

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

Lecture No. # 23
Application of NP Lemma

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 first result was the so called Neyman Pearson fundamental lemma. And this test gives the most powerful test for testing simple null hypotheses 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 may have composite hypothesis in the null hypothesis or in the alternative hypothesis. So, we will consider these applications 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.

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

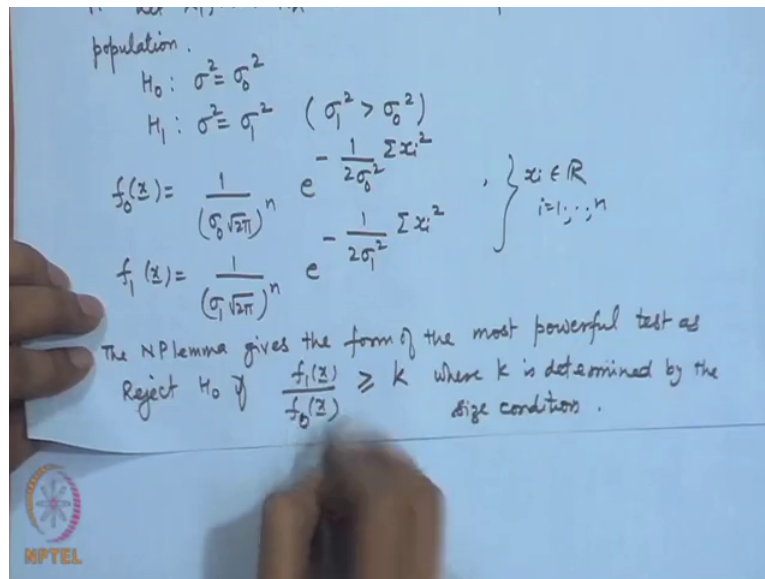
$H_1: \sigma^2 = \sigma_1^2 \quad (\sigma_1^2 > \sigma_0^2)$

$$f_0(x) = \frac{1}{(\sigma_0 \sqrt{2\pi})^n} e^{-\frac{1}{2\sigma_0^2} \sum x_i^2}$$
$$f_1(x) = \frac{1}{(\sigma_1 \sqrt{2\pi})^n} e^{-\frac{1}{2\sigma_1^2} \sum x_i^2}$$

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

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So, let me start with suppose we have a say x_1, x_2, x_n . Let x_1, x_2, x_n be a random sample from say normal 0 sigma square population. So, we were interested in testing the say a null hypothesis sigma square is equal to say sigma naught square against say sigma is square is equal to sigma 1 square. Now sigma 1 is square is not equal to sigma naught square. So, let us consider say the case sigma 1 square is greater than sigma not 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 a x_1, x_2, x_n under the null hypothesis and the alternative hypothesis, we call it f_{naught} and f_1 . So, f_{naught} x that is equal to 1 by sigma naught root 2 pi to the power n, e to the power minus 1 by 2 sigma naught square sigma x i square. So, f_1 x will then be equal to 1 by sigma 1 root 2 pi to the power n e to the power minus 1 by 2 sigma 1 square sigma x i a square.

Now, the Nyman Pearson lemma gives the form of the most powerful test as. So, we will consider the rejection region this is continuous distribution, if we remember the form of the Nyman Pearson lemma, the form of the test function I will recollect here. It is given in this particular fashion. The form of the test in the Nyman Pearson lemma is given by reject h naught when f_1 x is greater than k times f_{naught} x. And accept when f_1 is less than k f naught and we are considering the rejection with probability gamma there is a constant here when f_1 is equal to constant times f_{naught} 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

1 of the places either at the rejection are in the acceptance. So, for convenience I will include 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 $f_1(x)$ by $f_0(x)$ greater than or equal to k . Since these densities are valid for whole real line that is x_i is belong to R for ϕ 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 to take the log here some other constant is coming.

Now, earlier we mention 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 $\frac{1}{\sigma_0^2} > \frac{1}{\sigma_1^2}$. Now again this is a constant. So, I adjust this here; so this is equivalent to saying $\sum x_i^2$ is greater than or equal to some constant say k_2 .

Now, let us look at the determination of k_2 . So, if k_1 is determined by 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. $P(\text{Rejecting } H_0 \text{ when it is true}) = \alpha$

$$\Rightarrow P\left(\sum X_i^2 \geq k_2\right) = \alpha$$

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

$\sum Y_i^2 \sim \chi_{2n}^2$
 Test is then reject H_0 if $\frac{\sum X_i^2}{\sigma_0^2} \geq k_2$.

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

So, we write it like this in order to determine k_2 we employ the size condition that is probability of type 1 error is equal to α that is probability of a 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 $\sum X_i^2$ that is $\sum Y_i^2$ is equal to $\sum Y_i^2$ this should be equal to α . Consider here the original random variables X_i 's we had considered a random sample from normal $0, \sigma_0$ is square.

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 greater than or equal to some c for

example, test is the n 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 $\frac{\sum x_i^2}{\sigma_0^2} \geq c$ greater than or equal to α . When σ_0^2 is the 2 parameter value, if we want this probability to be α 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 α . 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

$$\frac{\sum X_i^2}{\sigma_0^2} \sim \chi_n^2 \text{ under } H_0$$

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

So, the test is then becoming. So, the most powerful test for testing $H_0: \sigma_0^2$ against $H_1: \sigma_1^2$ 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 that is we do not reject H_0 here.

Now, I will consider one variation in this problem here. Here I have considered $\sigma_1^2 > \sigma_0^2$. 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 $\sigma_1^2 > \sigma_0^2$ I take $\sigma_1^2 < \sigma_0^2$, if I do that then you look at the derivation of the test procedure, this quantity will become negative. If $\sigma_1^2 < \sigma_0^2$ then $\frac{\sigma_1^2}{\sigma_0^2} < 1$; that means, this quantity will become negative. Then the test procedure will get reversed, we will get $\frac{\sum x_i^2}{\sigma_0^2} \leq k_3$. 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 $\sum x_i^2 \leq k$. And as before the way we have derived the probability of type one 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 $\sum x_i^2$ by σ_0^2 that will follow χ^2_{n-1} . 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 $\sum x_i^2$ by σ_0^2 less than or equal to $\chi^2_{n-1, 1-\alpha}$. So, this is the most powerful test. So, here you have seen that how the application of Neyman Pearson lemma is helpful in deriving the most powerful tests for a fixed size; that means, then we are fixing the probability of type one 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 $\sum x_i^2$ by σ_0^2 and compare it with that tabulated value of $\chi^2_{n-1, \alpha}$. Suppose α is equal to say 0.05 and n say 10, then you consider the corresponding value of χ^2_{10} variable on 0.05. This value will be given the tables of chi square 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 a 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 were, 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 a part 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 against as one density f_1 as other density. So, I will consider few examples and exhibit that this Neyman Pearson lemma in each of these cases gives 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
 $f(x, \sigma) = \frac{1}{\sigma^n} e^{-\sum x_i / \sigma}$

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

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.

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

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

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

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.

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,

sigma is equal to sigma 1. And once again for convenience let us consider in the beginning say sigma one is greater than sigma naught. We want the most powerful test for given size alpha, 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 $f(x; \sigma)$, so $f(x; \sigma_1)$ by $f(x; \sigma_0)$ to the power n , $e^{-\sum x_i / \sigma_1}$ to the power n minus $\sum x_i / \sigma_1$ by $f(x; \sigma_0)$. Note here that for all x_i positive this densities positive therefore, we can consider the ratio that is $f(x; \sigma_1) / f(x; \sigma_0)$ 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^n / σ_1^n and then $e^{-\sum x_i / \sigma_1}$ by $e^{-\sum x_i / \sigma_0}$ plus $\sum x_i / \sigma_1$ by $\sum x_i / \sigma_0$.

So, the most powerful test will reject H_0 , if $f(x; \sigma_1) / f(x; \sigma_0)$ is greater than k . Where k as the determent 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 revision this equality point here, we may put it in the acceptance region also, and it does not makes an any difference in the nature of the test, because the probability of equality will be 0.

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This region is equivalent to

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

$\Rightarrow \sum x_i \geq k_2$

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

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

$\Rightarrow P_{\sigma_0} \left(\sum X_i \geq k_2 \right) = \alpha$

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

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

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

$W = 2Y$

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

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

$$\Rightarrow \sum X_i \geq k_2 \rightarrow$$

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

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

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

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

$$\frac{2 \sum X_i}{\sigma_0} \sim \chi_{2n}^2 \text{ when } H_0 \text{ is true.}$$

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

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

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

So, where k is 2 be determined by the size condition. So, if you consider this ratio here I am saying this greater than or equal to k . Now this is the constant σ_0 and σ_1 or non. So, I can adjust this with coefficient on the right hand side, and I can also take logarithm here. If I take the logarithm here I will get $\sigma_1 x_i$ into 1 by σ_0 minus 1 by σ_1 . So, this region is equivalent to $\sigma_1 x_i$ by σ_0 minus 1 by σ_1 greater than or equal to some constant k_1 . Now as before in the normal distribution case, this constant 1 by σ_0 minus 1 by σ_1 the sign of this will be positive, because I am taking σ_0 to be less than σ_1 .

So, this is positive. So, this region is equivalent $\sigma_1 x_i$ greater than or equal to some k_2 . And once again this k_2 is to determine from the size condition. So, if I consider probability of type one 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 $\sigma_1 x_i$ 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 $\sigma_1 x_i$ when σ_0 is equal to σ_0 .

Now, we know that the some 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 $\sigma_1 x_i$ by σ_0 , then that will follow gamma $n, 1$. If I consider twice $\sigma_1 x_i$ 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 $1/\Gamma(n) e^{-y} y^{n-1}$.

power $n - 1$. So, if I consider say w is equal to 2 then what will be the distribution of w . $1/\Gamma(n/2) \cdot (w/2)^{n/2-1} e^{-w/2}$, $w/2$ to the power $n/2 - 1$ into half that is equal to $1/2 \cdot (w/2)^{n/2-1} e^{-w/2}$ to the power $n/2 - 1$.

So, if we consider the form of a chi square distribution. The chi square distribution on n degrees of freedom is given by $1/\Gamma(n/2) \cdot (w/2)^{n/2-1} e^{-w/2}$ to the power $n/2 - 1$ this is the form of a chi square distribution on n degrees of freedom. So, if you compare this with this actually we are getting $2n$ degrees of freedom. So, chi square $\sum x_i^2 / \sigma^2$ will follow chi square distribution on $2n$ degrees of freedom when H_0 is true. Therefore, the rejection region can be written in the terms of chi square value on $2n$ degrees of freedom.

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So the MP test of size α is to

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

In case $\sigma_0 > \sigma_1$, the test procedure is modified as

$\sum X_i \leq k_3$

then we can determine $\frac{2 \sum X_i}{\sigma_0^2} \leq c$

The diagram shows a chi-square distribution curve with a shaded area under the curve to the right of a critical value $\chi_{2n, \alpha}^2$, representing the rejection region with probability α . Another diagram shows a similar curve with a shaded area to the left of a critical value $\chi_{2n, 1-\alpha}^2$, representing the rejection region for the modified test.

So, if we consider say chi square $2n$ density. So, this point is chi square $2n$ alpha. So, this probability is alpha say. So, the most powerful test of size alpha is to reject H_0 if $\sum x_i^2 / \sigma_0^2$ is greater than or equal to chi square $2n$, 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 significance fixed 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 σ_0 being greater than σ_1 , if σ_1 is less than σ_0 , 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 $\sigma_1 \leq k$. And therefore, the rejection region will then become left-handed. In case σ_0 is greater than σ_1 . The test procedure is modified as $\sigma_1 \leq k$. Then we can determine σ_1 by σ_0 twice less than or equal to say c . So, c will become then equal to $\chi^2_{2n-1, 1-\alpha}$, because now this is the left-handed point here this probability is α . So, $\chi^2_{2n-1, 1-\alpha}$ here. 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 the 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 2 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 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 2 densities are positive not on the full region, but on partial regions.

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

$H_0: f(x) = f_0(x)$ $f_0(x) = \begin{cases} x, & 0 < x \leq 1 \\ 2-x, & 1 < x < 2 \\ 0, & \text{elsewhere} \end{cases}$

$H_1: f(x) = f_1(x)$ $f_1(x) = \begin{cases} \frac{1}{2}, & 0 < x < 2 \\ 0, & \text{elsewhere} \end{cases}$

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

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

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

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

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

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

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

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

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

So, let us consider these cases. Let x be an observation from a density $f(x)$ and h is a function of x such that $h(f(x)) = f(h(x))$. And f and h are defined like this, f 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 0.1; whereas, the second density is having the same for throughout. So, and we write down the form of the most powerful critical region using the Neyman Pearson lemma we have to be

careful in writing down the regions. So, for example, consider this f_1 by f_{naught} . Here we assume that our decision making process based on 1 observation of course, we make consider n observation also and of course, it will increase the complex difficulty are you can say complication in the nature of the derivation.

So, this value is equal to now you look at f_1 by f_{naught} that will be $1/2 x$, if 0 is less than x less than or equal to 1 . And it will be equal to $1/2(2 - x)$, for 1 less than x less than 2 . Now the question is if an x is there which is outside this region the thing is that under h_{naught} and h_1 that will have probability 0 . So, we will $naught$ consider that situation here. So, if I consider the rejection region $1/2 x$ greater than k . Then this is equivalent to saying x is less than $1/2 k$. Now this is for the portion 0 less than x less than or equal to 1 . So, if we consider probability of this region that is 0 , less than x less than $1/2 k$, this is for under h_{naught} and here we will consider for 0 to 1 only, for 0 to 1 the densities x . So, if you integrate this it is becoming $x^2/2$.

So, you will get $1/4 k^2$ divided by 2 that is $1/8 k^2$; if we consider $1/2(2 - x)$ greater than k , then this is equivalent to $2 - x$ less than $1/2 k$; or x is greater than $2 - 1/2 k$; now, these $(())$ for 1 less than x less than 2 . So, the probability of x greater than $2 - 1/2 k$, that is equal to $2 - 1/2 k$ to 2 $1/2(2 - x) dx$. So, that is equal to $2 - x$ whole square by 2 with the minus sign from $2 - 1/2 k$ to 2 . So, this is again evaluated if you put here, no sorry this is up to 2 . So, if you look at the evaluate 2 this is becoming 0 and when we put $2 - 1/2 k$ this is again $1/2 k$ whole square. So, it is again $1/8 k^2$. So, it is again $1/8 k^2$.

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The size condition gives $P_0\left(0 < X < \frac{1}{2k}, 0 < X \leq 1\right)$
 $+ P_0\left(X > 2 - \frac{1}{2k}, 1 < X < 2\right) = \alpha$
 $\Rightarrow \frac{1}{8k^2} + \frac{1}{8k^2} = \alpha \Rightarrow \frac{1}{4k^2} = \alpha \Rightarrow \frac{1}{2k} = \sqrt{\alpha}$
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 1 error that is 0 less than x less than $1/2k$, for 0 less than x less than or equal to 1, plus x greater than $2 - 1/2k$, for 1 less than x less than 2 is equal to alpha. Note here that these regions are dependent upon these conditions. So, we have to consider the probability under this we have calculated both of this probability. So, it is becoming $1/8k^2 + 1/8k^2 = \alpha$, $1/4k^2 = \alpha$; that means, $1/2k$ is equal to square root of alpha.

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

So, for example, let us choose alpha is equal to say 0.01. Then alpha is equal to root alpha will become 0.1. So, test is then 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 reason to reject H_0 . On the 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 have to reject H_0 here. In this particular example I have shown that even the form of the distribution may be changing over the range of the sample space;

however, the Neyman Pearson lemma is able to provide exact test at a given size. Let me take another example, in which the range of the variable may be dependent upon the range of the parameter and let us see in that case how the Nyman Pearson lemma works.

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4. Let $X_1, \dots, X_n \sim U(0, \theta]$, $\theta > 0$

$H_0: \theta = 1 \in (\theta_0)$
 $H_1: \theta = 2 \in (\theta_1)$

$$f(x, \theta) = \begin{cases} \frac{1}{\theta^n}, & 0 \leq x_1 \leq x_n \leq \theta \\ 0, & \text{ew} \end{cases}$$

$$f_0(x) = \begin{cases} 1, & 0 \leq x_1 \leq x_n \leq 1 \\ 0, & \text{ew} \end{cases}, \quad f_1(x) = \begin{cases} \frac{1}{2^n}, & 0 \leq x_1 \leq x_n < 2 \\ 0, & \text{ew} \end{cases}$$

Case		f_0	f_1
1	$x_{(1)} \leq 0$	0	0
2	$0 < x_{(1)} \leq x_{(n)} \leq 1$	1	$\frac{1}{2^n}$
3	$x_{(1)} > 0, 1 \leq x_{(n)} < 2$	0	$\frac{1}{2^n}$
4	$x_{(n)} > 2$	0	0

	f_0	f_1
$x_{(1)} \leq 0$	0	0
$0 < x_{(1)} \leq x_{(n)} \leq 1$	1	$\frac{1}{2^n}$
$x_{(1)} > 0, 1 \leq x_{(n)} < 2$	0	$\frac{1}{2^n}$
$x_{(n)} > 2$	0	0

By NP lemma the MP test is rejecting H_0 if $f_1(x) > k f_0(x)$

Let us consider say x_1, x_2, \dots, x_n from uniform $0, \theta$ distribution. And we consider a hypothesis testing problem say $\theta = 1$ against say $\theta = 2$. We may also write here, say $\theta = \theta_0$ and here, I may write $\theta = \theta_1$ and then I may consider the case $\theta = \theta_0 < \theta_1$ or $\theta = \theta_0 > \theta_1$. So, for convenience we have considered this is special case, which $\theta = 1$ and $\theta = 2$. So, let us consider the most powerful test here. So, the joint distribution is $f_0(x)$ by $\theta = 1$ the power

n , and here the range of the variables from 0 to θ . So, we write it in this particular form. So, when we write for f_{θ} and f_1 , for f_{θ} this is simply 1. So, this is simply see we may if we write here open and travel we need not put equality here, we may put it like this, otherwise may out it quality the probability of those points will be 0.

So, it does not make any difference similarly, if we consider f_1 then under f_1 θ is equal to 2. So, it will become $1 - 2^{-n}$ less than x_1 , less than or equal to x_n , less than 2 it is equal to 0. I was mentioning here, that the range of the densities where the 2 densities are positive is not the same. Here you can see this density is positive for 0 to 1 and this densities positive for 0 to 2.

So, let us look at the various cases of f_1 and f_{θ} . So, we will make it in the form of a table let us consider say case 1, 2, 3, 4 like that we will write 1, 2, 3, 4. So, I will write all the cases which we may be trivial or nontrivial cases. If we observe x_1 to be less than 0; obviously, this is not possible. So, both the densities f_1 and f_{θ} they are 0 here. If we consider the case 0 is less than. So, x_1 and x_n is less than or equal to 1, in this case the first density 1, and second density $1 - 2^{-n}$. Then we may have say x_1 of course, may be greater than 0, but x_n is say beyond it is beyond 1 in that case what will happen that this first density becomes 0.

However the second density remains $1 - 2^{-n}$. And then we may have the extreme case that is x_n greater than 2, then this is 0 and this is 0. So, broadly speaking we have to consider the ray f_1 greater than $k f_{\theta}$ from the Neyman Pearson lemma under these four cases. By n p lemma the m p test is rejecting H_0 if $f_1(x)$ is greater than k times $f_{\theta}(x)$. So, here the values of k we have to choose.

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For each case $f_1 > k f_0$ & the values of k are listed below

Case	$f_1(x) > k f_0(x)$	$f_1(x) = k f_0(x)$	$f_1(x) < k f_0(x)$
I	Never	Always	Never
II	if $k < \frac{1}{2^n}$	$k = \frac{1}{2^n}$	$k > \frac{1}{2^n}$
III	Always	Never	Never
IV	Never	Always	Never

Case I: We may take $\phi_1(x)$ as any value
 Case II: Set $\phi_1(x) = 1$ if $k < \frac{1}{2^n}$, $\phi_1(x) = 0$ if $k > \frac{1}{2^n}$ and any value of $\phi_1(x)$ if $k = \frac{1}{2^n}$.
 Case III: $\phi_1(x) = 1 \forall k$. (Always reject H_0)
 Case IV: Any value of ϕ_1

For each case $f_1 > k f_0$ & the values of k are listed below

Case	$f_1(x) > k f_0(x)$	$f_1(x) = k f_0(x)$	$f_1(x) < k f_0(x)$
I	Never	Always	Never
II	if $k < \frac{1}{2^n}$	$k = \frac{1}{2^n}$	$k > \frac{1}{2^n}$
III	Always	Never	Never
IV	Never	Always	Never

Case I: We may take $\phi_1(x)$ as any value
 Case II: Set $\phi_1(x) = 1$ if $k < \frac{1}{2^n}$, $\phi_1(x) = 0$ if $k > \frac{1}{2^n}$ and any value of $\phi_1(x)$ if $k = \frac{1}{2^n}$.
 Case III: $\phi_1(x) = 1 \forall k$. (Always reject H_0)
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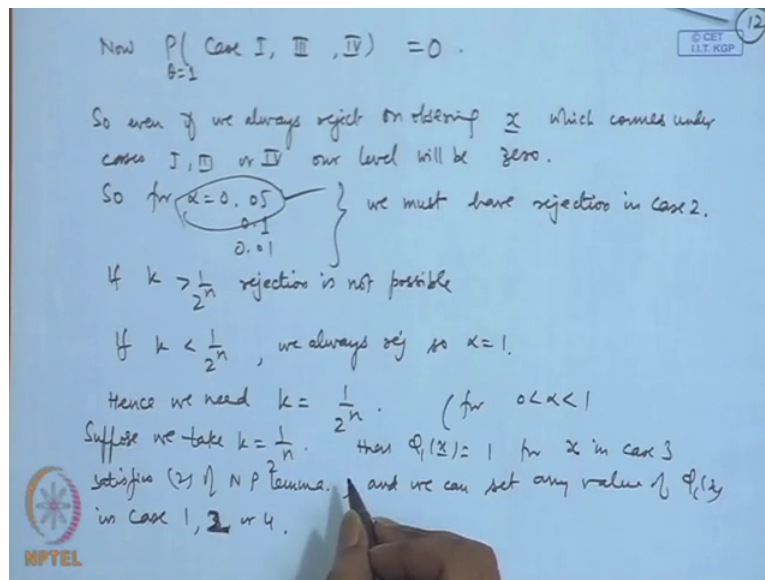
So, let us write the here, for each case $f_1 > k f_0$ and the values of k are listed below. So, let us consider each case. In the case 1 if we consider $f_1(x) > k f_0(x)$. Now both the values are 0. So, this is never possible whatever be the value of k it is never possible, $f_1(x)$ is equal to $k f_0(x)$, that is always true. And $f_1(x) < k f_0(x)$ is never possible. Let us consider second case in the second case, if we look at f_1 that is 1 by 2 to the power n , greater than k times f_0 . So, this condition is true, if case greater than **sorry** k is less than 1 by 2 to the power n , this is true if k is equal to 1 by 2 to the power n , this is true if k is greater than 1 by 2 to the power n . Let us look at the 3rd case in the 3rd case f_0 is 0.

So, f_1 greater than $k f_0$ is always true. And therefore, this equality is less than is never possible. Let us consider a case 4 once again both of them are 0. So, inequality is never possible whereas, the equality is always true. So, now based on this we should tell when to reject H_0 and when to accept H_0 ; that means, dependent upon these 4 cases and the choices of k , we should give what is the test function and at the same time, we should also tell that whether the probability of type 1 error is equal to α can be achieved for a given value of α . So, what we consider in case 1 since f_1 is equal to $k f_0$ is always possible always true therefore, whatever with the value of ϕ_1 it does not make any difference.

So, we may take ϕ_1 as any value. In case 2 if k is less than $1/2$ to the power n , in this case f_1 is greater than $k f_0$; that means, this is the corresponding case 2 rejecting H_0 . So, if k is less than $1/2$ to the power n we will say reject H_0 and in this case we will say accept H_0 ; that means, ϕ_1 is equal to 0. However when k is equal to $1/2$ to the power n , then we may again say a we may accept or reject depends upon we can assign something of course, a probability of this cases will be 0. So, we can say ϕ_1 that is the test function is equal to 1, if k is less than $1/2$ to the power n , it is equal to 0. If k is greater than $1/2$ to the power n , and any value of ϕ_1 , if k is equal to $1/2$ to the power n .

If you look at case 3 in the case 3 this condition is always true. So, we always reject that is ϕ_1 is equal to 1, whatever be k that is always reject H_0 . Note here that these are also heuristic, because what is happening if we are getting the 3rd case that is x_n is between 1 and 2; that means, naturally the observations are from the density uniform 0 to 2, otherwise observation cannot be greater than 1, and therefore, we should definitely reject H_0 and accept H_1 . And in the case, four once again we may put any value any value of ϕ_1 .

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Now, probability of case 1, 3 and 4 under the null hypothesis this is 0. So, even if we always reject on observing x which comes under cases 1, 3 or 4 our level will be 0. So, for α is equal to 0.05 etcetera some given value of α are say 0.01 or 0.1 etcetera, then what we should do, we should make the probability of rejection in case 2 to be possible. So, we must have rejection in case 2. Now again if I take k to be greater than 1 by 2 to the power n rejection is not possible.

So, the only rejection is possible for k less than 1 by 2 to the power n here rejection becoming always true. So, α will become 1 which is not acceptable. So, therefore we should have this k equal to 1 by 2 to the power n as a possible value. If k is greater than 1 by 2 to the power n rejection is not possible. If k is less than 1 by 2 to the power n we always reject. So, α is equal to 1 therefore, we should have k equal to 1 by 2 to the power n for 0 less than α less than 1 .

So, suppose we take k equal to 1 by 2 to the power n , then $\phi(x) = 1$ for x in case 3 satisfies 2 of NP lemma, and we can set any value of $\phi(x)$ in case 1, 2, 3 or 4 **sorry** 1, 2 or 4. Let me give complete case here, when I base our decision on x_n alone. You note here that when I am considering x_1, x_2, x_n random sample from you know from 0 to θ , the sufficient statistics actually x_n , and x_n is actually playing the role here as you have already noticed here.

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If we base our decision on $Y = X_{(n)}$.

In this case, analyzing as before, we write

$$E_{\theta=1} \phi_1(Y) = \gamma P(\text{Case 2}) + \underbrace{P_{\theta=1}(\text{Case I, III or IV})}_0$$

$$= \gamma \cdot 1 = \gamma = \alpha$$

So a MP test for level α is

$$\phi_1(x) = \begin{cases} \alpha & \text{if } Y \leq 1 \\ 0 & \text{otherwise.} \end{cases}$$

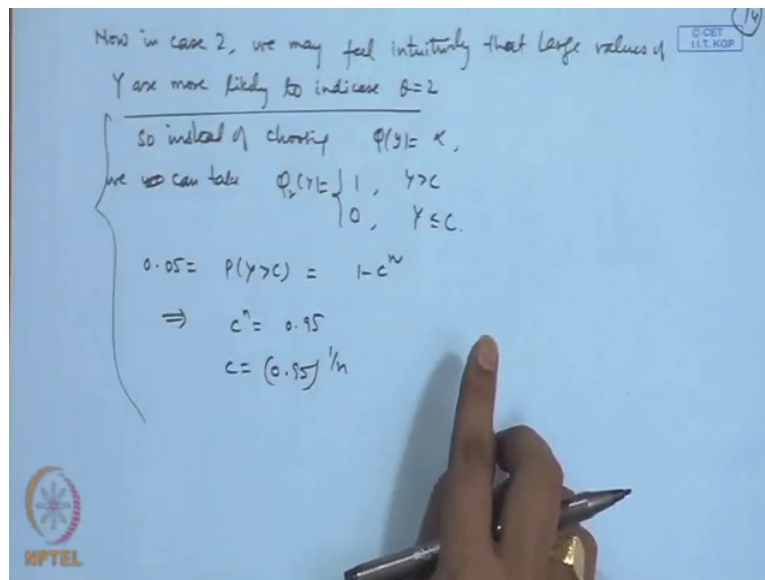
$E_{\theta < 1} \phi_1(Y) = \alpha P(Y \leq 1) + \dots$

$$= \alpha \cdot \left[\left(\frac{1}{\theta}\right)^n + \left(1 - \left(\frac{1}{\theta}\right)^n\right) \right] = \alpha$$

So, let me explain that part in detail. If we base our decision on say y is equal to x_n . So, in this case what is happening that? Let me write here, in this case analyzing as before we write expectation of $\phi_1(y)$ for θ is equal to 1, as some γ times probability of case 2, under θ is equal to 1 plus probability of θ is equal to 1, under case 1, 3 or 4 now these are all 0. So, that is equal to γ into 1 that is equal to γ .

So, we should choose γ is equal to α . So, a most powerful test for level α is $\phi_1(x)$ or $\phi_1(y)$ is equal to α if $y \leq 1$ otherwise; that means, what we are saying reject all the time, accept for the case when y is less than or equal to 1, if y is less than or equal to 1, then you are rejecting with probability 0.05 and otherwise you are accepting. We may also consider the power function here. So, for example, power function here that is equal to α into probability of say y less than or equal to 1 plus probability. So, here I am taking θ is equal to 1 into. So, those cases will not occur this will have probability 0. So, this is actually equal to α . For this is θ less than 1; and if I take θ greater than 1 then it will become equal to α into 1 by θ to the power n plus 1 minus 1 by θ to the power n .

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So, that is equal to well we can simplify this. So, what we are able to do is that we are able to provide an exact test here, for testing parameters in the uniform distribution. We may also consider in a slightly different fashion. Let me just explain it here, case 2 we may feel intuitively that large values of y are more likely to indicate θ is equal to 2. So, instead of choosing $\phi(y) = \alpha$, we can take say $\phi_2(y)$ is equal to 1 if y is greater than c , it is equal to 0 if y is less than or equal to c ; and if we consider the probability of this. So, we are getting here say 0.05 is equal to probability of y greater than c , that is equal to 1 minus c to the power n this means, we can take c to the power n is equal to 0.95 or c is equal to 0.95 to the power $1/n$. So, this is an alternative solution here, of course, this is based on heuristic consideration that large values of y are more likely to. So, this part is not coming from NP lemma in the NP lemma if we write exactly we will take that part and the test function is of this nature, that $\phi(y) = \alpha$ if y is less than or equal to c and it is 1 otherwise.

So, these are the two forms that have been considering here, friends today we have considered in detail, various application of the Neyman Pearson fundamental lemma. How it gives exact tests for testing simple hypothesis versus a say simple hypothesis. The important point that you should note here, is that we need the distribution of the criteria; that means, our criteria is based on certain function of the random variable, which we call test statistic. We should be able to say something about the distribution of that under the null hypothesis then

only the constant k can be determined. If we are unable to determine that then we will not be able to provide the exact form of the test function

So, in the next lecture, as I mentioned, we will consider extension of the Neyman Pearson lemma to consider the composite hypothesis also. So, in particular, we will consider the one sided composite hypothesis testing problems, so that I will be taking of in the following lecture.