $x_i - \mu_1$ and $y_j - \mu_2$. So, this will become simply $\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2 + \frac{m}{m+n} (\bar{x} - \bar{y})^2$ by $m+n$. So, $\hat{L}(\Omega_{H_0})$ that becomes equal to $\left(\frac{1}{2\pi \hat{\sigma}_{\Omega_{H_0}}^2} \right)^{\frac{m+n}{2}} \cdot e^{-\frac{m+n}{2}}$.

(Refer Slide Time: 22:57)

We reject H when

$$\lambda(z) = \frac{\hat{\sigma}_L^2}{\hat{\sigma}_{OH}^2} < C_1$$

or

$$\frac{\hat{\sigma}_L^2}{\hat{\sigma}_{OH}^2} < C_1 \quad \text{or} \quad \frac{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2}{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2 + \frac{mn}{m+n} (\bar{x} - \bar{y})^2} < C_1$$

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

$$\Rightarrow \sqrt{\frac{mn}{m+n}} \frac{(\bar{x} - \bar{y})}{S_p} > C_3 \quad S_p^2 = \frac{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2}{m+n-2}$$

Now, the rejection region is, we reject H when, $\lambda(x)$ that is $\hat{\sigma}_L^2$ by $\hat{\sigma}_{OH}^2$ that will become σ_L^2 by σ_{OH}^2 less than some C or we can say σ_L^2 by σ_{OH}^2 is less than C_1 . Now, we substitute the values here, this is $\frac{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2}{m+n}$ and in the denominator then I have $\frac{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2 + \frac{mn}{m+n} (\bar{x} - \bar{y})^2}{m+n}$ this is less than C_1 .

You take the reciprocal and then subtract then this will give us actually $\frac{mn}{m+n} \frac{(\bar{x} - \bar{y})^2}{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2} > C_2$. Note here that \bar{x} is greater than \bar{y} . \bar{x} is greater than \bar{y} . So, this means I can take the square root here $\sqrt{\frac{mn}{m+n}} \frac{(\bar{x} - \bar{y})}{S_p} > C_3$, where S_p^2 is nothing but $\frac{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2}{m+n-2}$.

(Refer Slide Time: 27:29)

$$P\left(\sqrt{\frac{mn}{m+n}} \left(\frac{\bar{X}-\bar{Y}}{S_p}\right) > c_3\right)$$

$$= P\left(\sqrt{\frac{mn}{m+n}} \left\{\frac{\bar{X}-\bar{Y} - (\mu_1 - \mu_2)}{S_p}\right\} > c_3 - \sqrt{\frac{mn}{m+n}} \left(\frac{\mu_1 - \mu_2}{S_p}\right)\right)$$

$$P\left(\underline{T}_{m+n-2} > c_3 - \sqrt{\frac{mn}{m+n}} \left(\frac{\mu_1 - \mu_2}{S_p}\right)\right)$$

This prob. is increasing in $\mu_1 - \mu_2$.
 So on Ω_H , the maximum value will be attained
 at $\mu_1 - \mu_2 = 0$.

ie the size condition becomes

$$P_{\mu_1 = \mu_2} \left(\sqrt{\frac{mn}{m+n}} \left(\frac{\bar{X}-\bar{Y}}{S_p}\right) > c_3\right) = \alpha \Rightarrow c_3 = t_{m+n-2, \alpha}$$

If this is the t distribution then this probability if I consider, probability of root m n by m plus n X bar minus Y bar by S p greater than C 3. That is equal to probability of root m n by m plus n X bar minus Y bar minus mu 1 minus mu 2 divided by S p greater than C 3 minus root m n by m plus n mu 1 minus mu 2 by S p. Now this is a T distribution on m plus n minus 2 degrees of freedom. So, we are saying probability of a T variable on this is bigger than C 3 minus root m n by m plus n mu 1 minus mu 2 by S p.

Now, mu 1 minus mu 2 is less than or equal to 0. Actually if I increase mu 1 minus mu 2 then this term will decrease. If this term decreases this probability will increase; so, this probability is increasing in mu 1 minus mu 2. So, on omega H the maximum value will be attained at mu 1 minus mu 2 equal to 0. That is the size condition becomes probability of root m n by m plus n X bar minus Y bar by S p greater than C 3; when mu 1 is equal to mu 2. So, this means C 3 is nothing, but t m plus n minus 2 alpha. You can compare it with the ump unbiased test that we derived. This form is the same.

So, in the likelihood ratio test what is happening is that some part we are having slightly different in the 1 sided testing problems. But in the 2 sided testing problem this is exactly same as the ump unbiased test. In the next lecture I will derive this test likelihood ratio test for mu 1 equal to mu 2 against mu 1 not equal to mu 2. we will also consider the testing for the equality of variances. So, sigma 1 square less than or equal to sigma 2

square, σ_1^2 is not equal to σ_2^2 these hypothesis testing problems also I will consider in the next lecture.