

Statistical Inference
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Lecture - 35
Application of NP- Lemma – I

In the last lecture, I have introduced the concept of most powerful test of a statistical hypothesis and we were developing the Neyman Pearson theory. In that, the first result was the so called Neyman Pearson fundamental Lemma. And this test gives the most powerful test for testing a simple null hypothesis against a simple alternative hypothesis.

As an example, I had given the normal distribution testing for the mean. Today, I will discuss various other applications of this Neyman Pearson lemma and how then it can be extended to cover the cases when we will may have composite hypothesis, in the null hypothesis or in the alternative hypothesis. So, we will consider these application today.

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Lecture 23

Applications of Neyman Pearson Lemma.

1. Let X_1, \dots, X_n be a random sample from $N(0, \sigma^2)$ population.

$H_0: \sigma^2 = \sigma_0^2$

$H_1: \sigma^2 = \sigma_1^2 \quad (\sigma_1^2 > \sigma_0^2)$

$f_0(x) = \frac{1}{(\sigma_0 \sqrt{\pi})^n} e^{-\frac{1}{2\sigma_0^2} \sum x_i^2}$

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The NP lemma gives the form of the most powerful test as

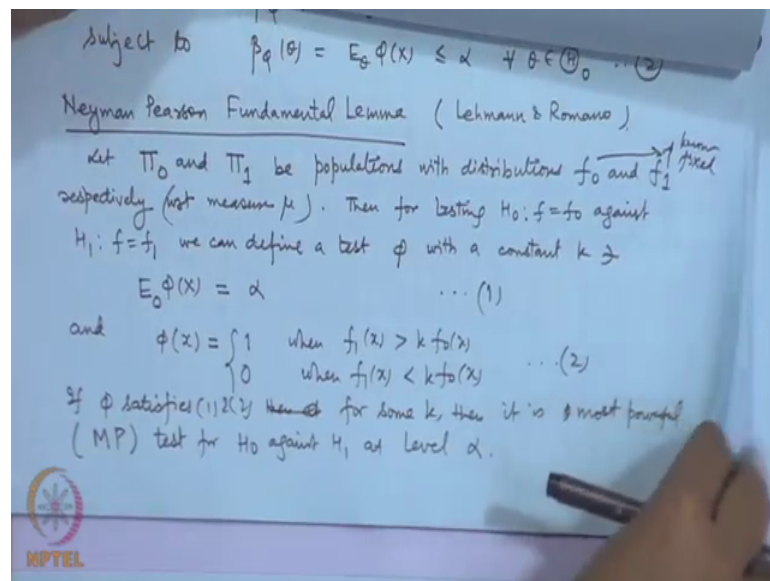
Let me start with suppose we have a say X_1, X_2, \dots, X_n , let X_1, X_2, \dots, X_n be a random sample from say normal 0 sigma square population. So, we were interested in testing the say null hypothesis sigma square is equal to say sigma naught square against say sigma square is equal to sigma 1 square. Now, sigma 1 square is not equal to sigma naught square. So, let us consider say the case sigma 1 square is greater than sigma naught square. So, in order to consider the application of the Neyman Pearson fundamental

lemma, we should write down the distribution which is the joint density of X_1, X_2, \dots, X_n under the null hypothesis and the alternative hypothesis. We call it f_0 and f_1 .

So, $f_0(x)$ that is equal to $\frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}}$ to the power n is equal to $\frac{1}{\sigma^n (2\pi)^{n/2}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n x_i^2}$. So, $f_1(x)$ will then be equal to $\frac{1}{\sigma_1^n (2\pi)^{n/2}} e^{-\frac{1}{2\sigma_1^2} \sum_{i=1}^n x_i^2}$.

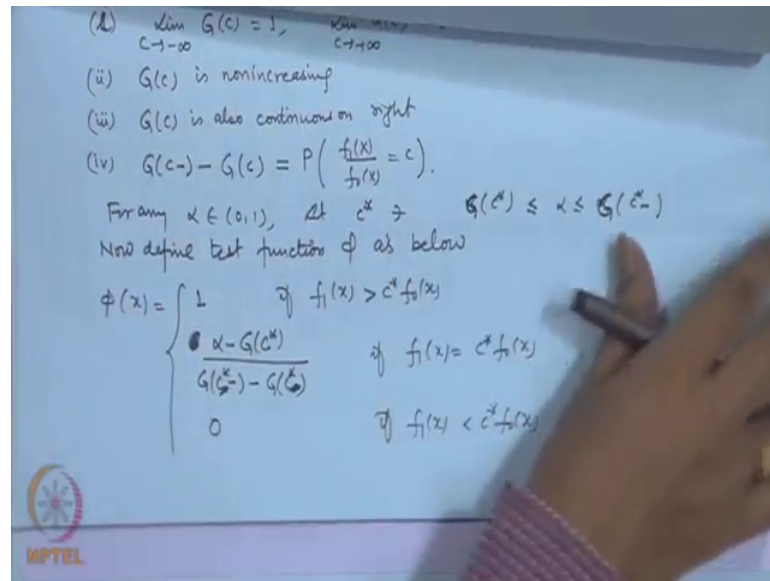
Now, the Neyman Pearson lemma gives the form of the most powerful test as. So, we will consider the rejection region this is a continuous distribution. If you remember the form of the Neyman Pearson lemma, the form of the test function I will recollect here. It is given in this particular fashion.

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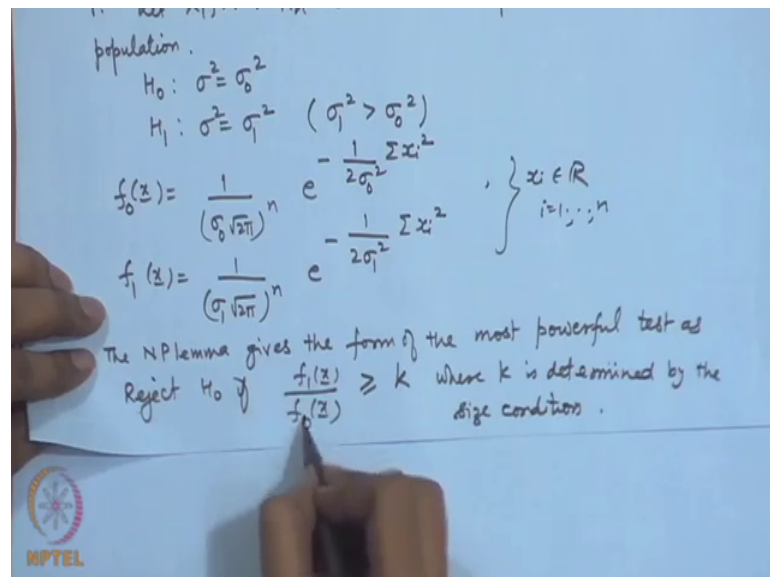
The form of the test in the Neyman Pearson lemma is given by reject H_0 when $f_1(x)$ is greater than k times $f_0(x)$ and accept when $f_1(x)$ is less than k times $f_0(x)$ and we are considering the rejection with probability γ .

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There is a constant here when f_1 is equal to constant times f_2 at x . Now, in the case of continuous distribution, this probability will be 0, the probability of this occurrence. Therefore, we do not have to write this thing. Rather, we can include the equality at one of the places either at the rejection or in the acceptance.

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So, for convenience, I will include it in the rejection region. So, the test is reject H_0 if $f_1(x)$ by $f_0(x)$ is greater than or equal to k , where k is determined by the size condition.

So, let us write down this f_1 by f_{naught} x greater than or equal to k . Since, these densities are valid for whole real line that is this x is belong to R for is equal to 1 to n . So, this ratio is defined for all values of x_1, x_2, \dots, x_n on the real line.

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This is equivalent to

$$\left(\frac{\sigma_1}{\sigma_0}\right)^n e^{\frac{1}{2}\left(\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}\right) \sum x_i^2} \geq k$$

Taking logarithms & adjusting the constants we can write the rejection region as

$$\frac{1}{2}\left(\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}\right) \sum x_i^2 \geq k_1, \text{ where } k_1 \text{ is determined by the size condition}$$

$\sigma_0^2 < \sigma_1^2 \Rightarrow \frac{1}{\sigma_0^2} > \frac{1}{\sigma_1^2}$

$\Rightarrow \sum x_i^2 \geq k_2$

So, we write the region as, this is equivalent to, so you will have σ_1 by $\sqrt{2\pi}$ divided by σ_0 $\sqrt{2\pi}$ to the power n e to the power $\frac{1}{2} \left(\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2} \right) \sum x_i^2$ greater than or equal to k .

Now, in this problem, σ_0 and σ_1 are known constants. So, I can adjust this here, I can also take log. Taking logarithms and adjusting the constants, we can write the rejection region as $\frac{1}{2} \left(\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2} \right) \sum x_i^2 \geq k_1$. I have changed the name of the constant here because I will be adjusting this here and then I have taken the log here. So, the some other constant is coming. Now, earlier we mentioned that k is determined by the size condition. So, we will say that k_1 is determined by the size condition. Now, note here, we had $\sigma_0^2 < \sigma_1^2$.

So, this means that $\frac{1}{\sigma_0^2}$ is greater than $\frac{1}{\sigma_1^2}$. Now, again this is a constant. So, I adjust this here. So, this is equivalent to saying $\sum x_i^2 \geq k_2$. Now, let us look at the determination of k_2 . So, if k_1 is determined by the size condition, then k_2 is also

determined by the size condition. Now, in order to determine this k_2 , we need the probability of rejecting H_0 when it is true and we will put it is equal to α .

So, let us look at this. So, basically what we need here is the distribution of $\sum X_i^2$ because when we consider the probability statement here, this will involve the distribution of $\sum X_i^2$.

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In order to determine k_2 , we employ the size condition i.e.

$$P(\text{Type I error}) = \alpha$$

i.e. $P(\text{Rejecting } H_0 \text{ when it is true}) = \alpha$

$$\Rightarrow P\left(\sum_{i=1}^n X_i^2 \geq k_2\right) = \alpha$$

$Y_i = \frac{X_i}{\sigma_0} \sim N(0, 1)$, (under H_0)
 Y_1, \dots, Y_n are independent.

$\sum Y_i^2 \sim \chi_n^2$
 Test is then reject H_0 if $\frac{\sum X_i^2}{\sigma_0^2} \geq c$

$P\left(\frac{\sum X_i^2}{\sigma_0^2} \geq c\right) = \alpha$
 $\Rightarrow c = \chi_{n, \alpha}^2$

So, we write it like this. In order to determine k_2 , we employ the size condition that is probability of type I error is equal to α that is probability of rejecting H_0 when H_0 is true, so when it is true that is equal to α . Now, let us look at this here we are saying $\sum X_i^2 \geq k_2$ when the distribution is σ_0^2 . That is $\sum X_i^2$ is equal to σ_0^2 , this should be equal to α .

Consider here, the original random variables X_i 's we had considered a random sample from normal $0, \sigma_0^2$. So, if you consider X_i by σ_0 that follows normal $0, 1$. And they are independent, let me call it Y_i . So, if we consider $\sum Y_i^2$ here, then under H_0 X_i by σ_0 that is Y_i , this will follow normal $0, 1$ and Y_1, Y_2, \dots, Y_n are independent.

So, if we consider $\sum Y_i^2$, that will follow chi square distribution on n degrees of freedom. So, this test then we can consider as $\sum X_i^2$ by σ_0^2

square greater than or equal to sum c. For example, test is then reject H_0 if $\frac{\sum X_i^2}{\sigma_0^2} \geq k_2$ by σ_0^2 which I write as c here.

Now, if we want probability of this $\frac{\sum X_i^2}{\sigma_0^2}$ greater than or equal to c, when σ_0^2 is the two parameter value, if we want this probability to be alpha. Then, this implies that c should be $\chi^2_{n, \alpha}$. That means, if we consider the curve of chi square distribution, then $\chi^2_{n, \alpha}$ that is this probability should be equal to alpha. So, c is here, this point will be c.

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So the MP Test for testing $H_0: \sigma_0^2$ vs. $H_1: \sigma_1^2$ at level α is

Reject H_0 if $\frac{\sum X_i^2}{\sigma_0^2} \geq \chi^2_{n, \alpha}$

Otherwise accept H_0 .

In case $\sigma_0^2 > \sigma_1^2$, the test procedure will get modified.

(*) then gives that the MP critical region is of the form $\sum X_i^2 \leq k_3$.

The value of k_3 can be determined from the size condition

$\frac{\sum X_i^2}{\sigma_0^2} \sim \chi^2_n$ under H_0

So MP test to rej H_0 if $\frac{\sum X_i^2}{\sigma_0^2} \leq \chi^2_{n, 1-\alpha}$.

The diagram shows a chi-square distribution curve with a vertical line at $\chi^2_{n, 1-\alpha}$ and the area to the left shaded, representing the rejection region.

So, the test is then becoming, so the most power full test for testing H_0 sigma square is equal to sigma naught square against H_1 sigma square is equal to sigma 1 square at level alpha is reject H_0 if $\frac{\sum X_i^2}{\sigma_0^2} \geq \chi^2_{n, \alpha}$. Otherwise, accept H_0 , that is we do not reject H_0 here. Now, I will consider one variation in this problem here. Here, I have considered sigma 1 square greater than sigma naught square. Accordingly, our test is rejecting for larger values of $\frac{\sum X_i^2}{\sigma_0^2}$. On the other hand, suppose I change here in place of sigma 1 square, I takes in sigma 1 square less than sigma naught square.

If I do that, then you look at the derivation of the test procedure. This quantity will become negative. If sigma naught square is greater than sigma 1 square, then $\frac{\sigma_1^2}{\sigma_0^2} < 1$. That means, this quantity will

be become negative. Then, the test procedure will get reversed. We will get $\sigma^2 \leq k$.

And therefore, in case σ^2 is greater than σ_0^2 , the test procedure will get modified. So, for example you may consider let me call this condition as a star. A star then gives that the most powerful critical region is of the form $\sigma^2 \leq k$. And as before, the way we have derived the probability of type I error is equal to α that will give me the value of k . So, in that case what will happen? The value of k can be determined from the size condition.

Now, once again we will have σ^2 by σ_0^2 that will follow χ^2_{n-1} under H_0 . So, now what is happening is that we need this less than or equal to quantity. So, this will become $\chi^2_{n-1, 1-\alpha}$. So, test is reject H_0 if $\sigma^2 \leq \chi^2_{n-1, 1-\alpha}$.

So, this is the most powerful test, NP test. So, here you have seen that how the application of Neyman Pearson lemma is helpful in driving the most powerful tests for a fixed size. That means, when we are fixing the probability of type I error, the most powerful test is giving me the exact method of deciding whether to accept or reject a null hypothesis. In this particular example you see, exactly we are getting the observations are X_1, X_2, \dots, X_n .

So, given the observations, you calculate σ^2 and compare it with the tabulated value of $\chi^2_{n-1, \alpha}$. Suppose α is equal to say 0.05 and n is a 10, then you consider the corresponding value of $\chi^2_{10, 0.05}$. This value will be given in the tables of χ^2 distribution and we are in a position to take an exact decision. On the other hand, we may also consider the P value; that means, what is the value of α for which we will be rejecting, what is the minimum value of α ?

So, in case if α is not specified beforehand, then we can consider the minimum value that and we can base our scientific decision on that fact. That this kind of situation occurs for example, in many medical problems or clinical trials where we may have to take a decision based on the given circumstances. So, we need not fix α in advance. This point about p value had mentioned earlier when I was giving the basic concepts here.

So, that can be done for almost all the test of this nature, that we can consider actually the P values. Now, apart from the normal distribution, let me also give applications to other distribution such as exponential distribution, double exponential distribution or we may not even be able to write down the form in a closed fashion. We may have f_1 as one density, f_2 is another density.

So, I will consider few examples and exhibit that this Neyman Pearson lemma in each of these cases gives a solution; that means, we are in a position to take a decision whether to accept or reject a null hypothesis when the cases are simple versus simple. Let us consider say exponential distribution.

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2. Let X_1, \dots, X_n be a random sample from an neg. exp. distⁿ with density $\frac{1}{\sigma} e^{-x/\sigma}$, $x > 0, \sigma > 0$

$H_0: \sigma = \sigma_0$ MP Test for size α
 $H_1: \sigma = \sigma_1$ ($\sigma_1 > \sigma_0$)

The joint density of X_1, \dots, X_n is
 $f(\underline{x}, \sigma) = \frac{1}{\sigma^n} e^{-\sum x_i / \sigma}$

$\frac{f_1(\underline{x})}{f_0(\underline{x})} = \frac{f(\underline{x}, \sigma_1)}{f(\underline{x}, \sigma_0)} = \left(\frac{\sigma_0}{\sigma_1}\right)^n e^{-\frac{\sum x_i}{\sigma_1} + \frac{\sum x_i}{\sigma_0}}$

The MP test will reject H_0 if $\frac{f_1(\underline{x})}{f_0(\underline{x})} \geq k$
 where k is to be determined by the size condition

So, let X_1, X_2, \dots, X_n be a random sample from an negative exponential distribution say with density function $\frac{1}{\sigma} e^{-x/\sigma}$; x is positive, σ is positive. Let us consider say hypothesis testing problem say σ is equal to σ_0 against σ is equal to σ_1 . And once again, for convenience let us consider in the beginning say σ_1 is greater than σ_0 . We want the most powerful test for given size α . We will use the Neyman Pearson lemma for determination of this.

So, let us consider the form of the joint distribution of X_1, X_2, \dots, X_n ; joint density of X_1, X_2, \dots, X_n is given by $f(\underline{x}, \sigma)$. So, $\frac{1}{\sigma^n} e^{-\sum x_i / \sigma}$; note here that for all x_i positive, this density is positive. Therefore, we can

consider the ratio that is $f_1(x)$ by $f_0(x)$, that is the densities corresponding to σ_1 and σ_0 value of the parameter.

So, when you write down the ratio, you will get a constant here, σ_0 by σ_1 to the power n and then e to the power minus $\sum x_i$ by σ_1 plus $\sum x_i$ by σ_0 . So, the most powerful test will reject H_0 , if f_1 by f_0 is greater than k where k is we determine from the size condition. Once again, a point to be noted here is that we are dealing with the continuous distributions. So, the probability of equality is 0, that is this is equal to k . Therefore, we may include rejection region, this equality point here. We may put it in the acceptance region also. It does not make any difference in the nature of the test because the probability of equality will be 0. So, where k is to be determined by the size condition.

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MP Test for Size α

$H_0: \sigma = \sigma_0$
 $H_1: \sigma = \sigma_1 \quad (\sigma_1 > \sigma_0)$

The joint density of X_1, \dots, X_n is
 $f(x, \sigma) = \frac{1}{\sigma^n} e^{-\sum x_i / \sigma}$

$\frac{f_1(x)}{f_0(x)} = \frac{f(x, \sigma_1)}{f(x, \sigma_0)} = \left(\frac{\sigma_0}{\sigma_1}\right)^n e^{-\frac{\sum x_i}{\sigma_1} + \frac{\sum x_i}{\sigma_0}} \geq k$

The MP test will reject H_0 if $\frac{f_1(x)}{f_0(x)} \geq k$
 where k is to be determined by the size condition.

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So, if you consider this ratio here, I am saying this greater than or equal to k . Now, this is a constant σ_0 and σ_1 are known. So, I can adjust this with this coefficient on the right hand side and I can also take logarithm here. If I take the logarithm here, I will get $\sum x_i$ into 1 by σ_0 minus 1 by σ_1 .

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This region is equivalent to

$$\sum x_i \left(\frac{1}{\sigma_0} - \frac{1}{\sigma_1} \right) \geq k_1$$

> 0

$$\Rightarrow \sum x_i \geq k_2 \rightarrow$$

$P(\text{Type I Error}) = \alpha$

$$\Rightarrow P(\text{Rejecting } H_0 \text{ when it is true}) = \alpha$$

$$\Rightarrow P\left(\sum X_i \geq k_2\right) = \alpha$$

$\frac{X_i}{\sigma_0} \sim e^{-x}$, $Y = \frac{\sum X_i}{\sigma_0} \sim \text{Gamma}(n, 1)$

$$\frac{2 \sum X_i}{\sigma_0} \sim \chi_{2n}^2$$

$f(y) = \frac{1}{\Gamma(n)} e^{-y} y^{n-1}$

$W = 2Y$

$$f_W(w) = \frac{1}{\Gamma(n)} e^{-\frac{w}{2}} \left(\frac{w}{2}\right)^{n-1} \cdot \frac{1}{2}$$

$$= \frac{1}{2^n \Gamma(n)} e^{-\frac{w}{2}} w^{n-1}$$

So, this region is equivalent to $\sum x_i$ greater than or equal to k_1 by $\sigma_1 - \sigma_0$ greater than or equal to some constant k_1 . Now, as before in the normal distribution case, this constant k_1 by $\sigma_1 - \sigma_0$ the sign of this will be positive because I am taking σ_1 to be less than σ_0 . So, this is positive.

So, this region is equivalent to $\sum x_i$ greater than or equal to k_2 . And once again, this k_2 is to be determined from the size condition. So, if I consider probability of type I error equal to α ; that means, probability of rejecting H_0 when it is true that is equal to α , then this is implying probability of $\sum X_i$ greater than or equal to k_2 ; when σ_0 is the true parameter value, then it is equal to α .

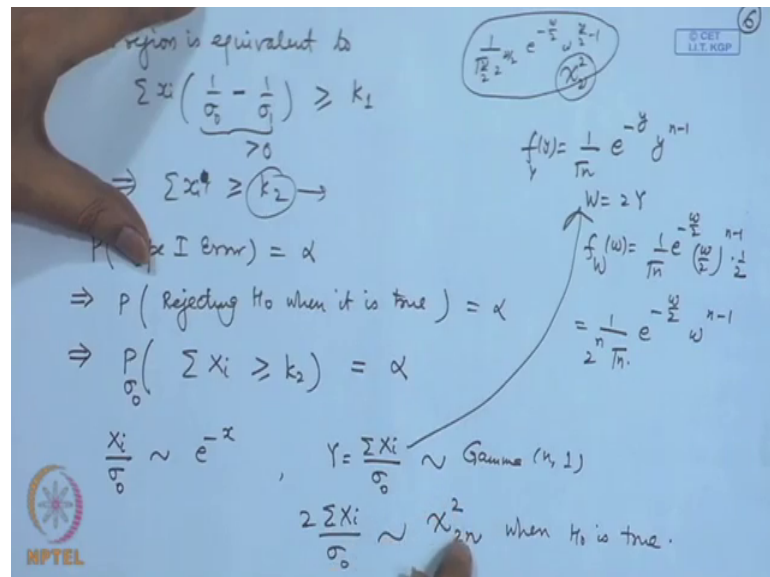
That means, I need to look at the distribution of $\sum X_i$ when σ is equal to σ_0 . Now, we know that the sum of independent exponentials of this nature is actually a gamma. So, we can consider the derivation of the constant k_2 based on this. So, let us look at this. If I consider, say X_i by σ_0 , then that will follow exponential with parameter simply 1. If I consider, say $\sum X_i$ by σ_0 , then that will follow gamma $n, 1$. If I consider twice $\sum X_i$ by σ_0 , then that will follow chi square distribution on $2n$ degree of freedom. See we can write down the density here, suppose I am considering this as say y .

So, what is the distribution of y ? $f(y)$ is equal to $\frac{1}{\Gamma(n)} e^{-y} y^{n-1}$. Say if I consider say w is equal to $2y$, then what will be the

distribution of w ? $\frac{1}{\Gamma(\frac{n}{2})} e^{-\frac{w}{2}} \left(\frac{w}{2}\right)^{\frac{n}{2}-1}$, w by 2 to the power n minus 1 into half that is equal to $\frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} e^{-\frac{w}{2}} \left(\frac{w}{2}\right)^{\frac{n}{2}-1}$.

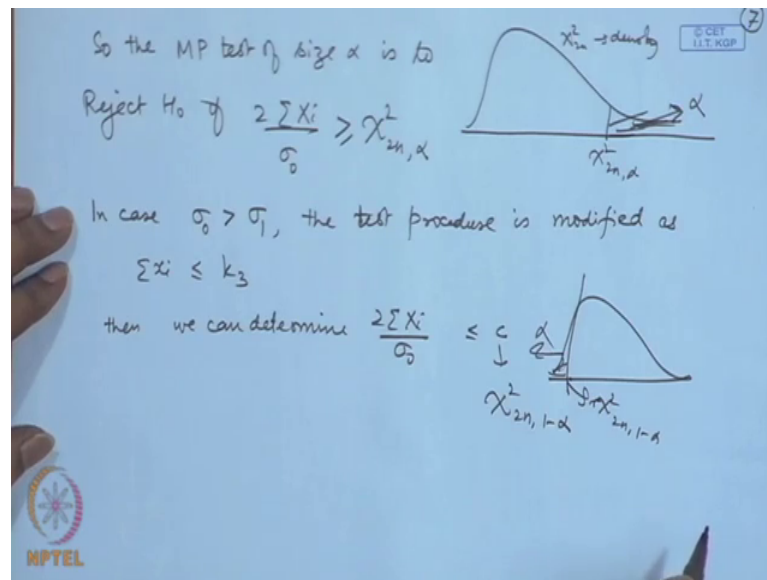
So, if we consider the form of a chi square distribution, the chi square distribution on new degrees of freedom is given by $\frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} e^{-\frac{w}{2}} \left(\frac{w}{2}\right)^{\frac{n}{2}-1}$. This is the form of a chi square distribution on new degrees of freedom. So, if you compare this with this, actually we are getting $2n$ degrees of freedom. So, chi square twice $\sum X_i$ by σ_0^2 , this will follow chi square distribution on $2n$ degrees of freedom when H_0 is true.

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Therefore, the rejection region can be written in the terms of chi square value on $2n$ degrees of freedom.

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So, if we consider say chi square 2 n density, so this point is chi square 2 and alpha, so this probability is alpha say. So, the most powerful test of size alpha is to reject H_0 if twice sigma X_i by sigma naught is greater than or equal to chi square 2 n alpha, accept otherwise. So, you can easily see here that we are able to give exact decision making procedure given the level of significance.

Now, if the level of significance is not specified in the beginning, then you can look at what is the probability of this that minimum level at which this test will be rejected, this null hypothesis will be rejected. So, that will be the P value. So, I have been, I am considering both of this P value thing and level of fix level of significance in all these situations. Once again, note here that if I have a modification in my original null hypothesis. In place of sigma one being greater than sigma naught, if sigma 1 is less than sigma naught, then there will be a modification here because this coefficient will become negative.

If this coefficient becomes negative, then the region will turn out to be sigma X_i less than or equal to something here and therefore, the rejection region will then become left handed. In case sigma naught is greater than sigma 1, the test procedure is modified as sigma X_i less than or equal to say k_3 . Then, we can determine sigma X_i by sigma naught twice less than or equal to say c . So, c will become than equal to chi square 2 n 1

minus alpha because now this is the left handed point here. This probability is alpha, so, chi square $2n - 1 - \alpha$.

Now, you can see here that in many of these problems, we are able to work out the exact distribution here and one interesting thing here is that the range of the random variables is a same. Therefore, this writing down the ratio f_1 by f_0 etcetera is quite convenient and when we write down the final test function here, then we are able to derive the distribution of that.

Now, in many cases this will be dependent upon the situation. We may not have state forwardly the full region divided by full region. We may have partial regions; sometimes the range of the variable will be dependent upon the parameter. Therefore, the range of the two densities may not be exactly the same. I will explain this through a couple of examples.

So, let me take case for when the full region is the same, but the distribution gets the form of the density gets modified midway. That means, for partial values of x , you have a form of density function. For another part, we may have another density function. So, let me take up this case and I will also consider one case when the range of the variable is dependent upon the parameter. Therefore, the two densities are positive not on the full region, but on partial regions. So, let us consider these cases.

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3. Let X be an observation from a density $f(x)$.

$H_0: f(x) = f_0(x)$
 $H_1: f(x) = f_1(x)$

$$f_0(x) = \begin{cases} x, & 0 < x \leq 1 \\ 2-x, & 1 < x < 2 \\ 0, & \text{else} \end{cases}$$

$$f_1(x) = \begin{cases} \frac{1}{2}, & 0 < x < 2 \\ 0, & \text{else} \end{cases}$$

$$\frac{f_1(x)}{f_0(x)} = \begin{cases} \frac{1}{2x}, & 0 < x \leq 1 \\ \frac{1}{2(2-x)}, & 1 < x < 2 \end{cases}$$

$$\frac{1}{2x} > k \Rightarrow x < \frac{1}{2k}$$

$$P_0\left(0 < x < \frac{1}{2k}\right) = \int_0^{\frac{1}{2k}} x dx = \frac{1}{8k^2}$$

$$\frac{1}{2(2-x)} > k \Rightarrow 2-x < \frac{1}{2k} \Leftrightarrow 1 < x < 2$$

$$\text{or } x > 2 - \frac{1}{2k}$$

$$P_0\left(x > 2 - \frac{1}{2k}\right) = \int_{2 - \frac{1}{2k}}^2 (2-x) dx$$

$$= -\frac{(2-x)^2}{2} \Big|_{2 - \frac{1}{2k}}^2 = \frac{1}{8k^2}$$

Let X be an observation from a density $f(x)$ and $H_0: f(x) = f_0(x)$ is equal to $f_1(x)$ and $H_1: f(x) = f_1(x)$. And $f_0(x)$ and $f_1(x)$ are defined like this, $f_0(x)$ is the triangular distribution it is equal to x for $0 < x \leq 1$ and it is equal to $2 - x$ for $1 < x < 2$. It is actually the triangular distribution and of course, it is 0 elsewhere. And $f_1(x)$ is half for $0 < x < 2$.

So, this is nothing but the uniform distribution on the interval 0 to 2. Now, you note here the distribution under H_0 is a distribution over the range 0 to 2, but the form of the density function changes at the point 1 whereas the second density is having the same form throughout. So, when we write down the form of the most powerful critical region the Neyman Pearson lemma, we have to be careful in writing down the regions. So, for example, consider this f_1 by f_0 . Here, we assume that our decision making process is based on one observation. Of course, we may consider n observations also and of course, it will increase the difficulty or we can say complication in the nature of the derivation.

So, this a value is equal to now you look at f_1 by f_0 that will be $1/2 \cdot x$ if $0 < x \leq 1$ and it will be equal to $1/2 \cdot (2 - x)$ for $1 < x < 2$. Now, the question is if an x is there which is outside this region, the thing is that under H_0 and H_1 that will have probability 0. So, we will not consider that situation here. So, if I consider the rejection region $1/2 \cdot x > k$, then this is equivalent to saying $x > 2k$.

Now, this is for the portion $0 < x \leq 1$. So, if you consider probability of this region that is $0 < X \leq 1/2k$, this is for under H_0 and here we will consider for 0 to 1 only for 0 to 1 the density is x . So, if you integrate this, it is becoming $x^2/2$. So, you will get $1/4k^2$ divided by 2 that is $1/8k^2$. If we consider $1/2(2 - x) > k$, then this is equivalent to $2 - x > 2k$ or $x > 2 - 2k$.

Now, this part is for $1 < x < 2$. So, the probability of $X > 2 - 2k$ that is equal to $\int_{2-2k}^2 (2-x) dx$. So, that is equal to $2x - x^2/2$ with the minus sign from $2 - 2k$ to 2. So, this is again evaluated. If you put here no sorry, this is a put 2. So, if you look at the value at 0

this is becoming 0 and when we put 2 minus 1 by 2 k, this is again 1 by 2 k whole square so, it is again 1 by 8 k square.

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$f_1(x) = \begin{cases} \frac{1}{2}, & 0 < x < 2 \\ 0, & \text{else} \end{cases}$
 $\frac{1}{2x} > k \Rightarrow x < \frac{1}{2k}$
 $\frac{1}{2(2-x)} > k \Rightarrow 2-x < \frac{1}{2k} \Leftrightarrow 1 < x < 2$
 $\text{or } x > 2 - \frac{1}{2k}$
 $P_0(0 < x < \frac{1}{2k}) = \int_0^{\frac{1}{2k}} x dx = \frac{1}{8k^2}$
 $P_0(x > 2 - \frac{1}{2k}) = \int_{2-\frac{1}{2k}}^2 (2-x) dx = \frac{1}{8k^2}$

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The size condition gives $P_0(0 < x < \frac{1}{2k}, 0 < x \leq 1) + P_0(x > 2 - \frac{1}{2k}, 1 < x < 2) = \alpha$
 $\Rightarrow \frac{1}{8k^2} + \frac{1}{8k^2} = \alpha \Rightarrow \frac{1}{4k^2} = \alpha \Rightarrow \frac{1}{2k} = \sqrt{\alpha}$
 So the MP test of size α for testing H_0 against H_1 is
 Reject H_0 : if $x < \sqrt{\alpha}$ or $x > 2 - \sqrt{\alpha}$
 For example, $\alpha = 0.01$, $\sqrt{\alpha} = 0.1$
 So test will reject H_0 if $x < 0.1$ or $x > 1.9$
 else it will accept H_0

So, if we write down the size condition here that is the probability of, so the size condition gives probability of type I error that is 0 less than X less than 1 by 2 k for 0 less than X less than or equal to 1 plus X greater than 2 minus 1 by 2 k for 1 less than x less than 2 is equal to alpha. Note here, that these regions are dependent upon this condition. So, we have to considered the probability under this. We have calculated both

of these probabilities. So, it is becoming $1 - 8k^2 + 1 - 8k^2$ is equal to $1 - 4k^2$ is equal to α ; that means, $1 - 2k$ is equal to a square root of α .

So, the region of rejection is becoming x is less than $\sqrt{\alpha}$ or x is greater than $2 - \sqrt{\alpha}$. So, the most powerful test of size α for testing H_0 against H_1 is reject H_0 , if X is less than $\sqrt{\alpha}$ or X is greater than $2 - \sqrt{\alpha}$. Once again you note here that we are able to provide exact test here, that is the test tells exactly what decision one has to take given a value of X .

So, for example, let us choose α is equal to say 0.01, then $\sqrt{\alpha}$ is equal to $\sqrt{0.01}$ will become 0.1. So, test is done test will reject H_0 if X is less than 0.1 or X is greater than 1.9; else it will accept H_0 ; that means, if I am having an observation between 0.1 to 1.9, then the test will accept H_0 ; that means, it will have no region to reject H_0 .

And other hand if X is less than 0.1 or X is greater than 1.9, then this is not supporting H_0 ; that means, you will tend to reject H_0 here. In this particular example, I have shown that even the form of the distribution maybe changing over the range of the sample space; however, the Neyman Pearson lemma is able to provide a exact test at a given so that I will be taking up in the following lecture.