

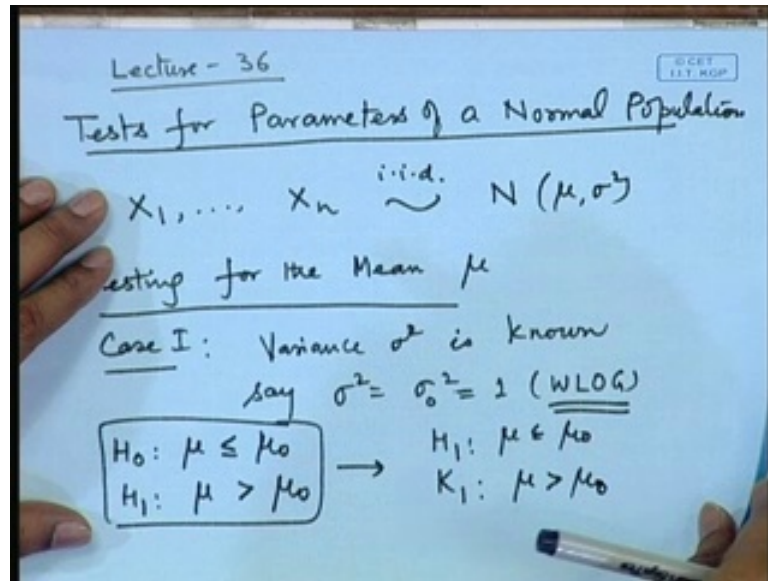
Probability and Statistics
Prof. Dr. Somesh Kumar
Department of Mathematics
Indian Institute of Technology, Kharagpur
Module No. #01

Lecture No. #36
Testing of Hypothesis IV

Now, more general situations will correspond to the test of simple versus composite hypothesis or composite versus composite hypothesis. So, to handle such situations, the generalization of Neyman Pearson Lemma was carried out and using concepts of the distribution satisfying monotone likelihood ratio property, there were uniformly most powerful test for certain hypothesis, certain composite versus composite hypothesis or certain simple versus composite hypothesis. And even then for there were situations where, when we have nuisance parameters and we do not have the uniformly most powerful test.

In certain situations the concept of unbiasedness in the test was introduced we had the concept of similar test, and so uniformly most powerful unbiased test are uniformly more powerfully invariant test have been studied. Another approach for testing is through like likelihood ratios and various tests have been discovered for new situations also. The theoretical derivations of the test for all these situations, will be part of another course called statistical inference in this particular course we will discuss only the applications of the test for parameters of normal distribution the test for proportions etcetera. So, let me begin with the test for the parameters of normal distribution where the testing problems may be composite.

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So, let us take the case of say testing for the mean. So, consider the situation say X_1, X_2, \dots, X_n following normal μ, σ^2 . So, we have a random sample from a normal distribution with parameters μ, σ^2 , we may be testing for the mean μ . So, there may be two cases, as in the case of confidence intervals we have the case when σ^2 that is variance σ^2 is known or unknown. So, if the variance σ^2 is say known, say $\sigma^2 = \sigma_0^2 = 1$ (WLOG) without loss of generality is equal to 1, without loss of generality you may take it to be 1 also.

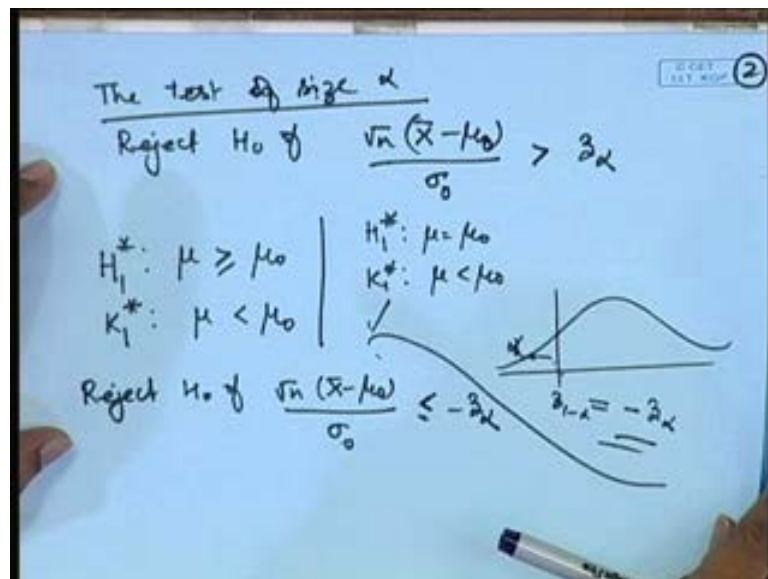
In this case now, let us go back to the application of the NP lemma, what we have observed here, that the test function is based on the value of \bar{X} , we have considered the testing for normal μ, σ^2 , when μ is equal to say μ_0 and against μ is equal to μ_1 . So, we also observed that if μ is less than μ_0 then, you reject for larger values of \bar{X} then μ is not as greater than μ_0 then you reject for the smaller values of \bar{X} . So, that gives rise to the general situation such as say $H_0: \mu \leq \mu_0$ or equal to μ_0 , against $H_1: \mu > \mu_0$. So, the situation may be like this that, we are having certain efficiency level certain measurement regarding a previous procedure.

Now, a new procedure is adopted and we want to see whether, the efficiency or the measurement or the effectiveness etcetera has decreased or increased corresponding to

the previous one or μ_0 may be a control kind of variable, so you want to test whether the value or you can say the mean is better than the control or worse than the control. So, accordingly we may say the null and alternative hypothesis. So, we may interchange the roles also, but let me take up this case in particular I will be considering four types of hypothesis. So, for convenience let me give some names to this, because I will be describing them in detail.

So, I will give a new notation to this, I will call H_1 as μ is less than or equal to μ_0 and K_1 is μ is greater than μ_0 , where null hypothesis is denoted by H_0 and the alternative hypothesis is denoted by K_1 .

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Now, we have already seen that, the test function is dependent upon of the value of \bar{X} . So, the test will be, so there will be various situations in this particular case we have uniformly most powerful test, since we have not introduced the concept of uniformly most powerful or uniformly most powerful unbiased, I will not be utilizing this terminology here, instead will be just mentioning the kind of the test that you are having.

So, the test is reject H_0 if $\sqrt{n}(\bar{X} - \mu_0) / \sigma_0 > z_\alpha$. So, if you have $\sigma_0 = 1$, then you need not put it here, so this is greater than z_α .

So, the test of size α is reject H_0 if this is so, once again whether you will include equality here or not does not make any difference, because the size does not change, because \bar{X} is a continuous random variable, in fact this random variable under H_0 is having a standard normal distribution, and that is why the probability point of the distribution has turned out to be as a z_{α} point.

Now, from here itself we can look at the other situation also for example, here if I have $\mu \geq \mu_0$ and here I will put $\mu < \mu_0$. So, accordingly the situations can be altered here, another point is I may put here say H_1 as $\mu = \mu_0$ against K_1 $\mu > \mu_0$.

Will the test change? The test will not change, because what we are testing is whether the value of mean is less or more, in the null hypothesis it is less, in the alternative hypothesis it is more, only the relative position is important, but that is determined by the test statistics or you can say the test function, because the value of the control is utilized here.

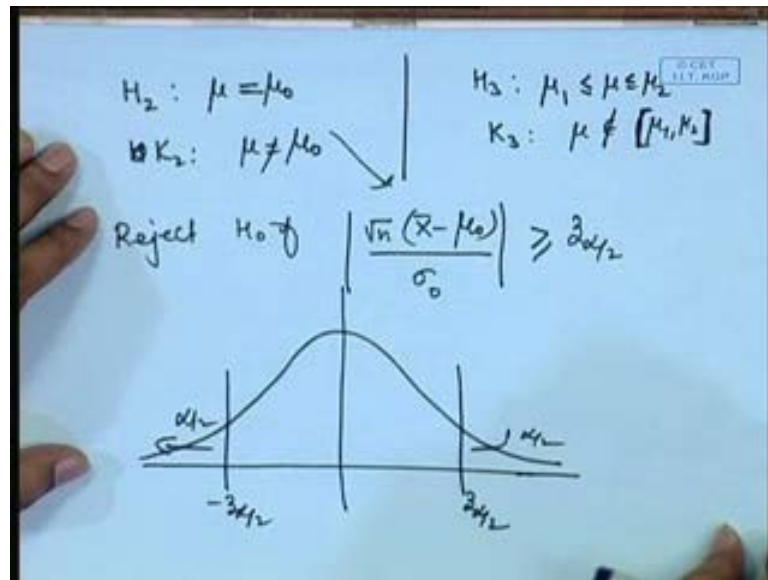
So, whether you say $\mu \leq \mu_0$ or $\mu = \mu_0$ does not play much role here in the test function, the test function will remain the same. On the other hand, if I have considered say H_1 say $\mu \geq \mu_0$ against say K_1 that is $\mu < \mu_0$, then the nature of the null and alternative hypothesis has got reversed.

So, you will be actually rejecting for smaller values of \bar{X} and when the size α is fixed then, the problem the point that you will be getting here, **this will become the** this probability will become α , so this point will be $z_{1-\alpha}$, but in the normal distribution $z_{1-\alpha}$ is equal to $-z_{\alpha}$.

So, this is reducing to then reject H_0 , if $\sqrt{n}(\bar{X} - \mu_0) / \sigma_0$ is less than or equal to $-z_{\alpha}$, once again whether you include equality or not that does not play any role here. And likewise, once again since the relative position is important therefore, H_1 $\mu = \mu_0$ against K_1 $\mu < \mu_0$ will also have the same test for hypothesis here. A point about the actual application here, when we observe a random sample then the value of \bar{X} can be calculated and therefore, the value of the test statistics which we call $\sqrt{n}(\bar{X} - \mu_0) / \sigma_0$ can be found out from the sample.

And therefore, and the value of z alpha can be seen from the tables of the normal distribution therefore, the test function is a or you can say it is very precise kind of test here, one can easily find it out here in the given situation. Now, we may have a situation of different type.

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For example, we may like to test let me give another name say H_2 μ is equal to μ_0 naught, against say K_2 μ is not equal to μ_0 naught. Now, this kind of situation occurs for example, we are looking at the error in the measurements, so if there is no error that means, your measuring device is unbiased then, may be μ is equal to zero. On other hand, if it is biased then you will have either μ is less than zero or μ is greater than zero. Suppose we are completely unaware of whether it is biased or unbiased, so we may not like to test whether μ is greater than zero that is over biased or unbiased, we do not have interest in under estimation or over estimation. So, we simply want to know whether it is biased or unbiased, in that case a test statistic of this form will be or you can say a test null and alternative hypothesis of his nature will be framed.

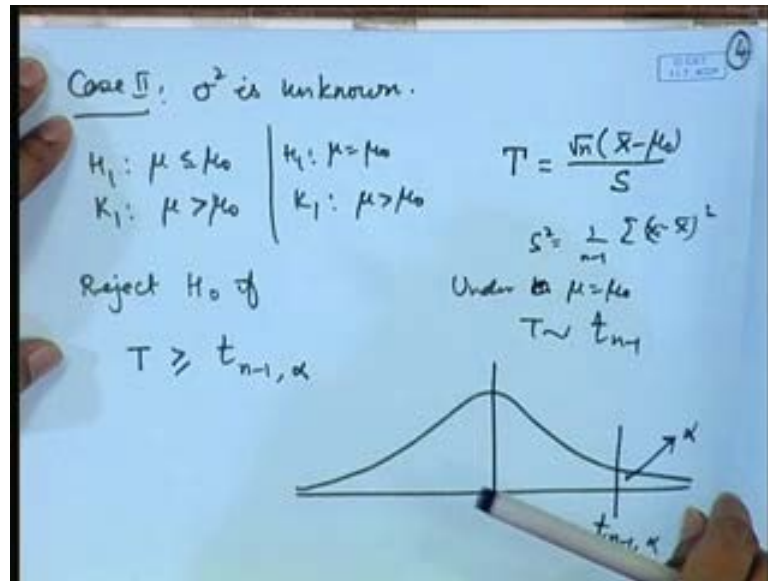
So, of course from the theory of testing of hypothesis when is a generalized Neyman Pearson Lemma etcetera applications of that, we get a uniformly most powerful test here once again let me not utilize a this terminology here. So, here what happens that you are going to accept let me write another one, which is parallel to this something like saying μ_1 is less than or equal to μ less than or equal to μ_2 , against K_3 when μ does

not belong to this interval μ_1 to μ_2 . If we see actually there is not much difference between the hypothesis, H_2 versus K_2 or H_3 versus K_3 as far as the theory of Neyman Pearson Lemma is concerned, because all that we are concerned about is the nature of the mean here.

So, for example here we are saying mean lies in a range and against μ does not lie in that range. So, here we are saying it is equal to a value or not equal to a value in a sense actually this problem is a generalization here, because in place of one value if we say, a small range we say, we are permitting a variation from say minus 0.5 to plus 0.5 in the measuring device, then in that case a more practical hypothesis will be something like minus half to plus half, against whether μ is having more variability in the measuring device than that.

So, likewise the test for both of this will be same and therefore, the test will be something like you will be rejecting for both large negative as well as large positive values of \bar{X} . So, test function will be reject H_0 if $\sqrt{n}(\bar{X} - \mu_0) / \sigma_0$ is greater than or equal to $z_{\alpha/2}$. Why is this $z_{\alpha/2}$ has come because, if we are looking at the probability of the type one error here, then you are having a rejection in both the regions. So, this point has to be then $\alpha/2$ and this point has to be minus $z_{\alpha/2}$. Now, difficulty will arise when σ is unknown, because in that case I will not be able to make use of this σ_0 value here.

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So, in that case what we do sigma square is unknown. As, you remember the case of the confidence interval the sigma square value was replaced by its estimate that is s square. So, if we do that then the test function will be dependent upon a T distribution, because in that case root n X bar minus mu naught by S that will have a T distribution on n minus 1 degrees of freedom when mu is equal to mu naught is consider to be proof.

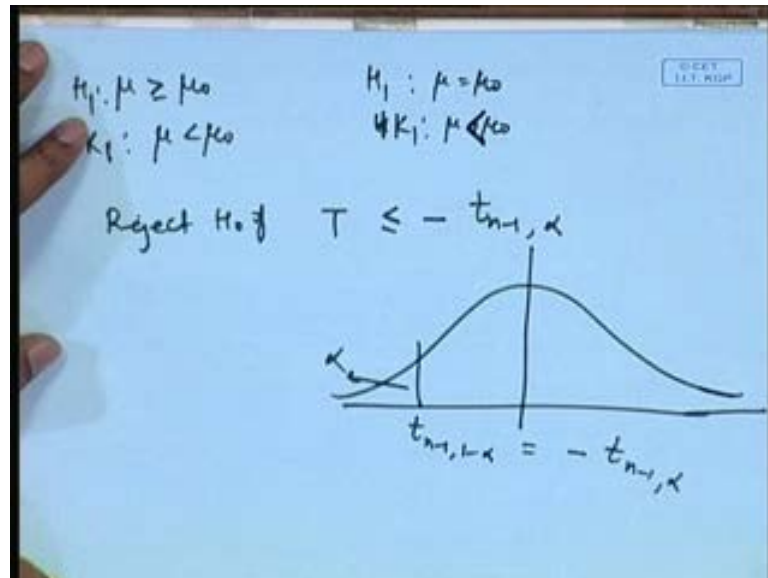
So, let me take the hypothesis problem say, H 1 that is mu is less than or equal to mu naught, against say K 1 mu is greater than mu naught or a variation of it that is mu is equal to mu naught, against say mu is greater than mu naught, then the test will be based on, so let me redefine statistic t that is equal to root n X bar minus mu naught by S, where S square is 1 by n minus 1 sigma X i minus X bar whole square. Then under H naught that is when mu is equal to mu naught T follows a T distribution on n minus 1 degrees of freedom.

So, what happens the test will become reject H naught, if T is greater than or equal to t n minus 1 alpha. Like the standard normal distribution T distribution is also a symmetric distribution, so if we keep this probability as alpha then t n minus 1 alpha 1. **will be becoming**

So, when this T value crosses this value then we reject H naught. So, you can see that the nature of the test has not change much, because it is still dependent upon X bar however

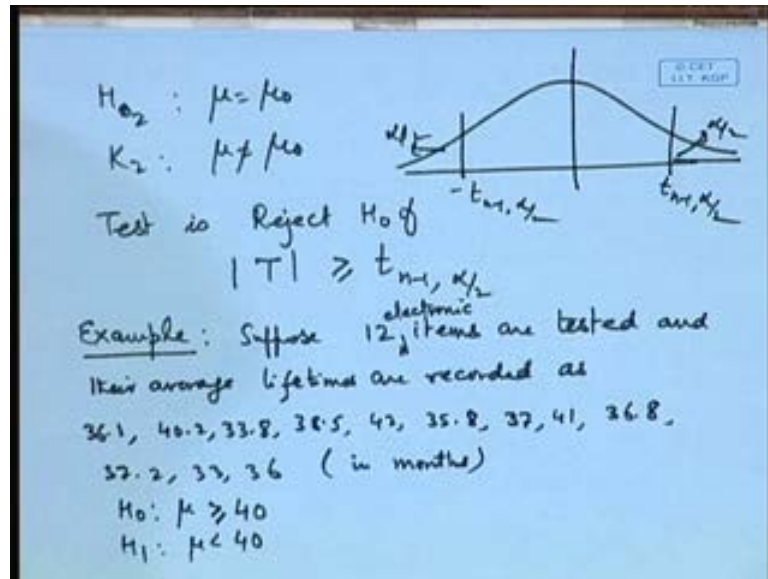
earlier the scaling factor was known, now it is unknown, so we have to replace it by an estimate of that that is calculated from the sample here.

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So, likewise if we get the reverse of the hypothesis say, μ is greater than or equal to μ_0 , against say μ is less than μ_0 or a variation of this could be $H_1: \mu = \mu_0$, against $\mu > \mu_0$ sorry $\mu < \mu_0$ then the test will be reject H_0 if less than or equal to minus $t_{n-1, \alpha}$. Because, if we are looking at the point on the T distribution here, then this probability is now α , so this point becomes $t_{n-1, 1-\alpha}$, because of the symmetry of the T distribution this becomes minus $t_{n-1, \alpha}$ here.

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In a similar way we can consider the case of two sided hypothesis that is H_2 say we use a notation say $H_2: \mu = \mu_0$ against, say $K_2: \mu \neq \mu_0$. Then the test will be reject H_0 , if modulus of T is greater than or equal to $t_{n-1, \alpha/2}$. This has happened because now, we have the rejection begins on both the sides. And therefore, this probability will become $\alpha/2$ now, so this point will becomes $t_{n-1, \alpha/2}$, this is $t_{n-1, \alpha/2}$.

Let me take one example here, suppose 12 items are tested and their average lifetimes are recorded as say 36.1, 40.2, 33.8, 38.5, 42, 35.8, 37, 41, 36.8, 37.2, 33, 36. Suppose certain electronic items are tested and this is in months.

Now, the claim here is that the average life is at least 40, against say $H_1: \mu < 40$. Now, if you want to do the test of hypothesis at a certain level of significance here then we will be making use of the T variable here.

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$$\begin{aligned}\bar{x} &= 37.2833 \\ s &= 2.7319 \\ T &= \frac{\sqrt{n}(\bar{x} - 40)}{s} = \frac{\sqrt{12}(37.2833 - 40)}{2.7319} \\ &= -3.4448 \quad t_{11, 0.05} \\ T &\leq -t_{11, 0.05} \quad t_{11, 0.95} = -t_{11, 0.05} \\ &= -1.796 \\ \text{We reject } H_0 &\text{ at 5\% level of significance.} \\ \text{Event at 1\% level we will reject } &H_0.\end{aligned}$$

So, for example here you can calculate \bar{x} turns out to be 37.2833, the s value turns out to be 2.7319, say the T value that is $\sqrt{n}(\bar{x} - 40)$ divided by s , that is $\sqrt{12}$ into $37.2833 - 40$ divided by 2.7319 . This value turns out to be minus 3.4448.

So, now the test function will be to reject H_0 if this value of T is less than or equal to $t_{n-1, \alpha}$ that is 11 at α . So, suppose here I take α is equal to 0.05, so we may consider $t_{11, 0.05}$, that is equal to minus $t_{11, 0.05}$, that is equal to minus 1.796, this we can see from the tables of the T distribution. Now, you see here T is less than or equal to $t_{11, 0.05}$. So, we reject H_0 at 5 percent level of significance. Suppose, we change the level of significance to another value, we make take say ten percent, let us see the values of T distribution from, so in case we decide to modify the level of significance here as say 0.1 or 0.01 etcetera. So, add that t value you can see here suppose in place of this we make 0.01, then you can see the value of T is 2.718, but this value minus 3.44 is a even smaller than that.

So, event at say 1 percent level we will reject H_0 . So, now you can see here the manufacturer of the items claims that the average life is more than or equal to 40 months, but his sample that does not support the hypothesis, because you can see from here the values are much smaller, another point is that \bar{X} is 37 which is of course less than 40, but it is really significantly smaller. So, the answer is yes because the standard deviation

also does not help too much it is 2.73. ((So, we with)) the 12 observations you are getting this value to be pretty high that is pretty negative value. On the other hand if we had tested something like.

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$H_0: \mu = 40$
 $H_1: \mu \neq 37$

$$\frac{\sqrt{n}(\bar{x} - 37)}{s} = \frac{\sqrt{12} \cdot 0.2833}{2.7319} = (\quad)$$

at 1%, 5% we will not reject H_0 .

Suppose, we want to test here H_0 say μ is equal to 40 against say H_1 in place of 40 suppose I put 37 against say μ is not equal to 37. Then, if you look at the value of $\sqrt{n}(\bar{X} - 37) / s$, that is $\sqrt{12}$ that becomes 0.2833 divided by 2.7319 , this value is much smaller and in fact, at say 1 percent or 5 percent etcetera we will not reject H_0 .

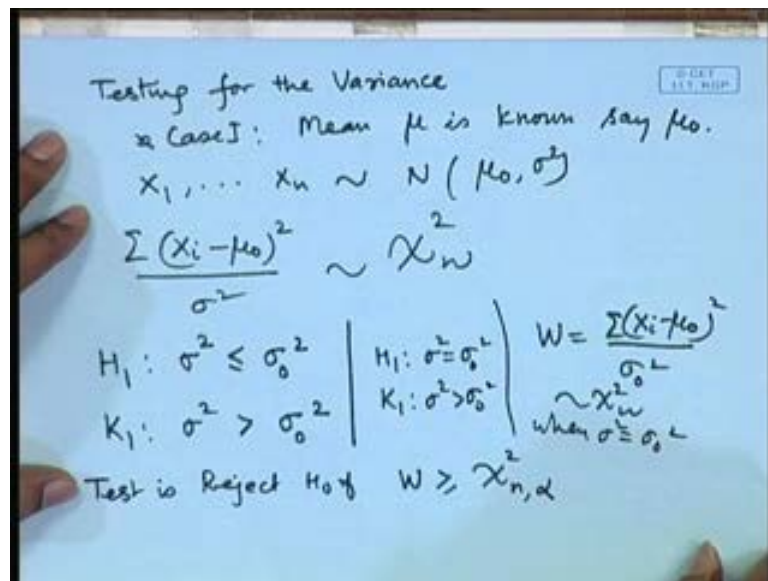
For example if we are looking at say 5 percent level says. So, 5 percent means we have to see the value of 0.025 here at 11, that is 2.201 which is pretty high. And this value will be much smaller, because if we are looking at $\sqrt{12}$ this value will be say three something and this is 1.5 , so this value will be become 0.3 something which is much smaller. So, even if you take say 0.1 , so the 0.05 you have to see that is 1.796 etcetera. So, all these values you will be you not able to reject H_0 . Why, because the value μ is equal to 37 is pretty close to the sample mean here, and the variance also support that in the sense that the value of this is not too small. If, the variability was extremely small then even this different would have become large here.

Now, in a similar way one can go about testing for the variance of a normal distribution. Now, once again we have seen here that the variability of the normal distribution was

tested in the Neyman Pearson Lemma setting by $\sum X_i^2$, that means how much the value of $\sum X_i^2$ is becoming it is more or less kind of thing.

So, when we consider the composite hypothesis for σ^2 , we will be basing decision on the distribution of $\sum X_i^2$ as we know the distribution of $\sum X_i^2$ by σ^2 is chi square, so we will actually be getting a chi square test.

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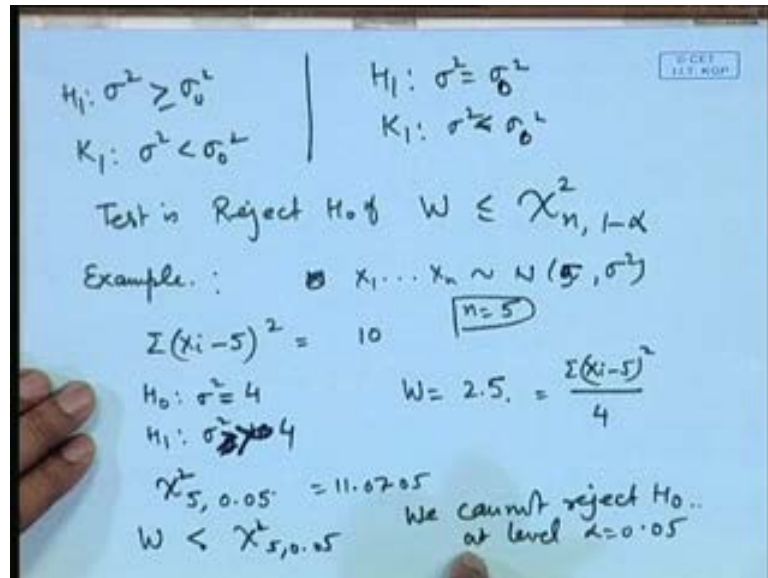


So, let us consider two different cases testing for the variance. When we are doing the testing for the variance let us write down the model here say mean is known, say μ_0 . So, we are having X_1, X_2, \dots, X_n following normal μ_0, σ^2 . Say if we go back to the setting of normal zero, σ^2 we can actually consider $\sum (X_i - \mu_0)^2$. So, summation of this that divided by σ^2 that will follow chi distribution on n degrees of freedom.

So, we make look at the hypothesis of the form say $H_1: \sigma^2 \leq \sigma_0^2$ against, say $K_1: \sigma^2 > \sigma_0^2$. So, when $\sigma^2 = \sigma_0^2$, we may consider $\sum (X_i - \mu_0)^2 / \sigma_0^2$. So, this will follow chi square distribution on n degrees of freedom when $\sigma^2 = \sigma_0^2$. So, we may use the test as reject H_0 if W is greater than or equal to $\chi_{n, \alpha}^2$.

The similar argument will be valid if I am considering sigma square is equal to sigma naught square against, sigma square is greater than sigma not naught square.

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So, if we consider carefully then, the reverse of this say sigma square is greater than sigma not naught square against, sigma square is less than sigma naught square, then the test will be reject H naught if W is less than or equal to chi square n 1 minus alpha. The same test will be valid if I use sigma square is equal to sigma naught square against, K 1 sigma square is less than sigma naught square. Because, what we are saying is sigma square is less or more and therefore, this is going to be useful.

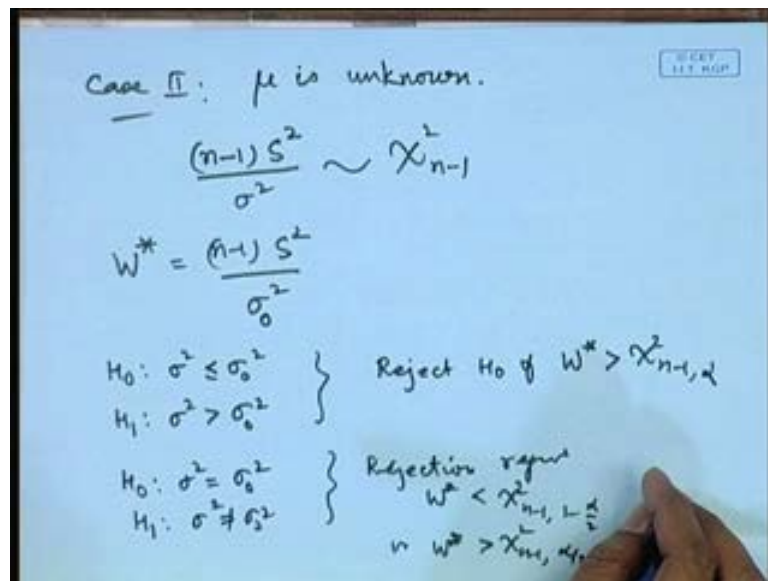
Let me take an example here. Suppose, the value of suppose we are considering say X 1, X 2, X N following normal 0 or if I could say 5, sigma square. And we are observing here, sigma X i minus 5 square is equal to say 10, we are testing the hypothesis say H naught sigma square is equal to say 4 against, H 1 say sigma square is equal to may be 10.

So, if you look at the value here W that value will become equal to 2.5, that is sigma of X i minus 5 square by sigma naught square that is 4 that is equal to 2.5. Now, we have to compare with the chi square value on, suppose I am taking n is equal to 5. Then, this I have to see this chi square 5 at alpha, suppose I say alpha is equal to 0.0 5. So, from the tables of the chi square distribution one may look at chi square 5, 0.0 5 as equal to 11.0 7 5. Naturally, you are getting W to be less than since we are testing here, so we may put

here greater than or equal to 4 say, this is equal to 4 and here greater than 4 suppose I am putting. So, the test is reject for larger value, so here W value that is 2.5 is less than chi square 5 0.05, so we can see here we cannot reject H_0 , at level alpha is equal to point 0.5.

Let us look at the interpretation of this, we are testing about the variability here that variability is equal to 4 or more than 4. Now, what is happening here is that $\sum (X_i - \bar{X})^2$ that is turning out to be 10. So, if you look at $\sum (X_i - \bar{X})^2$ by 2 that is $\frac{10}{2}$ by n which is the maximum likelihood estimator that will be equal to 2. So, if you are using that greater than estimator naturally, it is less than 4 therefore sigma square greater than 4 is not supported very much, and whether it is significantly not supported that we have to see from the probability of the type 1 error and here it turns out that actually we cannot reject H_0 .

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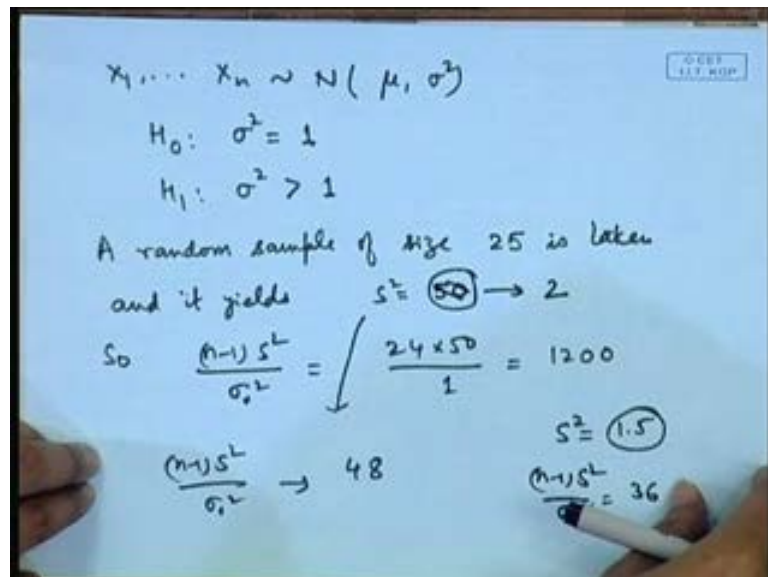


Now, let us consider the case of when μ is unknown. Then μ is unknown we cannot make use of W, in place of that we have to make use of the distribution of S square. So, $(n-1)S^2$ by sigma square follows chi square on $n-1$ degrees of freedom. So, let me call this statistic W star as $(n-1)S^2$ by sigma square sigma naught square here.

So, if we are testing the hypothesis say of the form, say $H_0: \sigma^2 \leq \sigma_0^2$ against, say $H_1: \sigma^2 > \sigma_0^2$ then the test function will be $W^* > \chi^2_{n-1, \alpha}$ if W^* is greater than $\chi^2_{n-1, \alpha}$.

Suppose, we are looking at two sided hypothesis $\sigma^2 = \sigma_0^2$ against, say $H_1: \sigma^2 \neq \sigma_0^2$, then the test function will be the rejection region will be $W^* < \chi^2_{n-1, \alpha/2}$ or $W^* > \chi^2_{n-1, 1-\alpha/2}$.

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Ah Let us look at the examples here. So, we want to test the hypothesis whether the sigma square is equal to 1 against sigma square is greater than 1. So, a random sample of size 25 is taken, and it S square is equal to say 50. So, if we are considering say $n-1$ S square by sigma naught square, then this value turns out to be 24 into 50 divided by 1 that is equal to 1200.

You can easily see that this value is extremely large, because S square is actually used as an estimate of sigma square, and this value 50 is much bigger than 1. Therefore, at any level of significance, which is practical the value of chi square will always be much smaller than 1200. On the other hand, suppose I am considering here the sample which gives say S square is equal to in place of 50 it value is turning out to be say something like say 2, then there is a change here because in the value of $n-1$ S square by

sigma naught square, in that case will become simply equal to 48. Now, if we are looking at the tables of the chi square distribution, one may easily observe the difference. Because chi square value and if I am looking at say 24 degrees of freedom, and here at a certain level of significance after 0.05 the value will cross this 1.

In fact, with little luck suppose I am taking say S square is equal to 1.5, then what will happen here n minus 1 S square by sigma naught square would become equal to 36, and here you can see even at say 1 percent level of significance the value is 36.19, and therefore we will not be able to reject H naught here. So, easily you can see that the acceptance or the rejection of the null hypothesis is dependent upon the of the type 1 error as well as the point sigma naught square or you can say theta is equal to theta naught in the null hypothesis that is used as a control here.

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

$$H_1: \sigma^2 \neq 2$$

$$S^2 = 2$$

$$n = 11$$

$$(n-1)S^2 = 20$$

$$\chi^2_{10, 0.05} = 18.30$$

Level $\alpha = 0.1$

$$W^* > \chi^2_{n-1, \alpha/2}$$

So H_0 is Rejected.

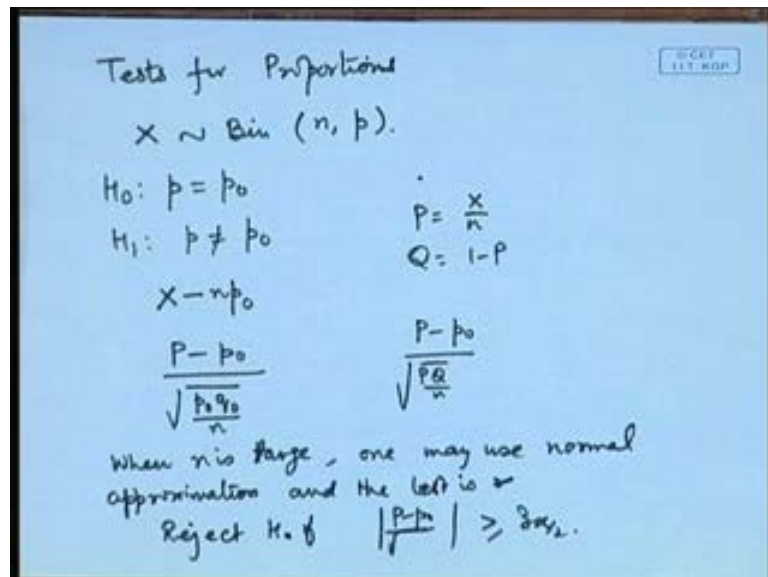
If we are considering say two sided here hypothesis. In that case, we may have something like say H not naught sigma square is equal to say 2 against say H 1 sigma square is naught equal to 2. Now, in this case what will happen, suppose I have observed say S square is equal to 2 itself? Then, if I have consider a sample of size n is equal to say 11, then you will have a n minus 1 s square is equal to 20.

Now, you look at chi square value on 10 degrees of freedom say at 0.05. Now, this value chi square 10 at 0.05 is equal to 18.30. So, here if I am considering say level alpha is

equal to 0.1, then you are seen that your W star is greater than chi square n minus 1 alpha by 2, so H naught is rejected.

Now, you may slightly wonder here that S square was 2 sigma square is equal to even then you are rejecting this. The region is that for the sample of size 11, if you are getting this value then there is a slight discrepancy, because chi square on 10 degrees of freedom is giving you a value, which is slightly smaller than this you are getting 18.30. So, this is even turning out to be in the rejection region. So, even a smaller value than this would have been supported here.

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Now, in the one sample problems we may consider tests for proportions. So, the setup is that we are observing a sample from Bernoullian trials. So, we may consider a sum and we have a setup like X following binomial n p distribution, and we may be interested in testing about say H not naught say p is equal to p naught against say H 1 p is naught equal to p naught.

Now, here we have seen we may consider the test statistics based on X, because the distribution of X is binomial. So, if we consider X minus n p naught. So, we may divide it by this, so we are dividing by p here, so p is equal to X by n. So, if we consider the value here to be P minus p naught divided by root p naught q naught divided by n then, we can use it as a test.

On other hand, one may use here the estimates of this also P minus p naught divided by root PQ by n , here P is this Q is 1 minus P . So, one may use either of these things and when n is large one may use normal approximations and the test is reject H naught, if z alpha by let me consider an example here.

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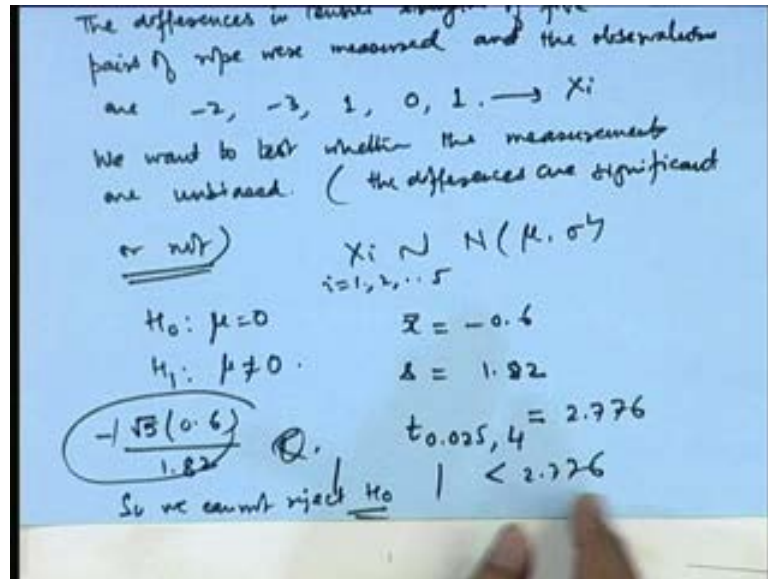
Handwritten calculations on a blue background:

- $n = 500$
- $X \rightarrow 41$
- $\hat{p} = \frac{41}{500} = 0.082$
- $\alpha = 0.05$
- Formula: $\sqrt{\frac{\hat{p}\hat{q}}{n}} \times z_{0.025}$
- Result: $= 0.024$
- Confidence interval for p : $(0.058, 0.106)$
- Hypothesis testing:
 - $H_0: p = \frac{1}{2}$
 - $H_1: p \neq \frac{1}{2}$
 - Naturally H_0 will be rejected
 - $H_0: p = 0.05$
 - $H_1: p \neq 0.05$
 - H_0 will be accepted at 5% level of significance.

Suppose, a random sample of 500 customers was considered, and here X is observed to be 41. Let us look at say p head and q head here. So, p head turns out to be 41 by 500 that is 0.082, see if you consider p head q head by n into say z 0.025 suppose I will take alpha is equal to 0.5 and this value turns out to be 0.024 say. So, if we are considering here the confidence interval say 95 percent confidence interval for p then that will be equal to 0.058 to 0.106.

So, easily you can see suppose I am testing here the hypothesis H naught p is equal to say half against H 1 p is say greater than half or p is naught equal to half, then naturally H naught will be rejected, you can easily see here the value is actually lying between 0.05 to 0.1. So, if I am testing the hypothesis p is equal to half then naturally it is will be rejected. On other hand if we are considering the hypothesis say p is equal to 0.05 against H 1 p is not equal to say p is greater than 0.5 sorry 0.05 or p is not equal to 0.05 then this will be accepted, this H naught will be accepted at 5 percent level of significance.

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Let me take one more example here, the differences in tensile strengths of five pairs of rope were measured and the observations are minus 2, minus 3, 1, 0, and 1. We want to see, whether the measurements are unbiased, that means the differences are significant or not.

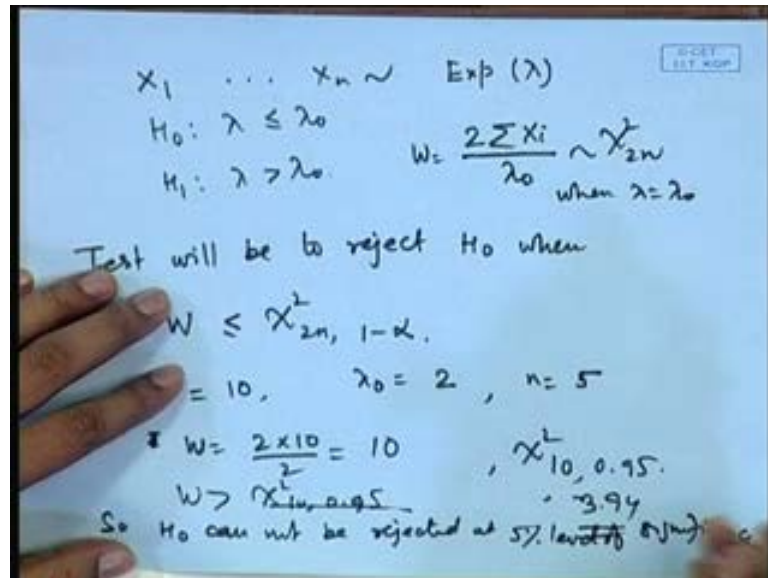
So, if you consider these values to be say X_i we may consider the model X_i follows normal μ sigma square, and the testing problem becomes for i is equal to 1, 2, 5, H naught whether the μ is equal to 0 or H_1 μ is not equal to 0. Now you see we need to calculate the mean etcetera, so \bar{X} bar is equal to minus 0.6 here say standard deviation turns out to be 1.82 say 2.

So, we need to look at root 5, since I am taking μ is equal to 0 then the test is about minus 0.6 divided by 1.82. Easily you can see suppose, I am seeing the value of t at say 0.025, that means I am making at test level of significance α is equal to 0.05 then this value is 2.776. Easily you can see that this value is less than this sorry if I am taking absolute value of this absolute value of this is less than 2.776.

So, we cannot reject H naught, that is also supported by this because here you are having 2 values which are slightly negative and 3 value 1 value is equal to 0 and 2 values are which are slightly positive. So, here you can see that, if I had calculated a 95 percent confidence interval for μ , then that would have included this value here. Now, this idea

of the extension of the Neyman Pearson Lemma to composite hypothesis can be applied to other distributions as well.

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Suppose, we are taking the example of say exponential distribution that we consider that X_1, X_2, \dots, X_n following say exponential distribution with parameter λ , and we are testing say hypothesis λ is less than or equal to λ_0 against say λ is greater than λ_0 .

We had already seen the interpretation of the λ here, which is reciprocal of the mean. So, we had seen that for the larger value of the mean, larger value of the sample mean, we will be having smaller value of the rate, that means we will tend to except H_0 . And for a smaller value of the mean we will be tending to reject H_0 that means, tending to go in favor of H_1 . And the test function we had devised in terms of a chi square distribution, because we had let use of $\sum X_i$, so we considered twice $\sum X_i$ if we consider twice $\sum X_i$ divided by λ_0 then, let me call it W then this will follow chi square distribution on $2n$ degrees of freedom when λ is equal to λ_0 .

So, the test function will be to reject H_0 when say W is, so since W is favoring H_1 by λ higher value. So, smaller value of $1/\lambda$ will become corresponding to less than or equal to chi square $2n, 1 - \alpha$.

Ah Let, us just take a example here. Where, σX_i turns out to be say ten we are testing about say λ naught is equal to say, 2 and say n is equal to say 5, and say then this test statistics could become equal to σX_i , so W will become equal to twice into 10 by 2 that is equal to 10. Now, if you look at chi square value of 10 at say 0.95 then the from the tables of chi square distribution, this value turns out to be equal to the value of the chi square at this will turn out to be at 10 degrees of freedom, if you look at 0.95 values 3.94. So, easily you can see that this W is bigger than this chi square 10.95, so H_0 cannot be rejected at 5 percent level here.

Here λ naught is 2 and if I am considering a natural estimator for $1/\lambda$, that will be equal to \bar{X} that is equal to 2. So, that value is not significantly different from this. So, we are testing whether this is less or not. So, then that is supported by the data here.

In the 4th coming lecture we will be considering when we are comparing two populations. So, we will be discussing tests for the differences of the means or the ratios of variances for two normal populations as well as, we will take of cases for comparing the proportions of two binomial populations, we will also look at the chi square test for the goodness of it etcetera.