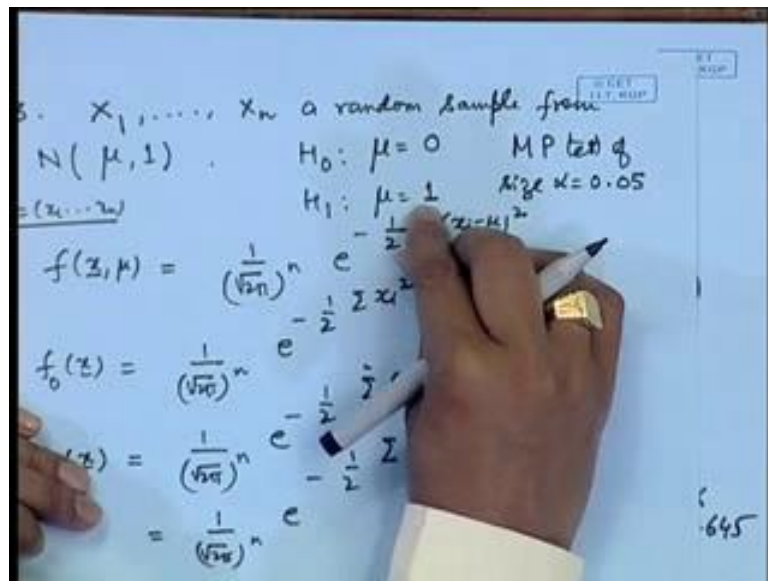


**Probability and Statistics**  
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**Lecture - 69**  
**Applications of N-P Lemma – II**

So, we may actually consider it in a slightly broader sense.

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In place of mu is equal to 0 and mu is equal to 1 if we substitute say some values mu naught and mu 1 and then let us see the effect of this.

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$X_1, \dots, X_n \sim N(\mu, 1)$   
 $H_0: \mu = \mu_0$   
 $H_1: \mu = \mu_1$

$\mu_0 < \mu_1$   
 $-\frac{1}{2} \sum (x_i - \mu_1)^2$

$$\frac{f_1(x)}{f_0(x)} = \frac{\frac{1}{(\sqrt{2\pi})^n} e^{-\frac{1}{2} \sum (x_i - \mu_1)^2}}{\frac{1}{(\sqrt{2\pi})^n} e^{-\frac{1}{2} \sum (x_i - \mu_0)^2}}$$

$$= e^{-\frac{n}{2}(\mu_1^2 - \mu_0^2)} \cdot e^{(\mu_1 - \mu_0) \sum x_i}$$

So, now let me generalize this problem  $X_1, X_2, X_n$  follows normal  $\mu_1$ . And we are testing the hypothesis whether  $\mu$  is equal to  $\mu_0$  against  $H_1$   $\mu$  is equal to  $\mu_1$  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  $\frac{1}{(\sqrt{2\pi})^n} e^{-\frac{1}{2} \sum (x_i - \mu_1)^2}$  divided by  $\frac{1}{(\sqrt{2\pi})^n} e^{-\frac{1}{2} \sum (x_i - \mu_0)^2}$ . Now you can see that these terms cancel out  $e^{-\frac{1}{2} \sum (x_i - \mu_1)^2}$  if you expand this you get  $\sum x_i^2 - 2\mu_1 \sum x_i + n\mu_1^2$  minus  $\sum x_i^2 - 2\mu_0 \sum x_i + n\mu_0^2$ . So, after simplification this term becomes  $e^{-\frac{n}{2}(\mu_1^2 - \mu_0^2)} \cdot e^{(\mu_1 - \mu_0) \sum x_i}$ ; remaining term gets canceled out here.

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The MP test will Reject  $H_0$  if

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

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

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

Under  $H_0$

$$P_{\mu=\mu_0}(\bar{x} \geq k_2) = \alpha$$

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

where  $Z = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}}$

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

$$k = \frac{z_\alpha \sigma}{\sqrt{n}}$$

So now if we 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 values 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 deciding factor is the value of  $\bar{x}$ , but we wanted to know the scale of  $\bar{x}$  that on what scale we will consider  $\bar{x}$  to be large what should be the small value that is decided by the probability of the type one error.

So, in the same way here you are seeing that if  $\mu_0$  is less than  $\mu_1$  the reason is actually same, but how much it is same that will be dependent upon the probability of type one error. So, if we write here probability of  $\bar{x} \geq k_2$  then  $\mu_1$  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 here by 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  $Z$  greater than or equal to some  $k$  is equal to  $\alpha$ , in place of  $k$  let me write here  $k^*$  where  $Z$  is defined to be  $\sqrt{n}(\bar{x} - \mu_0)$ . So, this point  $k^*$  becomes the upper hundred  $\alpha$  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.

So, as a practical example if we substitute different values here say  $\mu_0$  is equal to minus 1 then there is  $X_n$  region is changing the  $\sqrt{n}(\bar{x} + 1)$  greater than or equal to  $Z_\alpha$ . We have seen the example of here.

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

That if I am putting say  $\alpha$  is equal to 0.05 then  $Z_\alpha$  is equal to 1.645. So, the test will become in that case  $\sqrt{n}(\bar{x} - \mu_0)$  greater than or equal to 1.645, this is the rejection region. So, if I say  $\mu_0$  is equal to say minus 1 then this will become  $\sqrt{n}(\bar{x} + 1)$  greater than or equal to 1.645. If we compare with the previous example where  $\mu_0$  was 0 then it was  $\sqrt{n}\bar{x}$  greater than or equal to 1.645. So, the magnitude of  $\bar{x}$  which will be considered to be large depends upon the probability of the type one error. And that means, what is a 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 square. Now once again let us write down the density function here;  $f(x)$  sigma square, so we need to write for the joint distribution 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  $X_1, X_2, \dots, X_n$  turns out to be this one.

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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 to 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 square is equal to sigma naught square 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  $\frac{1}{(\sqrt{2\pi}\sigma_1)^n} e^{-\frac{1}{2\sigma_1^2} \sum x_i^2}$  to the power minus 1 by 2 sigma 1 square sigma xi square.

So, if you consider the ratio  $f_1(x)$  by  $f_0(x)$  that is equal to. So, now this will become 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 loss 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  $f_2$  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  $\sigma_0^2$  and  $\sigma_1^2$  are the known constants, this condition is gone.

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Handwritten notes on a blue background:

$$\frac{1}{2} \left( \frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2} \right) \sum x_i^2 \geq k_1$$

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

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

$$P_{\sigma_0^2} \left( \sum X_i^2 \geq k_2 \right) = \alpha$$

$$P_{\sigma_0^2} \left( W \geq k^* \right) = \alpha$$

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

Right side notes:
   
 $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} N(0, \sigma^2)$ 
  
 $\frac{\sum X_i^2}{\sigma^2} \sim \chi_n^2$ 
  
 Under  $H_0$ 
  
 $W = \frac{\sum X_i^2}{\sigma_0^2} \sim \chi_n^2$

A graph of the  $\chi_n^2$  distribution is shown with a vertical line at  $k^*$  and the area to the right shaded as the rejection region.

And if you take the logarithm then we get it as this condition is equivalent to  $\frac{1}{\sigma_0^2} \sum x_i^2 \geq k_1$  by  $\frac{1}{\sigma_1^2} \sum x_i^2$  square minus  $\frac{1}{\sigma_0^2} \sum x_i^2$  square greater than or equal to some  $k_1$ .

Now, once again the relative position of  $\sigma_0^2$  and  $\sigma_1^2$  is playing a role here. Suppose I take  $\sigma_0^2$  to be less than  $\sigma_1^2$ , then this will be equivalent to  $\frac{1}{\sigma_0^2} \sum x_i^2$  greater than  $\frac{1}{\sigma_1^2} \sum x_i^2$  square. Therefore, the region will be equivalent to  $\sum x_i^2$  greater than or equal to say  $k_2$ . Where, this  $k_2$  as to be chosen in such a way that  $\sum x_i^2$  greater than or equal to  $k_2$  as a probability equal to  $\alpha$  when  $\sigma_0^2$  is equal to  $\sigma_1^2$ . So, the condition becomes  $\sum x_i^2$  greater than or equal to  $k_2$  when  $\sigma_0^2$  is equal to  $\sigma_1^2$  is equal to  $\alpha$ .

So, in order to find out the value of  $k_2$  we need to look at the distribution of  $\sum x_i^2$  when  $\sigma_0^2$  is equal to  $\sigma_1^2$ . So, we look at our statement here  $X_1, X_2, \dots, X_n$  they followed normal  $0, \sigma^2$ , and therefore if we consider

$\frac{\sum_{i=1}^n x_i^2}{\sigma^2}$  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  $\frac{\sum_{i=1}^n x_i^2}{\sigma_0^2}$  that follows chi square distribution on  $n$  degrees of freedom.

So, we can write down this statement as  $w \geq k$  is equal to  $\alpha$ . Since  $w$  is following chi square and distribution the point  $k$  becomes upper hundred  $\alpha$  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  $\frac{\sum_{i=1}^n x_i^2}{\sigma_0^2}$  is greater than or equal to  $\chi^2_{n, \alpha}$ .

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  $\frac{\sum_{i=1}^n x_i^2}{n}$  is a estimator we have actually calculated the maximum likelihood estimator, so that is an estimator for  $\sigma^2$ . So, as a Neyman you will based your decision on the value of  $\frac{\sum_{i=1}^n x_i^2}{n}$ . That means, for a smaller value of  $\frac{\sum_{i=1}^n x_i^2}{n}$  we will 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  $\frac{\sum_{i=1}^n x_i^2}{n}$  should be considered a small or large that is decided by the probability of the type one error. So, if the probability of the type one error is  $\alpha$  the relative position of  $\frac{\sum_{i=1}^n x_i^2}{n}$  is decided by  $\chi^2_{n, \alpha}$  and  $\sigma_0^2$ , and of course the value  $\sigma^2$  also plays a role. Because if  $\sigma_0^2$  is much smaller compare to  $\sigma^2$  then that value will play a 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 binomial distribution. So, this is a very general result, because I can consider any distribution and if we have a simple versus simple hypothesis. In fact, it is

not even necessary that we have a same form of the distribution as we have seen in the first example, where under the null hypothesis we had a uniform distribution and under the alternative hypothesis we had another distribution which was having the density  $2x$ .

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 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 maximum likelihood estimator as we have seen in the example of the normal distribution; where for a  $\mu$  you are in terms of  $\bar{x}$  and for  $\sigma^2$  we when we are doing the test then it is coming in terms of  $\sum x_i^2$ .

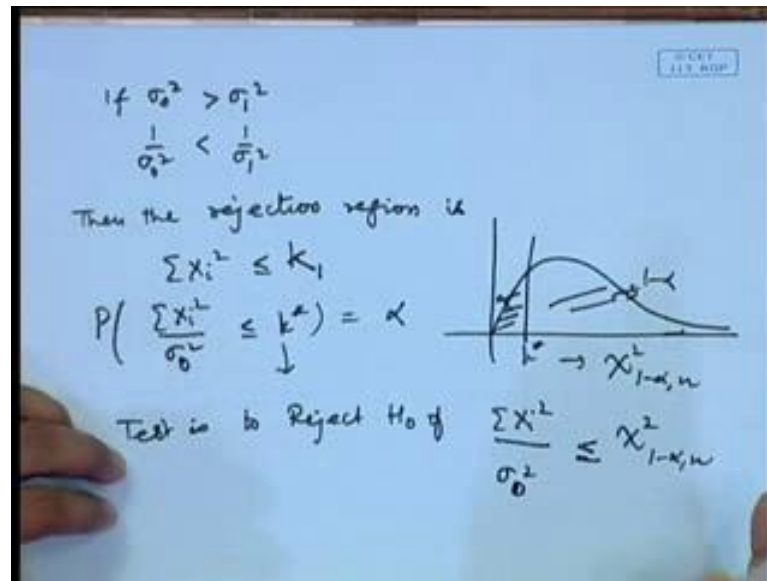
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$x_1, \dots, x_n$   
 $f(x, \lambda) = \begin{cases} \lambda e^{-\lambda x}, & x > 0, \lambda > 0 \\ 0, & \text{else} \end{cases}$   
 $H_0: \lambda = 1$   
 $H_1: \lambda = 2$   
 $f(x, \lambda) = \begin{cases} \lambda^n e^{-\lambda \sum x_i}, & x_i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

Naturally we can check for certain other distributions also such as say let  $X_1, X_2, \dots, X_n$  this follow an exponential distribution with some parameter say  $\lambda$ . Before I discuss this example let me take the other case also where  $\sigma^2$  may be greater than  $\sigma_0^2$ , then let us see how we are distinguishing.



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If sigma naught square was greater than sigma 1 square then 1 by sigma naught square is becoming less than 1 by sigma 1 square. 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 square is less than or equal to k say k 1 or let me put in another way in place of. So, once again we will have probability of sigma xi square by sigma naught square less than or equal to some k star 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 minus alpha. So, this k star in this case becomes chi square 1 minus alpha n. That means, the test is to reject H naught if sigma xi square by sigma naught square is less than or equal to chi square 1 minus alpha n.

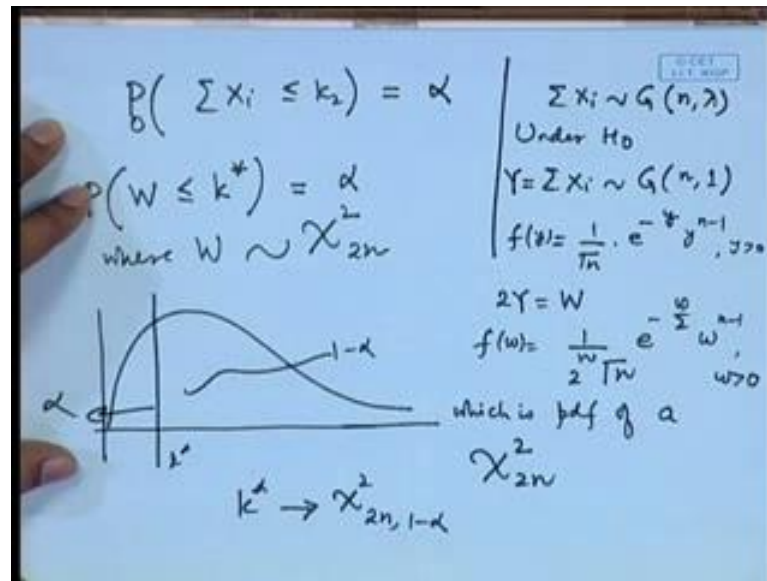
So, you can see here that the region as got reverse, why because now the null hypothesis supports a larger value of sigma square; that is sigma naught square I have taken to be bigger than sigma 1 square. So, a smaller value of sigma xi square will be favor of the alternative hypothesis which is against the previous case where higher values are supporting the alternative hypothesis. And once again that on the relative scale that how much value of sigma xi square will be considered very larger or a smaller that is determined by the probability of the type one 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 distributions which are different than the normal distribution etcetera we may get a statistic where the distribution of the statistic which is appearing in the test function may not be simple. Then we 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  $f(x)$  by  $f(x)$   $\lambda$   $x$ ; so here, the joint distribution  $f(x)$   $\lambda$  that becomes  $\lambda$  to the power  $n$   $e$  to the power minus  $\lambda$   $\sum x_i$  when all the  $x_i$ 's are positive it is 0 elsewhere. So,  $f(x)$  will be correspond to the value of  $\lambda$  is equal to 2 then this becomes 2 to the power  $n$   $e$  to the power minus twice  $\sum x_i$  divided by; when I put  $f(x)$  that is corresponding to  $\lambda$  is equal to 1 I will get  $e$  to the power minus  $\sum x_i$ .

So, we are saying the test is reject  $H_0$  if this is greater than  $k$ . Once again we have loss of generality we may include equality here or we may delete equality, because the distribution of  $x_i$ 's are continuous therefore the distribution of  $\sum x_i$  will also be continuous. In fact, we know the distribution of  $\sum x_i$  here. Firstly, let us simply this. So, this region is equivalent to if we take this in the numerator it is reducing to  $\sum x_i$  greater than or equal to some  $k$ , because this coefficient we can remove. And when we take logarithm this is reducing to  $\sum x_i$  less than or equal to some  $k$ .

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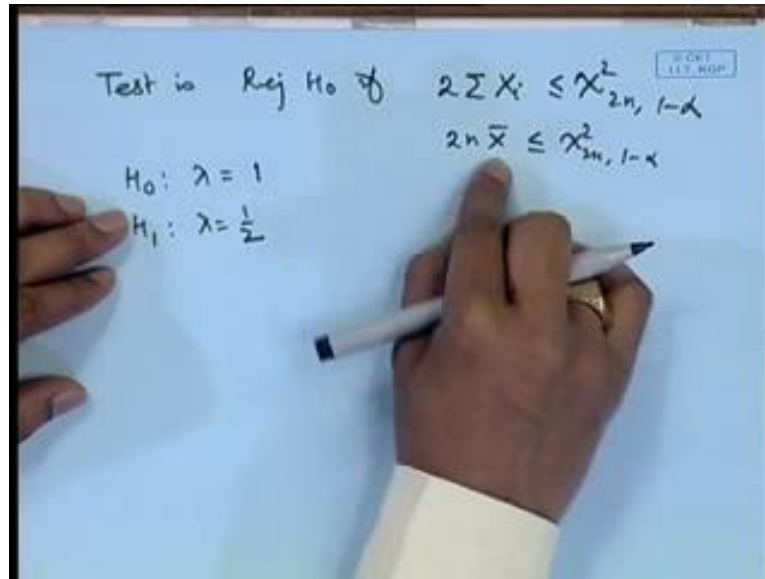


Now, we have to find out the value of  $k_2$  such that the probability of type one error that is  $\sum x_i$  less than or equal to  $k_2$  is equal to  $\alpha$ . So, we make use of the distribution theory; here as I was mentioning  $\sum x_i$  will follow gamma distribution with parameters  $n$  and  $\lambda$  by the additive property of the exponential distribution. The sum of independent exponential variables is a gamma variable. So, under  $H_0$   $\sum x_i$  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 square 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, it is  $w$  is having a chi square 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 square  $2n, 1 - \alpha$ .

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So, the test function then becomes reject  $H_0$  if twice sigma xi is less than or equal to chi square  $2n(1-\alpha)$ . Let us again analyze this statement in a practical sense.

Here lambda is the rate of the Poisson process, so basically the mean was 1 by 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 reciprocal of that. 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 would have been  $\bar{x}$  which is of course proportional to summation of the values here. So, you may even write it in this particular form, this is actually equal to twice in  $\bar{x}$ .

So, 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 a smaller. So, the mean is represented or you can say estimated by the sample mean. So, for the sample 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 you are considering say 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 a smaller, sorry mean is larger and in the alternative hypothesis the mean is smaller. That means, when we are using the sample mean as an estimate of that for by smaller value of the sample mean we will tend

to favor the alternative hypothesis. And for the larger value we will tend to favor the null hypothesis. And the relative significance of how much is larger or how much is bigger is dependent upon the probability of the type one error, as well as the value of  $\lambda$  is equal to 1 and  $\lambda$  is equal to 1 has been utilized here

On the other hand, if we had say  $H_0: \lambda = 1$  against say  $H_1: \lambda = \frac{1}{2}$ . Suppose just I made the change here then what will happen, in the case of the null hypothesis you will have a same value whereas in the for the alternative hypothesis this will become half and this will become  $e^{-\frac{\sigma^2 x^2}{2}}$ . So, in that case in the numerator we will get  $e^{-\frac{\sigma^2 x^2}{2}}$  with give a positive sign. And then the test function will become  $\sigma^2 x^2$  is greater than or equal to something rather than less than something.

So, when we analyze this we get here that test would be to reject for larger value of  $\bar{x}$ , which is natural because when I say  $\lambda = \frac{1}{2}$ . That means, I am saying  $\frac{1}{2}$  by  $\lambda = 2$  which is bigger than  $\frac{1}{2}$  by  $\lambda = 1$  here. So, you can also see that in the Neyman-Pearson Lemma it the test which we are obtaining it by using the theory of most powerful test they are conforming to a Neyman approach or you can say 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.