

**Probability and Statistics**  
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**Module No.# 01**  
**Lecture No. # 35**  
**Testing of Hypothesis - III**

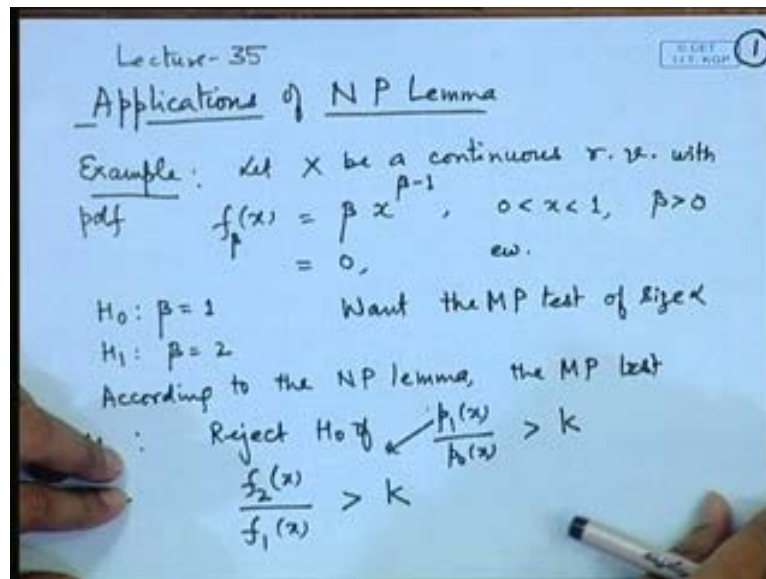
In the previous lecture, I had introduced the basic concepts of testing of hypothesis. So, let me review the basic terminology. A test of statistical hypothesis is testing about the probability distribution of a certain population. We may be able to know that what is the proper probability distribution and then, we may test about the parameters of that distribution. We have null hypothesis and then, alternative hypothesis.

So, the test is to decide on the basis of a random sample, whether to accept or reject a null hypothesis. So, if the sample supports the hypothesis; that means it is in favor of the hypothesis. Then, we say that we cannot reject the hypothesis or we say we accept a null hypothesis. Otherwise, we say that we reject the null hypothesis.

We have classifications of the hypothesis as a simple hypothesis and a composite hypothesis. So, a simple hypothesis is the one, when the hypothesis statement completely specifies the probability distribution, otherwise we call it a composite hypothesis. When we conduct a test of hypothesis; that means, **it is based on** the decision is based on a sample. Then, we may commit 2 types of errors, which we call as type I error and type II error, that is we may reject a true hypothesis or we may accept a false hypothesis.

We have seen that, it is not possible to minimize both types of errors. The probability of both types of errors is minimum. So, a practical approach is to fix the highest level for 1 type of error. Usually, we fix for the type I error and find out a test of hypothesis for which the other type of error is minimized or 1 minus, that is maximized, which we call the power of the test that gave the concept of the most powerful test. In the last lecture, I explained that there is a result known as Neyman–Pearson fundamental lemma, which for simple hypothesis versus a simple hypothesis problem gives a most powerful test.

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So, now, let me go for the applications of this Neyman–Pearson lemma. Let me start with a following example. Let  $x$  be a continuous random variable with probability density function given by  $f_x$  is equal to say,  $\beta x$  to the power  $\beta$  minus 1 for  $0 < x < 1$ , where  $\beta$  is a positive parameter and the density is 0 elsewhere. We want to test, say hypothesis  $\beta$  is equal to 1 against say  $H_1$   $\beta$  is equal to 2.

So, here, if we see this is  $f_{\beta}$ , the density is dependent upon the parameter  $\beta$ . So, we are interested to test that whether  $\beta$  is equal to 1 or  $\beta$  is equal to 2. Now, you can see here, that both of these are simple hypothesis.

So, if we want to find out, if we want the most powerful test, then we can make use of the Neyman–Pearson lemma. So, we want the most powerful test of size, say  $\alpha$  or level  $\alpha$ . So, according to the Neyman–Pearson lemma, the most powerful test is rejecting  $H_0$  if  $\frac{f_1(x)}{f_0(x)}$  is greater than  $k$ .

So, now this is the quantity which we can analyze here. What is  $f_1$  and what is  $f_0$ ? Here, this is corresponding to, that is  $f_1$  is corresponding to the value of the probability distribution or density, when the alternative hypothesis is true. So, here it will be  $f_2(x)$  divide by  $f_1(x)$  is the value of the hypothesis value of the probability distribution, when the null hypothesis is true. Here,  $\beta$  is equal to 1. That means, it will become  $f_1(x)$ . This is greater than  $k$ , where the constant  $k$  is chosen in such a way that the probability of the type I error is equal to  $\alpha$ . So, now, first of all, let us look at when we

are actually going to reject. So, this statement is equivalent to.

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$$f_1(x) = 1, \quad 0 < x < 1$$

$$= 0, \quad \text{else}$$

$$f_2(x) = 2x, \quad 0 < x < 1$$

$$= 0, \quad \text{else}$$

So (\*) is equivalent to

$$2x > k \quad 0 < x < 1$$

Test is:  $\therefore$  Reject  $H_0$  if  $2X > k$ .

$$P(2X > k) = \alpha$$

$$\int_{k/2}^1 dx = \alpha$$

$$\Rightarrow 1 - \frac{k}{2} = \alpha \Rightarrow k = 2(1 - \alpha)$$

So the test is Reject  $H_0$  if  $2X > 2(1 - \alpha)$

So, we have to consider the value here. What is  $f_1(x)$ ?  $f_1(x)$  will be obtained by substituting beta is equal to 1 here, which give us simply 1. That means the uniform distribution on the interval 0 to 1. In a similar way,  $f_2(x)$ , if I put beta is equal to 2 here, I will get  $2x$ .

So, by statement  $f_2(x)$  by  $f_1(x)$  greater than  $k$ , this is equivalent to. So, this statement let me call it star. This is equivalent to  $2x$  divided by 1 is greater than  $k$ . Of course, here you are taking  $0 < x < 1$ . Now, we want that probability of type I error must be  $\alpha$ . So, the test is reject  $H_0$  if  $x$  is greater than  $k/2$  or you can say  $2x$  is greater than  $k$ . Now, we want probability of  $2x$  greater than  $k$ , then it is true. That means, when beta is equal to 1, this probability to be equal to  $\alpha$ .

Now, when beta is equal to 1, we have written here the density is uniform distribution. So, this value can be calculated. This is probability of  $x$  greater than  $k/2$ . So, this becomes integral of, say  $dx$  from  $k/2$  to 1. This is equal to  $\alpha$  or you can say  $1 - k/2 = \alpha$ , which is implying  $k$  is equal to twice  $1 - \alpha$ . So, the test is in theoretical terms. We can write reject  $H_0$  if  $2x$  is greater than twice  $1 - \alpha$ , which is equivalent to  $x$  is greater than  $1 - \alpha$ .

So, a most powerful test of size  $\alpha$  is rejecting  $H_0$  when  $x$  is greater than  $1 - \alpha$ .

minus alpha. So, this is the most powerful test. So, you can see here, now the decision making process is quite simple. We observe a random variable from this population and we see its value.

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Suppose  $\alpha = 0.01$   
 $X > 0.99$  (Reject  $H_0$ )  
 2. Let  $X \sim \text{Bin}(3, p)$ .  
 $H_0: p = \frac{1}{2}$  Find MP test for  $H_0$  vs.  $H_1$   
 $H_1: p = \frac{3}{4}$  at level  $\alpha = 0.05$ .  
 $f(x, p) = \binom{3}{x} p^x (1-p)^{3-x}, x=0, 1, 2, 3$   
 $f_0(x) = \binom{3}{x} \left(\frac{1}{2}\right)^x \left(\frac{1}{2}\right)^{3-x} = \binom{3}{x} \left(\frac{1}{2}\right)^3$   
 $f_1(x) = \binom{3}{x} \left(\frac{3}{4}\right)^x \left(\frac{1}{4}\right)^{3-x}, x=0, 1, 2, 3$   
 $= \binom{3}{x} \left(\frac{1}{4}\right)^3 \cdot 3^x$

So, suppose, I say that alpha is equal to, say suppose alpha is equal to say 0.01, then I should observe x to be greater than 0.99. Then, only you will reject  $H_0$ .

On the other hand, if you observe x to be between, say less than 0.99 or less than or equal to 0.99, you have no reason to reject  $H_0$ . So, this is the test function for the most powerful test. Another point which you should observe here, that when we wrote the Neyman–Pearson lemma, we wrote acceptance region to be when this is less than k and there was a probability gamma of rejecting, when this is equal to k, but since this is a continuous distribution, we do not have to look at that reason because we are able to achieve the exact level alpha by this test here.

So, we can simply state in the form that, when we are rejecting or when we are accepting the point x equal to 1 minus alpha does not make any difference because that has probability 0.

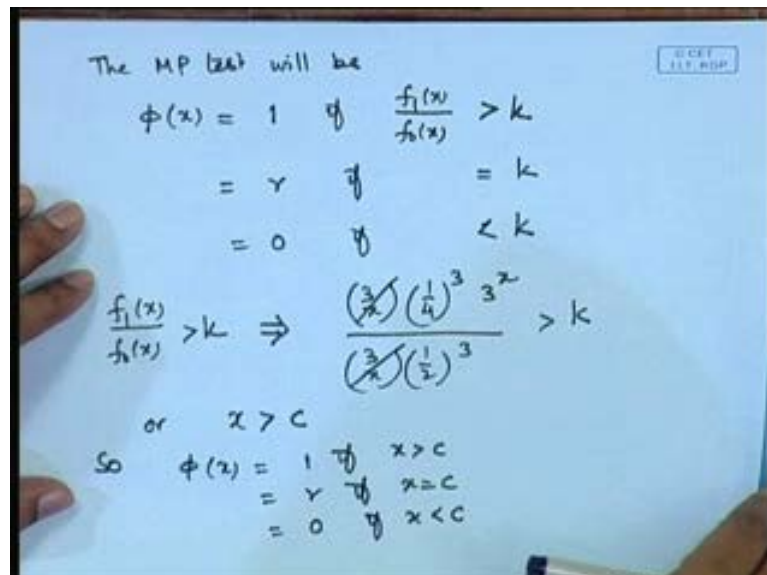
In the case of discrete distribution, we may have to take some randomization which is explained through the following example. Let me take this example here. Let x be a

binomial random variable with parameter, say 3, that is n is equal to 3 and probability of head is, say p. We want to test; say  $H_0: p = \frac{1}{2}$  against  $H_1: p = \frac{3}{4}$ . So, find most powerful test for  $X$  against  $H_1$  at level, say  $\alpha$  is equal to say 0.05.

Now, this is again a case of simple versus simple hypothesis because  $p = \frac{1}{2}$  or  $p = \frac{3}{4}$ , completely specifies this probability distribution. Therefore, we will consider the application of the Neyman–Pearson lemma here. So, let us write down the distribution first. So,  $f_0(x)$ , that is equal to  $\binom{3}{x} (\frac{1}{2})^3$ , that is  $\binom{3}{x} (\frac{1}{2})^3$  to the power  $x$   $(1 - \frac{1}{2})^{3-x}$ . You will need the values of  $f_0(x)$  and  $f_1(x)$ . So,  $f_0(x)$  is the value, when  $p$  is equal to half which is reducing to  $\binom{3}{x} (\frac{1}{2})^3$  to the power  $x$  into half to the power  $3 - x$ . This is 3, here  $x$  is equal to 0 1 2 3.

So, naturally, this is simply equal to  $\binom{3}{x} (\frac{1}{2})^3$ , whereas  $f_1(x)$  is the density when the alternative hypothesis is true, that is  $p = \frac{3}{4}$ . So, the value is  $\binom{3}{x} (\frac{3}{4})^x$  to the power  $x$   $(\frac{1}{4})^{3-x}$  for  $x = 0 1 2 3$ . Now, this can also be simplified little bit. We can write it as  $\binom{3}{x} (\frac{3}{4})^x (\frac{1}{4})^{3-x}$ .

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So, the most powerful test form, we can write the most powerful test will be. So, since here randomization may be required, we write the test function. So,  $\phi(x)$  is equal to 1, if  $f_1(x) / f_0(x)$  is greater than  $k$ . It is equal to  $\gamma$ , if this is equal to  $k$ . It is equal to 0, if this is less than  $k$ .

So, this condition that  $f(x) > k$ , let us write down this condition. Here,  $3cx^{-1/4} > k$ . So, this term cancels out. This is some constant and if I take logarithm here, then this will become  $x \log 3 > \text{some constant}$ . So, we can say,  $x$  is greater than some  $c$ . So,  $\phi(x)$  function can be written to be 1, if  $x$  is greater than  $c$ . It is equal to  $\gamma$ , if  $x$  is equal to  $c$ . It is equal to 0, if  $x$  is less than  $c$ . This is the test function that we will be getting. That means, rejecting when  $x$  is greater than  $c$ , accepting when  $x$  is less than  $c$  and rejecting with probability  $\gamma$  when  $x$  is equal to  $c$ . This is the randomization part here. Here, it may be required as you will see now.

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The size of the test

$$E_0 \phi(X) = 0.05$$

$$\Rightarrow P_0(X > c) + \gamma P_0(X = c) = 0.05$$

$$\Rightarrow \sum_{x>c} \left(\frac{3}{x}\right) \left(\frac{1}{x}\right)^3 + \gamma \sum_{x=c} \left(\frac{3}{x}\right) \left(\frac{1}{x}\right)^3 = 0.05$$

This equation is satisfied only when

$$c = 3, \gamma = 0.4.$$

So the MP test

$$\phi(x) = \begin{cases} 1 & \text{if } x > 3 \\ 0.4 & \text{if } x = 3 \\ 0 & \text{if } x < 3 \end{cases}$$

Now, the size of this test must be equal to  $\alpha$ , that is, 0.05. So, if we put that condition, the size of the test, that is expectation of  $\phi(x)$  when null hypothesis is true, that is equal to 0.05. So, this value is equal to probability  $x > c$ , when  $p$  is equal to half plus  $\gamma$  times probability  $x = c$ , when  $p$  is equal to half, that is equal to 0.05.

Now, you can see here, when the null hypothesis is true, the density function is written as  $3cx^{-1/4}$ . So, this becomes that we have to consider the values of  $x$  for which it is greater than  $c$  and the probability distribution has to be added up is this, that is  $3cx^{-1/4}$  summation, when  $x$  is greater than  $c$  plus  $\gamma$  into, well this is becoming  $3c^{-1/4}$  when  $x$  is actually equal to  $c$ .

So, basically there is a point here, which will be satisfied for integer values only. So, we will see that when is it satisfied  $0.05$  this equation is satisfied only when. So, we will substitute the values of  $c$  is equal to  $0, 1, 2$  and  $3$ . You get here,  $c$  is equal to  $3$  and  $\gamma$  is equal to  $0.4$ . So, the mp test is  $\phi(x)$  is equal to  $1$ , if  $x$  is greater than  $3$ . It is equal to  $0.4$ , if  $x$  is equal to  $3$ . It is equal to  $0$ , if  $x$  is less than  $3$ .

So, let us look at the interpretation of this. The interpretation of this test is because  $x$  is taking values  $0, 1, 2, 3$  only. That means, this test, it is never rejecting with probability  $1$ . It is rejecting only with probability  $0.4$ ; that means, when we conduct the experiment and if I observe  $x$  is equal to  $3$ , then we will reject with probability  $0.4$  and accept with probability  $0.4$ . In all other cases, we accept the null hypothesis; that means, if  $x$  is equal to  $0, 1, 2$ , then we do not reject  $H_0$ .

So, this may look surprising, but if we see carefully our problem, the problem was to test that whether the coin is fair against, whether it is biased in favor of head. So, based in favor of head, we are accepting if  $x$  is greater than  $3$  only. That means and which is not possible even if  $x$  is equal to  $3$ . We are only partially agreeing; that means, we are accepting in favor of  $H_1$  only. That means, we are rejecting only with probability  $0.4$ ; that means, there is the hypothesis is heavily biased in favor of  $H_0$  here, because  $x$  equal to  $0, 1, 2, 3$ .

So, only you are having the rejection for  $x$  equal to  $3$  that too with the probability  $0.4$  here. So, you can see here that by application of the Neyman–Pearson fundamental lemma, we are able to get the most powerful test. Of course, it is another matter that if we change this  $\alpha$  to be say  $0.01$  or  $0.1$ , then the test will be slightly modified here. Let us look at the applications to the normal distribution here.



(Refer Slide Time: 19:09)

3.  $X_1, \dots, X_n$  a random sample from  $N(\mu, 1)$ .  $H_0: \mu = 0$  MP test of size  $\alpha = 0.05$   
 $H_1: \mu = 1$   $-\frac{1}{2} \sum (x_i - \mu)^2$   
 $\underline{x} = (x_1, \dots, x_n)$

$$f(\underline{x}, \mu) = \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2} \sum x_i^2}$$

$$f_0(\underline{x}) = \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2} \sum (x_i - 0)^2}$$

$$f_1(\underline{x}) = \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2} \sum (x_i^2 - 2x_i + 1)}$$

$$= \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2} \sum x_i^2 + \sum x_i - \frac{n}{2}}$$

Consider say  $x_1, x_2, \dots, x_n$ , a random sample from, say normal distribution with mean  $\mu$  and variance, say unity. We want to test the hypothesis, say  $\mu$  is equal to 0 against say  $\mu$  is equal to 1. We want the most powerful test of a certain size say  $\alpha$  is equal to point 0.5.

So, the first thing is that in application of the Neyman–Pearson lemma, we need to write down the probability density function, that is  $f_{\underline{x}|\mu}$ . Now, here  $\underline{x}$  means we are observing a sample  $x_1, x_2, \dots, x_n$ , therefore, we need to write down this density function as a joint density function of  $x_1, x_2, \dots, x_n$ . So, this is terming out to be  $(1/\sqrt{2\pi})^n e^{-1/2 \sum x_i^2}$ . So, our  $f_0$  value that is there when  $\mu$  is equal to 0 and this terms out to be  $(1/\sqrt{2\pi})^n e^{-1/2 \sum x_i^2}$ .

In a similar way,  $f_1(\underline{x})$  is equal to  $(1/\sqrt{2\pi})^n e^{-1/2 \sum (x_i - 1)^2}$ . Now, this term can be simplified a little bit. We get it as  $(1/\sqrt{2\pi})^n e^{-1/2 \sum (x_i^2 - 2x_i + 1)}$ . So, if we take the most powerful test because the hypothesis  $H_0$  and  $H_1$  both are simple hypothesis.



(Refer Slide Time: 21:46)

The MP test of a given size  $\alpha$  is to  
 Reject  $H_0$  if  $\frac{f_1(x)}{f_0(x)} \geq k$   
 or  $e^{\sum x_i - \frac{n}{2}} \geq k$   
 $\Rightarrow \sqrt{n} \bar{X} \geq c$   
 $P(\text{Type I Err}) = \alpha$   
 $P(\text{Rejecting } H_0 \text{ when it is true}) = \alpha$   
 $P_{H_0}(\sqrt{n} \bar{X} \geq c) = \alpha$

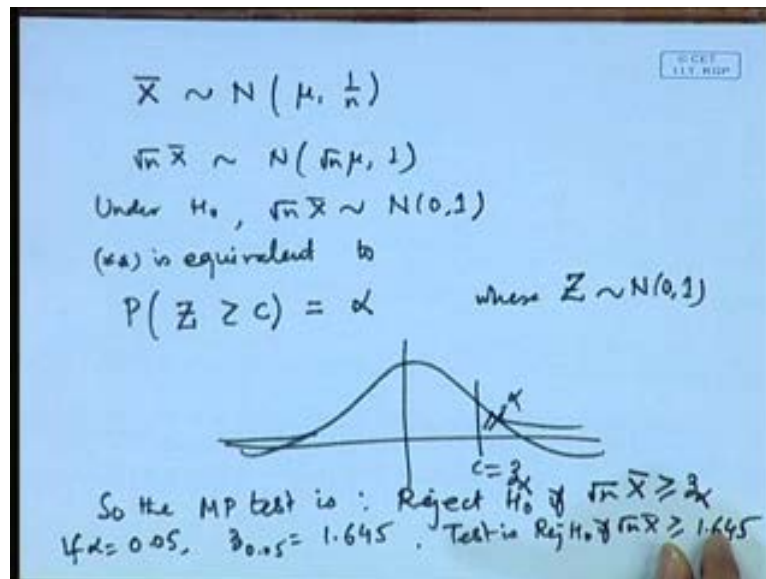
So, we can apply the Neyman–Pearson fundamental lemma to get the most powerful test for a given size. So, the most powerful test of a given size, says alpha is to reject  $H_0$  if  $f_1(x)$  by  $f_0(x)$  is greater than  $k$ .

Since, it is a continuous distribution; we will be able to achieve the exact level alpha by a non-randomized test itself. So, we need not put here gamma for  $f_1(x)$  by  $f_0(x)$  is equal to  $k$ . We may just consider  $f_1(x)$  by  $f_0(x)$  is greater than  $k$  or greater than or equal to  $k$ . It does not make any difference here because the probability of the equality will be equal to 0 for the case of a continuous random variable.

So, if we write these functions here, now you are getting the  $f_1$  and  $f_0$  term here both had the same factor. So, when we write the ratio, this coefficient cancels out and also  $e$  to the power minus 1 by 2 sigma xi square will also cancel out. So, we will be left with  $e$  to the power sigma xi and then, there will be a constant term minus  $n$  by 2 is greater than or equal to  $k$ .

If we take the logarithm, then this is reducing to  $\bar{x}$  greater than or equal to say  $c$  term and we may multiply by root  $n$  here to get a proper form of the distribution. Why that is useful? Because we want probability of type I error equal to alpha. So, that is probability of rejecting  $H_0$  when it is true, that is equal to alpha.

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So, probability of root N x bar greater than or equal to c, when mu is equal to 0 is equal to alpha. Now, you see the distribution of x bar since x 1, x 2, x n is a random sample from normal distribution x bar follows normal mu 1 by n. So, root n x bar follows normal root n mu 1. So, under h naught root n x bar follows normal 0 1.

So, from here, the statement that probability of mu is equal to 0. So, that this statement let me call it, say statement double star. This is equivalent to probability of z greater than or equal to c is equal to alpha, where z is a standard normal random variable. That means, if we are considering a standard normal probability density function, then c is the point such that the probability beyond this is alpha. So, this is equal to z alpha. So, the most powerful test is reject h naught, if root n x bar is greater than or equal to z alpha.

So, if i am considering alpha is equal to 0.05, then 0.05 we know from the tables of normal distribution, it is 1.645. So, the test is reject H naught if root nx bar is greater than or equal to 1.645. So, you can see the Neyman–Pearson lemma gives us a precise test for taking the decision to accept or reject a null hypothesis in a given situation.

Now, let us also look at the interpretation of this. We were testing the hypothesis whether mu is equal to 0 against mu is equal to 1. So, you can see here, we want that whether the value of mean is less or more because we may consider here this mu 0 is value which is less than 1. So, naturally here, you can see that as a layman, you would have made a

decision that for a larger value of  $\bar{x}$ , you will tend to favor  $H_1$  and for a small value of  $\bar{x}$ , you will tend to favor  $H_0$ , but how much value of  $\bar{x}$  is considered to be larger or smaller, that is dependent upon the probability of type I error. Therefore, we are now able to formulate in the terms of this decision making process as that  $\sqrt{n}(\bar{x} - \mu_0)$  should be greater than, that means,  $\bar{x}$  is greater than  $\mu_0 + 1.645/\sqrt{n}$ .

Of course, if  $\sqrt{n}$ , if  $n$  is large, then this value will become much smaller. That means, even for a smaller value of  $\bar{x}$ , you will consider it to be little larger, but that much distinction is permissible because on an absolute scale, we cannot compare 0 and 1, may the difference between 0 and 1 is 1, but what is the scale here. So, if we are having a pretty large value of  $n$ , then that difference may be still considered to be large, that is for a very small value  $N$ , that difference may not be considered to be large.

So, we may actually consider it in a slightly broader sense. In place of  $\mu_0$  is equal to 0 and  $\mu_1$  is equal to 1. If we substitute, say some values  $\mu_0$  and  $\mu_1$  and then, let us see the effect of this. So, now, let me generalize this problem  $X_1, X_2, \dots, X_n$  follows normal  $\mu_1$  and we are testing the hypothesis whether  $\mu$  is equal to  $\mu_0$  against  $H_1: \mu > \mu_0$ , where let me take  $\mu_0$  to be less than  $\mu_1$ .

Now, let us write down the density ratio, that is  $f_1(x)$  divided by  $f_0(x)$ . So, it is  $1/\sqrt{2\pi} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu_1)^2}$  divided by  $1/\sqrt{2\pi} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu_0)^2}$ . Now, you can see that these terms cancel out  $e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu_0)^2}$ . If you expand this, you get  $\sum_{i=1}^n (x_i - \mu_1)^2 - \sum_{i=1}^n (x_i - \mu_0)^2$ . So, after simplification, this term becomes  $e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu_1)^2 - \sum_{i=1}^n (x_i - \mu_0)^2}$ . Remaining terms get cancelled out here.

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The MP test will Reject  $H_0$  if

$$\frac{f_1(x)}{f_0(x)} \geq k$$

$$e^{(\mu_1 - \mu_0) \sum x_i} \geq k_1$$

$$\Rightarrow \bar{x} \geq k_2$$

Under  $H_0$

$$\bar{x} \sim N(\mu_0, \frac{\sigma^2}{n})$$

$$P(\bar{x} \geq k_2) = \alpha$$

$$P(Z \geq k^*) = \alpha$$

where  $Z = \sqrt{n}(\bar{x} - \mu_0)$

$$k^* = \frac{z_\alpha}{\sigma}$$

$$k_2 = \frac{\sigma}{\sqrt{n}} z_\alpha + \mu_0$$

So, now if you look at the most powerful test, this is reject  $H_0$  if  $f_1(x)$  by  $f_0(x)$  is greater than or equal to  $k$ . So, if we utilize this here given  $\mu_1$  and  $\mu_0$ , whatever be the value, this is some constant here. So, this region is reducing to  $e^{(\mu_1 - \mu_0) \sum x_i} \geq k_1$ . So, if  $\mu_1$  is greater than  $\mu_0$ , then this region is equivalent to  $\bar{x} \geq k_2$ .

Therefore, the test is to once again reject  $H_0$  for larger values of  $\bar{x}$ . So, if you compare with the previous situation where I had taken  $\mu_0$  to be 0 and  $\mu_1$  is equal to 1, then we were rejecting for larger value of  $\bar{x}$ . So, as I mentioned here, that the only designing factor is the value of  $\bar{x}$  and, but we wanted to know the scale of  $\bar{x}$ , that on what scale we will consider  $\bar{x}$  to be large or what should be the small value, that is decided by the probability of the type I error.

So, in the same way, here you are seeing that if  $\mu_0$  is less than  $\mu_1$ , the region's actually same, but how much it is same that will be dependent upon the probability of type I error. So, if we write here probability of  $\bar{x} \geq k_2$  when  $\mu$  is equal to  $\mu_0$ , this is equal to  $\alpha$ . Then, we observe the distribution here. So, the distribution of  $\bar{x}$  here is normal  $\mu_1$  by  $n$ . So, under  $H_0$   $\bar{x}$  follows normal  $\mu_0$  by  $n$ .

So, we can do the calculations hereby simplification  $\bar{x} - \mu_0$  into  $\frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}}$ ,

that will follow normal 0 1 distribution. So, under  $H_0$ , this statement can be written to be equivalent to  $Z \geq k$  where  $k$  is equal to  $Z_{\alpha}$ . Let me write here,  $k^*$  where  $Z$  is defined to be  $\sqrt{n}(\bar{X} - \mu_0)$ . So, this point  $k^*$  becomes the upper handed  $\alpha$  percent point of the standard normal distribution. This is the point  $k^*$ , this probability is  $\alpha$ . Therefore, this  $k^*$  is actually  $Z_{\alpha}$  point here.

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Handwritten notes on a whiteboard:

- $\alpha = 0.05$
- $Z_{\alpha} = 1.645$
- Rejection region:  $\sqrt{n}(\bar{X} - \mu_0) \geq 1.645$
- $\mu_0 = -1$        $\sqrt{n}(\bar{X} + 1) \geq 1.645$
- $X_1, \dots, X_n \sim N(0, \sigma^2)$
- $H_0: \sigma^2 = \sigma_0^2$
- $H_1: \sigma^2 = \sigma_1^2$
- $\underline{X} = (x_1, \dots, x_n)$
- $f(\underline{X}, \sigma^2) = \frac{1}{(\sqrt{2\pi}\sigma)^n} e^{-\frac{1}{2\sigma^2} \sum x_i^2}$

So, as a practical example, if we substitute different values here, say  $\mu_0$  is equal to minus 1, then the rejection region is changing  $\sqrt{n}(\bar{X} + 1) \geq Z_{\alpha}$ . We have seen the example earlier, that if I am putting say  $\alpha$  is equal to 0.05 that  $Z_{\alpha}$  is equal to 1.645. So, the test will become in that case,  $\sqrt{n}(\bar{X} + 1) \geq 1.645$ . This is the rejection region.

So, if I say take  $\mu_0$  is equal to say minus 1 then this will become  $\sqrt{n}(\bar{X} + 1) \geq 1.645$ . So, if we compare with the previous example, where  $\mu_0$  was 0, then it was  $\sqrt{n}\bar{X} \geq 1.645$ . So, the magnitude of  $\bar{X}$  which will be considered to be large depends upon the probability of the type I error and that means, what is the value of the probability distribution point when  $\mu_0$  is equal to  $\mu_0$ .

A similar behavior is observed, suppose we consider testing for the variance in normal

distribution case. Let me take the case of, say  $x_1, x_2, \dots, x_n$  for convenience. Let me take the mean to be 0 and variance to be  $\sigma^2$  and we are interested to make a test of hypothesis about, say  $\sigma^2$ . Now, once again let us write down the density function here  $f(x; \sigma^2)$ . So, we need to write for the joint estimation of  $x_1, x_2, \dots, x_n$  here. So, that is  $\frac{1}{(\sqrt{2\pi}\sigma)^n} e^{-\frac{1}{2\sigma^2} \sum x_i^2}$ . Since, I have taken the mean of the normal distribution to be 0, so the joint distribution of  $x_1, x_2, \dots, x_n$  terms out to be this 1.

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The image shows a whiteboard with handwritten mathematical formulas and text. The formulas are:

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

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

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

So by NP Lemma, the MP test of  $H_0$  vs  $H_1$  is Reject  $H_0$  if

$$\frac{f_1(x)}{f_0(x)} \geq k$$

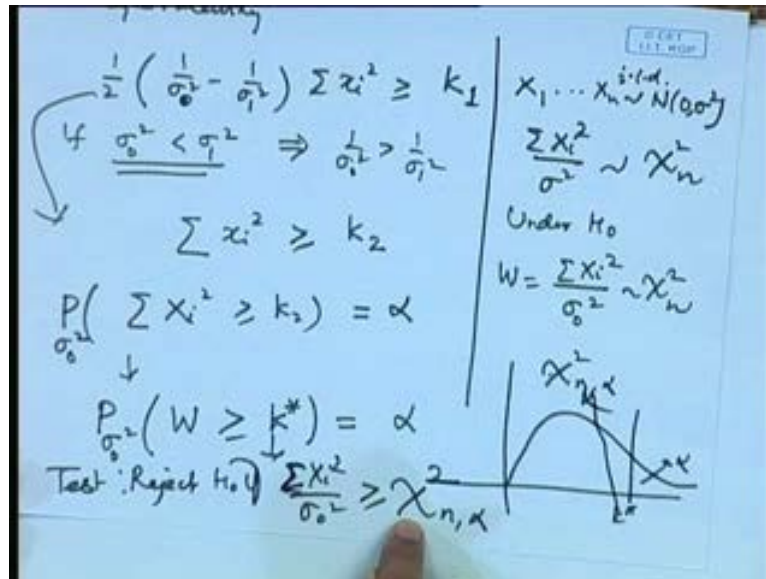
So, we write down this value corresponding to the null and the alternative hypothesis. So, when  $\sigma^2$  is equal to  $\sigma_0^2$ , then this is becoming  $\frac{1}{(\sqrt{2\pi}\sigma_0)^n} e^{-\frac{1}{2\sigma_0^2} \sum x_i^2}$  and  $f_1(x)$ . In a similar way, will become  $\frac{1}{(\sqrt{2\pi}\sigma_1)^n} e^{-\frac{1}{2\sigma_1^2} \sum x_i^2}$ . So, if you consider the ratio  $f_1(x)$  by  $f_0(x)$ , that is equal to  $\left(\frac{\sigma_0}{\sigma_1}\right)^n e^{\left(\frac{1}{2\sigma_1^2} - \frac{1}{2\sigma_0^2}\right) \sum x_i^2}$ .

So, by Neyman–Pearson lemma, the most powerful test of  $H_0$  versus  $H_1$  is reject  $H_0$ , if  $f_1(x)$  by  $f_0(x)$  is greater than or equal to  $k$ . Once again, we notice here that this distribution of  $x$  is continuous distribution. So, the distribution of the variables involved here, for example, here  $\sum x_i^2$  is involved, that is, also continuous distribution. So, here without lots of generality, we can write greater than or equal to

because the probability of the statement being equal to  $k$ , that is  $f(1)$  by  $f$  naught equal to  $k$  that probability will be 0. So, this equality can be included here.

So, now, if we look at the ratio here, this is greater than or equal to  $k$ . Then, this will reduce to because  $\sigma_0$  and  $\sigma_1$  are the known constant.

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So, this condition is gone and if you take the logarithm, then we get it as this condition is equivalent to  $1$  by  $2$ ,  $1$  by  $\sigma_0$  square minus  $1$  by  $\sigma_1$  square  $\sigma_0$   $x_i$  square greater than or equal to some  $k_1$ .

Now, once again the relative position of  $\sigma_0$  square and  $\sigma_1$  square is playing a role here. So, if suppose, I will take  $\sigma_0$  square to be less than  $\sigma_1$  square, then this will be equivalent to  $1$  by  $\sigma_0$  square greater than  $1$  by  $\sigma_1$  square. Therefore, the region will be equivalent to  $\sigma_0 x_i$  square greater than or equal to say  $k_2$ , where this  $k_2$  has to be chosen in such away that  $\sigma_0 x_i$  square greater than or equal to  $k_2$  has a probability equal to  $\alpha$  when  $\sigma_0$  square is equal to  $\sigma_1$  square. So, the condition becomes  $\sigma_0 x_i$  square greater than or equal to  $k_2$ , when  $\sigma_0$  square is equal to  $\sigma_1$  square is equal to  $\alpha$ .

So, in order to find out the value of  $k_2$ , we need to look at the distribution of  $\sigma_0 x_i$  square when  $\sigma_0$  square is equal to  $\sigma_1$  square. So, we look at our statement



here,  $x_1, x_2, \dots, x_n$ . They follow normal  $0, \sigma^2$  and therefore, if we consider  $\frac{\sum x_i^2}{\sigma^2}$  that will follow chi square distribution on  $n$  degrees of freedom because we are considering this to be random sample. So, these are independent and identically distributed random variables. So, under  $H_0$  let me call it  $w$ , that is,  $\frac{\sum x_i^2}{\sigma_0^2}$  that follows chi square distribution on  $n$  degrees of freedom.

So, we can write down this statement as  $w \geq k^*$  is equal to  $\alpha$ . So, since  $w$  is following chi square  $n$  distribution, the point  $k^*$  becomes upper handed  $\alpha$  percent point. This point is  $k^*$  and this is  $\alpha$ . So, this point is nothing, but  $\chi^2_{n, \alpha}$ . That means, the test is reject  $H_0$ , if  $\frac{\sum x_i^2}{\sigma_0^2} \geq \chi^2_{n, \alpha}$ .

Let us interpret this test here. We wanted to test whether the variance of a normal distribution is less or more because  $\sigma_0^2$  we took to be less than  $\sigma^2$ . Now, when mean is taken to be  $0$   $\frac{\sum x_i^2}{n}$  is an estimator, we have actually calculated the maximum likelihood estimator. So, that is an estimator for  $\sigma^2$ .

So, as a layman, you will base your decision on the value of  $\frac{\sum x_i^2}{n}$ . That means, for a smaller value of  $\frac{\sum x_i^2}{n}$  will be tend to accept  $H_0$  and for a larger value of this, we will tend to accept  $H_1$ , that is rejecting  $H_0$ . So, now, how much value of  $\frac{\sum x_i^2}{n}$  should be considered? Small or large, that is decided by the probability of the type I error.

So, if the probability of the type I error is  $\alpha$ , the relative position of  $\frac{\sum x_i^2}{n}$  is decided by  $\chi^2_{n, \alpha}$  and of course, the value  $\sigma_0^2$  also plays a role because if  $\sigma_0^2$  is much smaller compared to  $\sigma^2$ , then that value will play role. So, the test here you can see the relative position is dependent upon the value of the parameter in the null hypothesis and for the power function, it is reverse. We are making use of the alternative hypothesis value, that is a power will increase or decrease according to the value of the parameter in the alternative hypothesis here.

Now, we have seen here application of the Neyman–Pearson lemma to some continuous distribution, especially normal distribution. We have seen the application to some discrete distribution such as a binomial distribution. So, this is a very general result because I can consider any distribution and if we have a simple versus simple hypothesis, so in fact, it is not even necessary that we have a same form of the distribution as we have seen. In the first example, we are under the null hypothesis. We had a uniform distribution and under the alternative hypothesis, we had another distribution which was having a density  $2x$ , so in general, we are able to test whether we have this probability distribution which is completely specified or another one which is again completely specified by making use of the Neyman–Pearson fundamental lemma.

Another important point that you may notice here, that is, that in most of the situations, the test function is coming in terms of the statistic which is actually a sufficient statistic. You can also say that it is coming in the terms of the maximum likelihood estimator as we have seen in the examples of the normal distribution, where for  $\mu$ , you are in terms of  $\bar{x}$  and for  $\sigma^2$  when we are doing the test, then it is coming in terms of  $\sum x_i^2$ .

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$x_1, \dots, x_n$   
 $f(x, \lambda) = \begin{cases} \lambda e^{-\lambda x}, & x > 0, \lambda > 0 \\ 0, & \text{elsewhere} \end{cases}$   
 $H_0: \lambda = 1$   
 $H_1: \lambda = 2$   
 $f(x, \lambda) = \begin{cases} \lambda^n e^{-\lambda \sum x_i}, & x_i > 0 \\ 0, & \text{elsewhere} \end{cases}$   
 $\frac{f_1(x)}{f_0(x)} = \frac{2^n e^{-2 \sum x_i}}{e^{-\sum x_i}} \geq k$   
 $\Rightarrow e^{-\sum x_i} \geq k_1$   
 $\sum x_i \leq k_2$

Naturally, we can check for certain other distributions also such as, say let  $x_1, x_2, \dots, x_n$ . This follows an exponential distribution with some parameter, say  $\lambda$ . Before this, before I discuss this example. Let me take the other case also, where  $\sigma^2$  is not

square may be greater than  $\sigma_1^2$ , then let us see how we are distinguishing.

If  $\sigma_0^2$  was greater than  $\sigma_1^2$ , then  $1/\sigma_0^2$  is becoming less than  $1/\sigma_1^2$ . Now, if you see here, this value will become negative. Therefore, if I divide by that value, the region is becoming reverse. So, we are getting the region as then the rejection region is  $\sigma_{xi}^2$  is less than or equal to  $k$ , say  $k_1$  or let me put it in another way in place of, so once again, we will have probability of  $\sigma_{xi}^2$  by  $\sigma_0^2$  less than or equal to some  $k^*$  is equal to  $\alpha$ . So, here it is turning out to be the left hand point. We are saying this value is  $\alpha$ . That means, this upper value is  $1 - \alpha$ . So, this  $k^*$  and this case becomes  $\chi^2_{1 - \alpha, n}$ , that means, the test is to reject  $H_0$  if  $\sigma_{xi}^2$  by  $\sigma_0^2$  is less than or equal to  $\chi^2_{1 - \alpha, n}$ .

So, you can see here that the region has got reverse  $y$  because now the null hypothesis supports larger value of  $\sigma^2$ , that is  $\sigma_0^2$  are taken to be bigger than  $\sigma_1^2$ . So, a smaller value of  $\sigma_{xi}^2$  will be in favor of the alternative hypothesis which is against the previous case, where a higher value was supporting the alternative hypothesis and once again, that on the relative scales that how much value of  $\sigma_{xi}^2$  will be considered. Larger or smaller, that is determined by the probability of the type I error and the value of the parameter in the null hypothesis here.

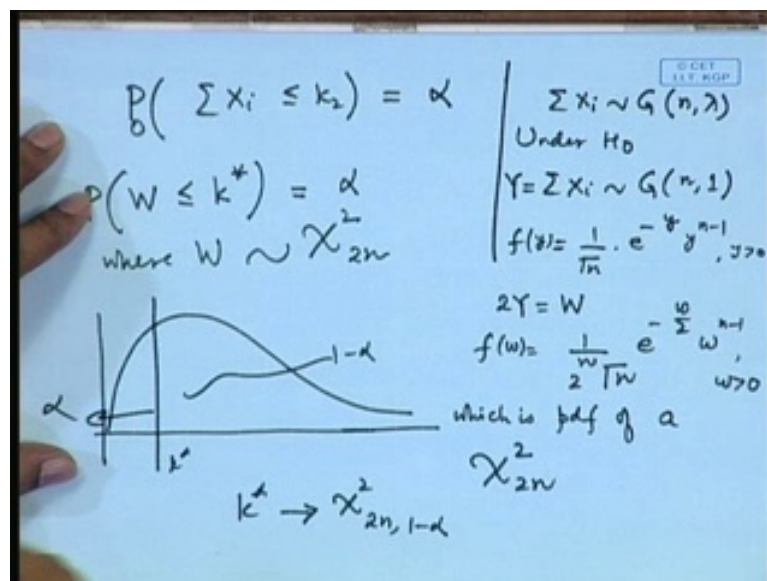
Now, let me consider the example which I mentioned earlier, that is of an exponential distribution and we may like to test, say  $\lambda$  is equal to say 1 against say  $\lambda$  is equal to 2. Now, the question is that when we are discussing distribution, which are different than the normal distribution etcetera, we may get statistic where the distribution of the statistic which is appearing in the test function may not be simple. Then, you may have to use certain transformations and get the distribution of that. So, that one may make use of the tables of the standard distributions to find out the exact test of the hypothesis.

So, in this particular case, for example, let us write down the joint distribution, so  $f_1(x)$  by  $f_0(x)$ . So, here, the joint distribution  $f(x; \lambda)$ , that becomes  $\lambda^n e^{-\lambda \sum x_i}$ , when all the  $x_i$  are positive, it is 0 elsewhere. So,  $f_1$  will correspond to the value of  $\lambda$  is equal to 2, then this becomes  $2^n e^{-2 \sum x_i}$  when I put  $f_0$ , that is

corresponding to lambda is equal to 1. I will get e to the power minus sigma x i.

So, we are saying the test is reject  $H_0$ , if this is greater than  $k$ . Once again, we outlaws of generality. We may include equality here or we may delete equality because the distribution of  $d_i$ 's are continuous. Therefore, the distribution of  $\sigma x_i$  will also be continuous. In fact, we know the distribution of  $\sigma x_i$  here. Firstly, let us simplify this. So, this region is equivalent to, if we take this in the numerator, it is reducing to  $\sigma x_i$  greater than or equal to some  $k_1$  because this coefficient we can remove and when we take logarithm, this is reducing to  $\sigma x_i$  less than or equal to some  $k_2$ .

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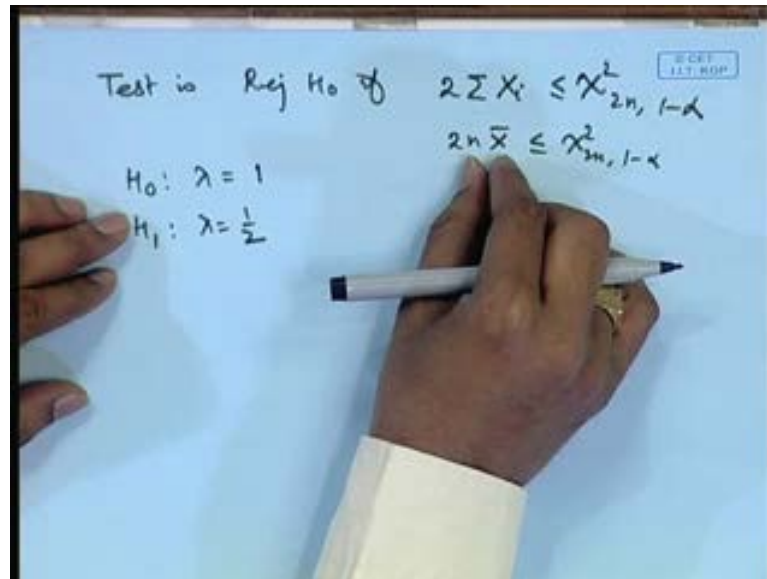
Now, we have to find out the value of  $k_2$  such that the probability of type I error, that is  $\sigma x_i$  less than or equal to  $k_2$  is equal to  $\alpha$ . So, we make use of the distribution theory here, as I was mentioning  $\sigma x_i$  will follow gamma distribution with parameters  $n$  and  $\lambda$  by the additive property of the exponential distribution. The sum of independent exponential variables is a gamma variable.

So, under  $H_0$   $\sigma x_i$  will follow gamma distribution on  $n$  and 1 degree of freedom. Now, what is this distribution? If we write down, let me denote it by, say  $y$ , then the density of  $y$  is  $\frac{1}{\Gamma(n)} e^{-y} y^{n-1}$ .

So, if we consider, say  $2y$  is equal to say  $w$ , then the distribution of  $w$  is equal to  $\frac{1}{2^n \Gamma(n)} e^{-\frac{w}{2}} w^{n-1}$  for  $w > 0$ , which is nothing, but probability density function of a chi squared

distribution on  $2n$  degrees of freedom. So, now, under  $H_0$ , we can write this as probability of  $w$  less than or equal to some  $k^*$ , that is equal to  $\alpha$ . So, this  $w$  is having a chi squared distribution on  $2n$  degrees of freedom. So, this point that you are having, here this is such that this probability is equal to  $\alpha$  and this probability is  $1 - \alpha$ . So,  $k^*$  naturally turns out to be  $\chi^2_{2n, 1-\alpha}$ .

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So, the test function then becomes reject  $H_0$  if  $2 \sum X_i$  is less than or equal to  $\chi^2_{2n, 1-\alpha}$ . Let us again analyze this statement in a practical sense. Here,  $\lambda$  is the rate of the Poisson process. So, basically, it has mean  $1/\lambda$ . So, you want to test whether the mean is less or more. So, in fact, the alternative hypothesis is having a higher value because mean is  $1/\lambda$ . So, this is actually rate. So, rate is less or more. Now, for the rate for the average, the variable or you can say the statistic, you would have been  $\bar{x}$  which is, of course, proportional to summation of the values here. So, we may even write it in this particular form. This is actually equal to  $2n\bar{x}$ .

So, a natural thing would be to go in favor of the null hypothesis if  $\bar{x}$  is smaller because if rate is larger, if rate is smaller, this is corresponding to the mean to be smaller. So, the mean is represented or you can say estimated by the sample mean. So, for the smaller value of the sample mean, we will tend to favor  $H_0$ , whereas, for the, I am sorry, I just made the reverse statement here. The null hypothesis is corresponding to

$\lambda$  is equal to 1 against the alternative hypothesis  $\lambda$  is equal to 2.

See, if we are considering mean, then  $1$  by  $\lambda$  is  $1$  and  $1$  by  $\lambda$  is equal to half here. That means, under the null hypothesis, the mean is smaller. Sorry, mean is larger and in alternative hypothesis, the mean is smaller. That means, when we are using the sample mean as an estimate of that for the smaller value of the sample mean, we will tend to favor the alternative hypothesis and for a larger value, we will tend to favor the null hypothesis. The relative significance of how much is larger or how much is bigger is dependent upon the probability of the type I error as well as the value of  $\lambda$  is equal to 1 and  $\lambda$  equal to 1 has been utilized here.

On the other hand, if we had say  $H_0: \lambda = 1$  against, say  $\lambda = 2$ , suppose just I make the change here. Then, what will happen in the case of the null hypothesis? You will have the same value, whereas for the alternative hypothesis, this will become half and this will become  $e^{-\frac{\sigma^2}{2}}$ . So, in that case, in the numerator, we will get  $e^{-\frac{\sigma^2}{2}}$  without with a positive sign and then the test function will become  $\sigma^2$  is greater than or equal to something, rather than less than something.

So, when we analyze this, we get here the test would be to reject for larger value of  $\bar{x}$  which is natural because when I say  $\lambda = 2$ , that means, I am saying  $1$  by  $\lambda = 2$  which is bigger than  $1$  by  $\lambda = 1$  here. So, you can also see or that in the Neyman–Pearson lemma, the tests which we are obtaining it by using the theory of most powerful test, they are confirming to a layman's approach or you can say a likelihood approach for testing the hypothesis. In the next lecture, I will be discussing in the more detail how to find out the test for the composite hypothesis.