Statistical Methods for Scientists and Engineers
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Lecture - 14
Parametric Methods - VI

In the last lecture, I introduced the concept of testing of hypothesis. We saw that Neyman Pearson approach in which they considered the probabilities of type 1 error and type 2 error and based on that the test procedures are devised in which we put a restriction on 1 type of error usually the type 1 error and we call it the size of the test and subject to the tests function satisfying the size of the test condition.

We find out those test which have the maximum power so they are called most powerful test as some solution was proposed for simple versus simple hypothesis cases and later on these procedures were extended to the case of certain type of composite hypothesis and then for certain type of composite hypothesis uniformly most powerful unbiased tests were also devised.

In place of giving the full details of the derivation of the test, I will be basically explaining to you the procedures that the test that have been obtained using this and how to use them.

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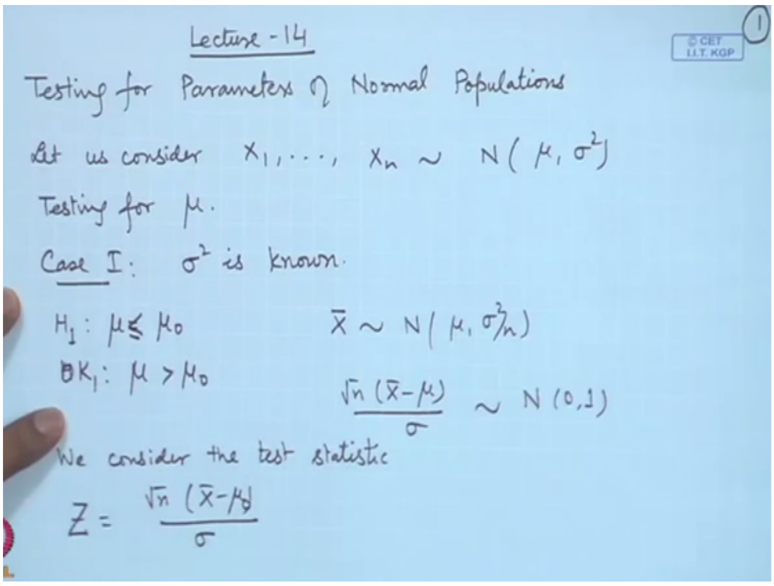

So let us consider testing for the parameters of normal populations. So let us consider X1, X2, Xn following normal mu sigma square distribution. We consider testing for mu. Now let us consider say case 1 when sigma square is known. Now we consider various kind of hypothesis. We consider say first problem. I will call the hypothesis testing problem says H1 K1 so H1 mu=say mu is <= mu 0 against say K1 mu>mu 0.

In this particular case, we consider X bar that is following normal mu sigma square/n so we consider root n X bar-mu/sigma that follows normal 0, 1. So we consider the test statistic Z=root n X bar-mu 0/sigma.

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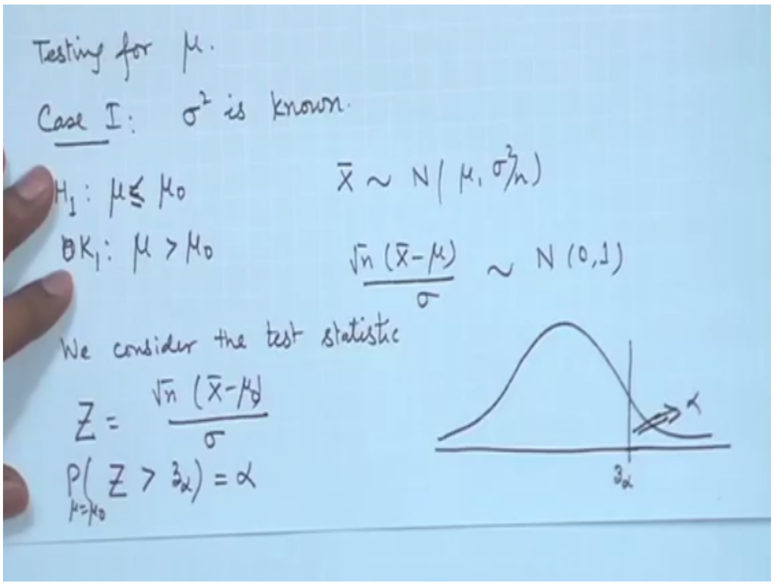

So if I consider this as z alpha then this probability is alpha, so if we consider probability of Z>z alpha=alpha and here we are considering mu=mu 0.

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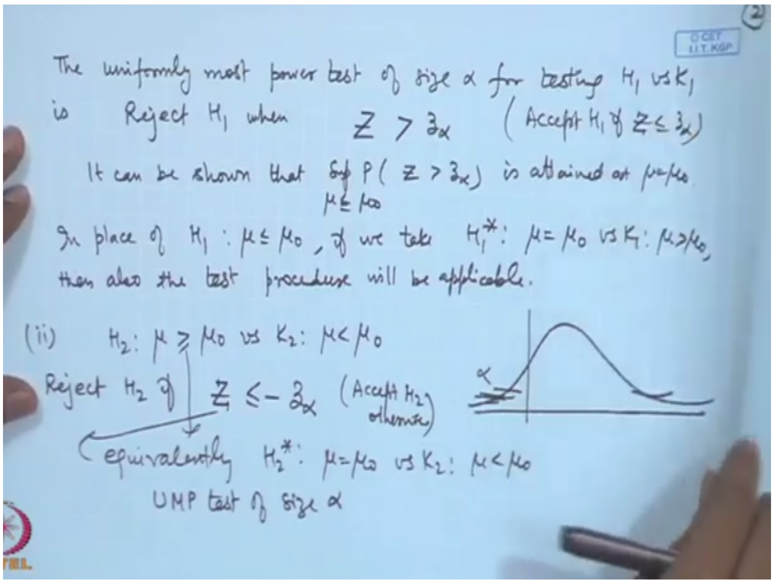

So the uniformly most powerful test of size alpha for testing H1 against K1 is a reject H1 when Z>z alpha where Z is given by root n X bar-mu 0/sigma. Actually, it can be shown that if I consider probability Z>z alpha then the supremum of mu <= mu 0 is attained at mu=mu 0. Therefore, this is the most powerful test of size alpha, so of course since this is composite hypothesis situation we will say it is the uniformly most powerful test here.

Now we have the variations, in place of H1 that is mu <= mu 0 if we take H1 star that is say mu=mu 0 versus K1 mu>mu 0 then also the same test procedure will be applicable. Now the main reason is that actually since here the maximization is occurring that mu=mu 0 therefore when the null hypothesis 2 mu=mu 0 will be coming here and in this case the maximum is occurring at that point and the power is decided by the alternative.

Therefore, the test function will not change and the test procedure will also not change. So you will say accept H1 if Z <= z alpha. Here equal to z alpha has no significance because the probability that Z=z alpha will be 0 because Z is a continuous random variable. Now naturally one may think what happens if we change the null and alternative hypothesis?

For example, here alpha is the maximum probability of type 1 error that means we are rejecting and the null hypothesis is true. Now if that is considered to be more serious for the beta, in that case you may like to interchange the hypothesis and we may consider so let me call it say H2 mu is >= mu 0 against K2 say mu<mu 0. I have interchanged the role of null and alternative hypothesis.

But the equality I have included in the null hypothesis. So in this case, we will be considering the rejection on the left side because you will be considering here. So you will consider reject H2 if Z is <= –z alpha and of course accept H2 otherwise. See in this case, this hypothesis is also equivalently we may test H2 star mu=mu 0 against K2 mu<mu 0.

Basically, once again if we are considering this one then the probability of say Z <= –z alpha. When mu=mu 0 that will be alpha and when we are considering for a general mu in this region then the maximum value will be attained when mu=mu 0 and therefore the size will be alpha so this is the uniformly most powerful test of size alpha. Now there may be situations where we may not like to test greater than or less than rather whether a value is equal or not.

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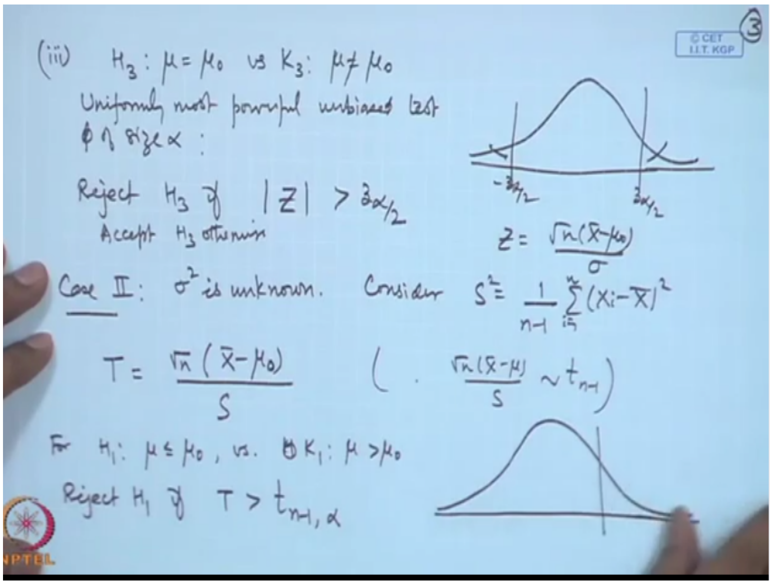

In that case, we formulate the hypothesis testing problem in the following fashion. We consider say H3 mu=mu 0 against K3 mu is not equal to mu. Now naturally in this case the rejection region will be on both the sides. So we consider say z alpha/2 and –z alpha/2. So you will consider actually this is uniformly most powerful unbiased test of size alpha. So that is reject H3 if modulus of Z>z alpha/2 where Z is the same quantity.

That is Z=your root n X bar-mu 0/sigma. So you are rejecting in this region and in this region and in the intermediate region you are in favor of the hypothesis accept H3 otherwise. Now in case sigma square is unknown, then naturally this Z cannot be used. If you remember the development of the confidence interval, there in place of sigma we had used S there where S square was 1/n-1 sigma Xi-X bar square.

That is the sample variance. So we consider the situation sigma square is unknown. Then consider S square=1/n-1 sigma Xi-X bar square. So we consider say T=root n X bar-mu 0/S. So if we consider say root n X bar-mu/S then that follows T distribution on n-1 degrees of freedom as we have seen in the confidence interval problem. So if we consider this mu replaced by mu 0 then the test statistic will be following a T distribution.

And we can consider the problems so for H1 mu <=mu 0 against say K1 mu>mu 0 then we will have the test as reject H1 if T>tn-1, alpha.

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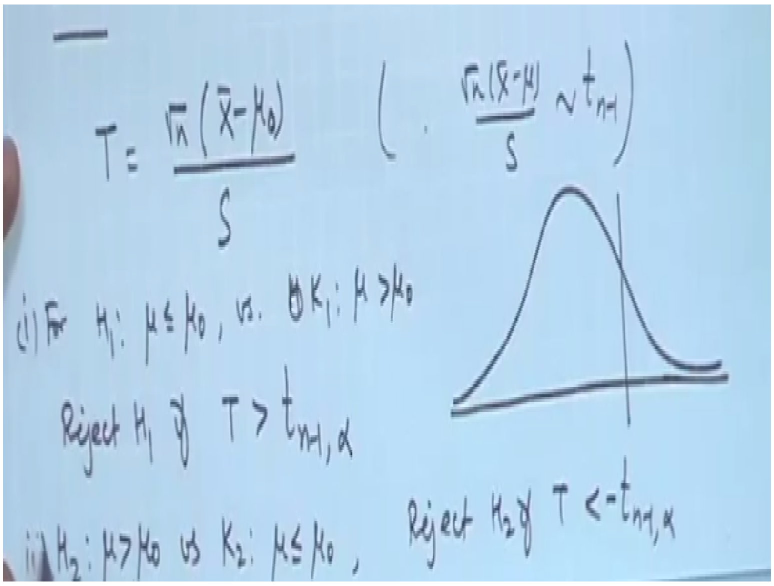

If we consider mu>mu 0 against K2 mu is <=mu 0 then the test will be reject H2 if T<tn-1, 1-alpha that is –tn-1, alpha because of the symmetry.

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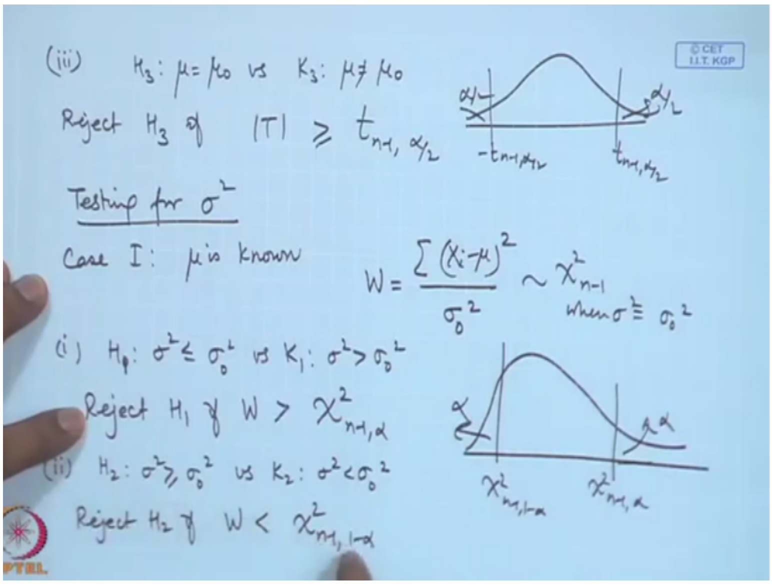

Then the third situation comes for the 2 sided tests that is for mu=mu 0 against mu is not equal to mu 0. Then we will consider reject H3 if modulus of T is >= tn-1, alpha/2. So you will have 2 sided rejection region here. This is alpha/2 and this is alpha/2. So these are the most powerful unbiased tests for the size alpha for these problems here. Now one may like to test for the variance also.

So if we consider the test for the variance, testing for sigma square and again you will have 2 cases, 1 case will be when mu is known. If mu is known, then we can consider sigma Xi-mu square/sigma 0 square. So if we consider this as W then this is following chi square distribution on n-1 degrees of freedom when sigma square=sigma 0 square. So if we consider the hypothesis testing problems based on this.

So for example let us consider say sigma square <=sigma 0 square against say sigma square>sigma 0 square then we will consider the rejection region as reject H1 if W>chi square n-1, alpha because chi square is Q distribution and we will have this situation here, chi square n-1, alpha so this probability is simply alpha. As I mentioned earlier, we can also consider sigma square=sigma 0 square.

And here sigma square>sigma 0 square, still the test function and the test region will be same and we may consider reverse situation sigma square >= sigma 0 square against K2 sigma square<sigma 0 square then the test procedure will be reject H2 if W<chi square n-1, 1-alpha. This probability is alpha, so this is not a symmetric distribution therefore we cannot write minus here.

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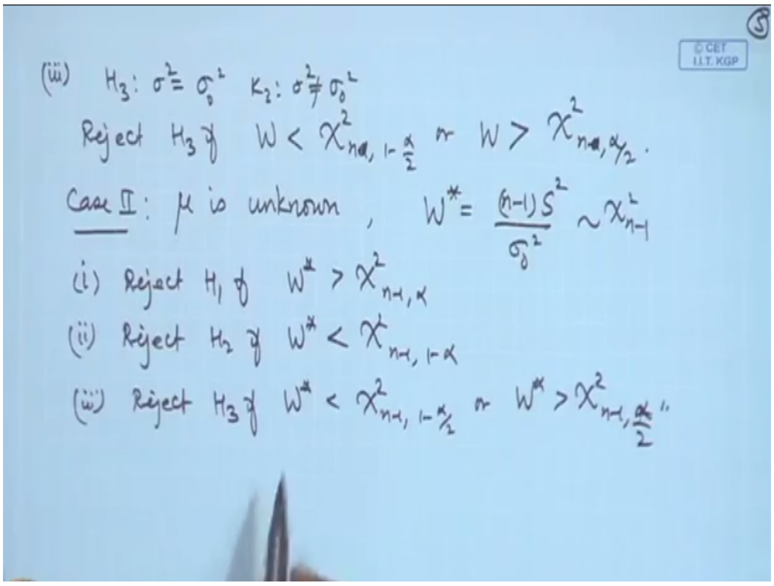

And we will have a 2 sided region if we consider sigma square=sigma 0 square against sigma square is not equal to sigma 0 square. So the test procedure will be reject H3 if W<chi square n-1, 1-alpha/2 or W>chi square n-1, alpha/2. So this will be uniformly most powerful test of size alpha here in the case 1 and 2 and in the case 3 it will be uniformly most powerful unbiased test of size alpha here.

Now in the case when mu is unknown then we base our decisions on let us call it W star that is n-1 S square/sigma 0 square so that follows chi square distribution.

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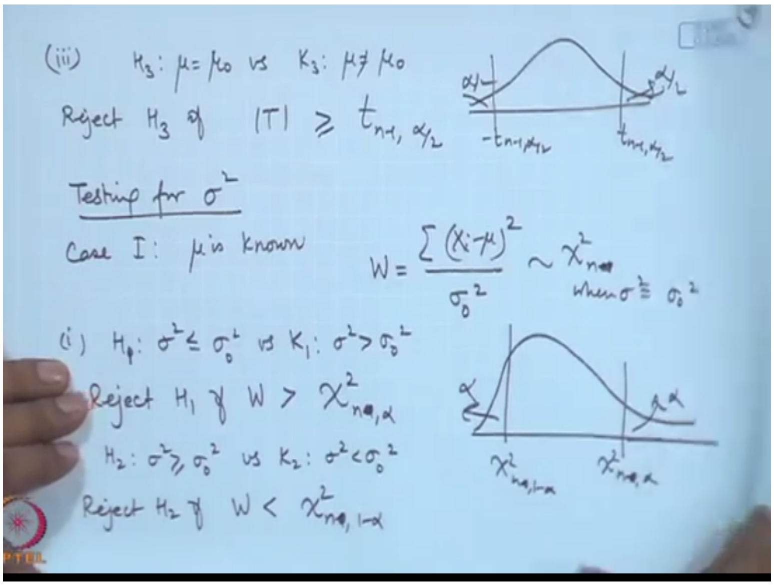

Actually, I made a mistake here this should be n here because this is following n, this will be n, this will be n. These are all will be n degrees of freedom. When mu is unknown then you will have n-1 degrees of freedom and then the test procedures will be for first case reject H1, in the second case it will be a reject H2 if W star< and in the third case reject H3 if W star<chi square n-1, 1-alpha/2 or W star>chi square n-1, alpha/2.

This is about the testing for the parameters of a 1 normal population. Now this type of methods can be applied actually to other distribution also in which certain nice properties for example if the distributions are in the exponential family, if the distributions are having monotone likelihood ratio even though they may not been in the exponential family, in all those situations this type of testing procedures are applicable.

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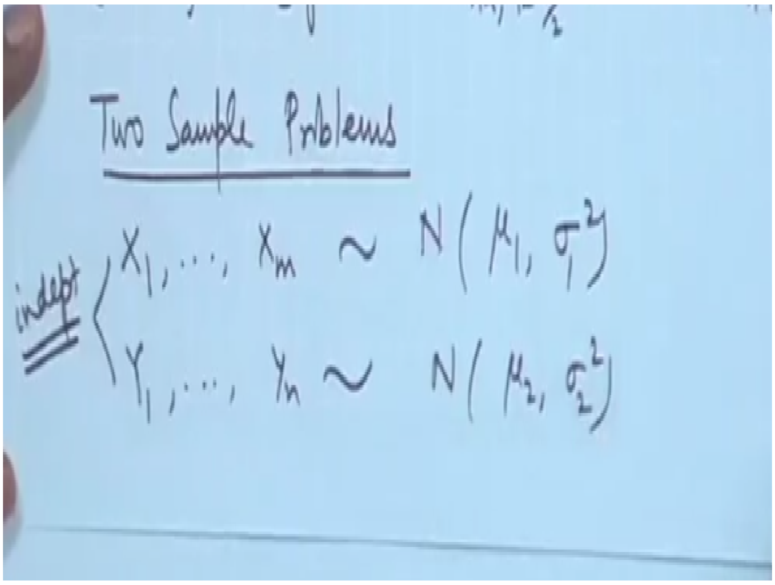

Now I will briefly touch upon the 2 population model for the normal populations. So we consider 2 sample problems like in the case of confidence intervals we have 2 samples available to us, 1 is from say a normal distribution with mean mu1 and variance sigma 1 square and another independent random sample that is available from normal with mean mu2 and variance sigma 2 square.

And these 2 samples are taken independently. Now we consider say parameters mu1, mu2, sigma 1 square, sigma 2 square, this could be our testing problems. Now you can say commonly used problems could be to test whether the mean of the first population is less than the mean of the second population or equal or greater than etc. that means we are interested in the difference here.

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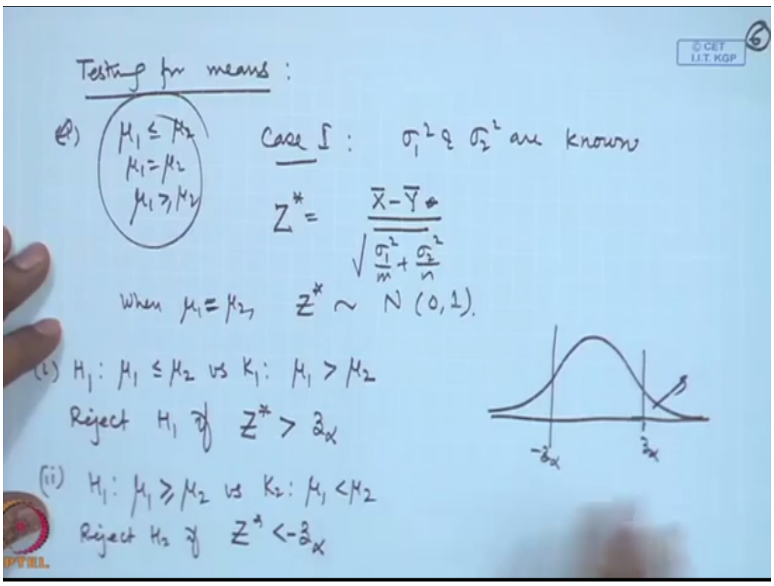

Now naturally this is a problem which can be handled easily using the Neyman Pearson theory. So we consider testing for means. If we consider the testing for means we may consider hypothesis problems of the nature say mu1 <=mu2, mu1=mu2, mu1 >= mu2 and so on. These are the types of hypothesis problems that we may have.

So again as before we consider case 1 when sigma 1 square and sigma 2 square are known. If sigma 1 square and sigma 2 square are known, then we consider the statistic of the form let me call it Z star=X bar-Y bar/square root sigma 1 square/m+sigma 2 square/n. Now when mu1=mu2 then Z star follows normal 0, 1. So we utilize this actually. In fact, it can be shown that the maximum of the probability of type 1 error will be achieved when mu1=mu2.

Let us consider various hypothesis testing problems here say mu1 <=mu2 against say mu1>mu2. Naturally, if in the alternative case we are saying mu1>mu2 that means we will be considering the rejection region on the larger side. So we will consider here that is z alpha so we will consider reject H1 if Z star>z alpha. In the second case, here we will be rejecting for the small values of Z star.

Now if you consider the small values and then on the left hand side we can consider z1-alpha=-z alpha so the rejection region will be reject H2 if Z star<–z alpha.

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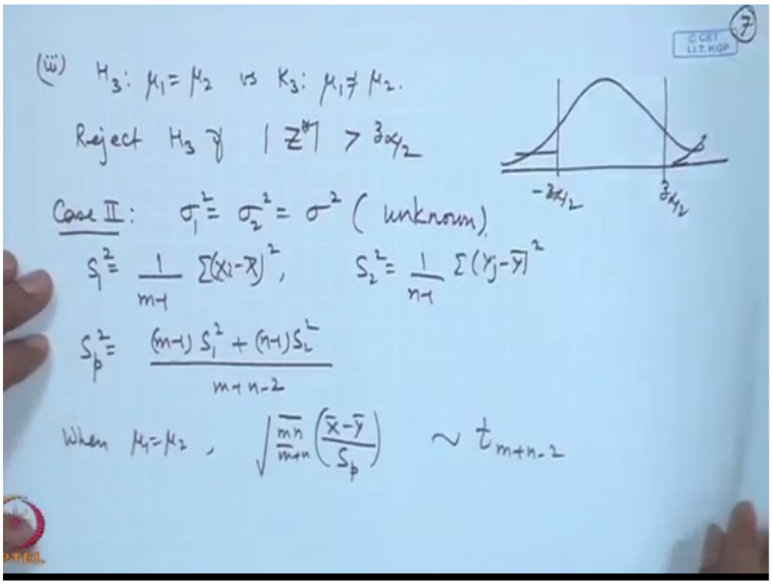

And once again for the 2 sided problem, we may consider this as H2 here so this will be H3 mu1=mu2 against K3 mu1 is not equal to mu2. So you will consider reject H3 if modulus of Z star>z alpha/2 that means we will be rejecting on both the sides of the normal curve that means if the value is in this zone or in this zone that is –z alpha/2. Now we can see that the second case when sigma square=sigma 2 square=say sigma square but this is unknown.

If this is unknown, then we formulate the test statistic. Now let me briefly mention about the large sample cases also. See if we look at the case that I discussed in the beginning here we are considering the approximation by the normal 0, 1. Now suppose the original distribution need not be normal.

But if we are considering the testing for the mean and we have large sample in that case we can consider by applying central limit theorem that this will be approximately normal 0, 1. So the test procedure that I have mentioned here will still be applicable for the large sample cases. However, when sigma square is unknown in that case this procedure will not be applicable.

Similarly, in this problem when I considered comparison of mu1 mu2 when sigma 1 square and sigma 2 square are known, in that case even if the original populations need not be normal then by central limit theorem this result will be applicable. However, when sigma 1 square, sigma 2 square are unknown, then this result central limit theorem will not be applicable and we are about to go for the exact procedures.

So let us consider here if we remember our notations that we developed for the confidence intervals that is we considered S1 square=1/m-1 sigma Xi-X bar square and we considered S2 square=1/n-1 sigma Yj-Y bar square and SP square was taken as m-1 S1 square+n-1 S2 square/m+n-2. Then based on this we had considered that when mu1=mu2 then you have X bar-Y bar*mn/m+n/Sp.

This has T distribution on m+n-2 degrees of freedom. Therefore, we can write down the tests for all the 3 situations and let me just repeat it again.

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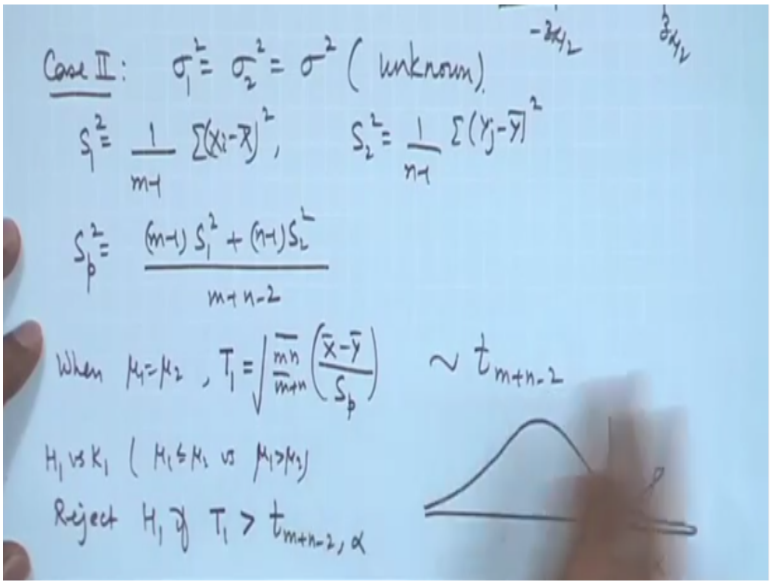

We are having the testing problems that is H1 versus K1 that is mu1 <=mu2 versus mu1>mu2, in this case your rejection region will be on the right hand side that is tm+n-2 alpha. So your region will be reject H1 so let us call this quantity say T1 so this is equal to T1>tm+n-2, alpha.

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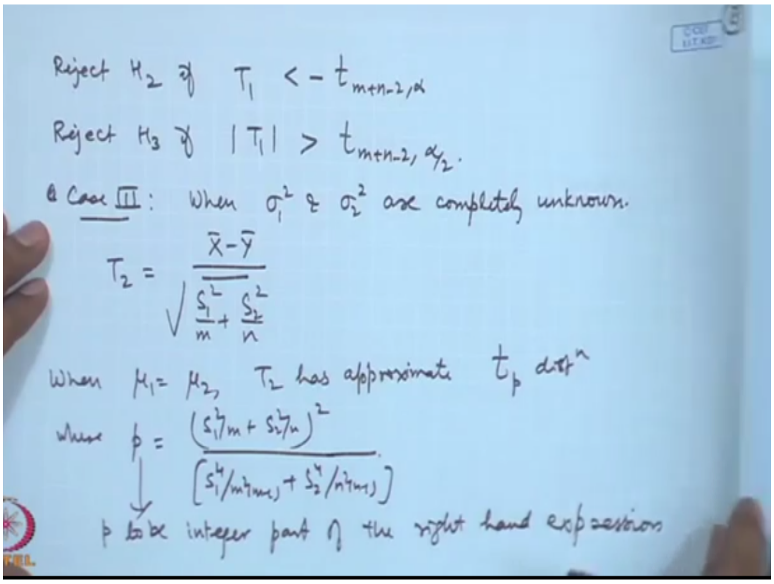

In the second case, you will be on the left hand side so you will say reject H2 if T1<-tm+n-2, alpha and for the 2 sided case, it will be reject H3 if modulus of T1>tm+n-2, alpha/2. Now the third case is when sigma 1 square and sigma 2 square are completely unknown. If they are completely unknown in this particular case, we consider say T2=X bar-Y bar/square root S1 square/m+S2 square/n.

When mu1=mu2 then T2 has approximate t distribution on some p degrees of freedom where p is given by S1 square/m+S2 square/n whole square/S1 to the power 4/m square*m-1+S2 to the power 4/n square*n-1. We usually take p to be integer part of the right hand expression.

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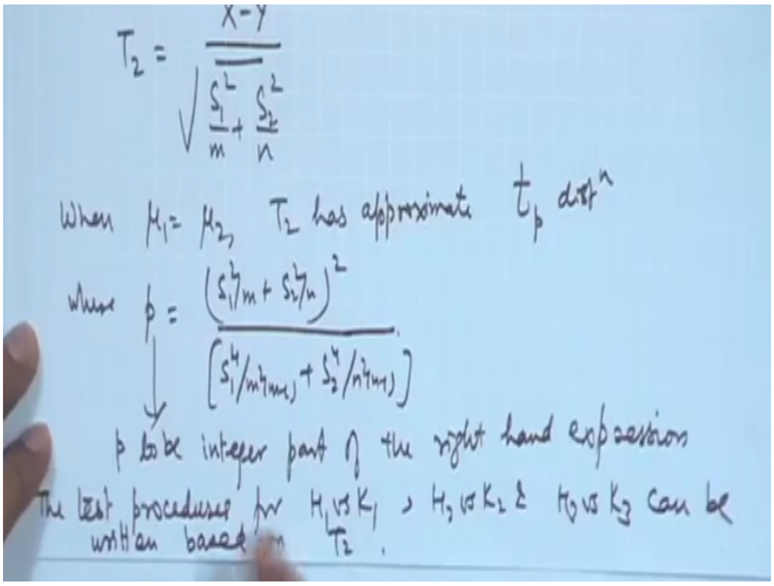

So the test procedures can be formulated. The test procedures for H1 versus K1, H2 versus K2 and H3 versus K3 can be based on T2. So I am not describing here for example in the first case it will be rejecting H1 if T2>tp alpha. Similarly, in the second case, it will be reject H2 if T2<-tp alpha and in the third case it will be reject H3 if modulus of T2>tp alpha/2.

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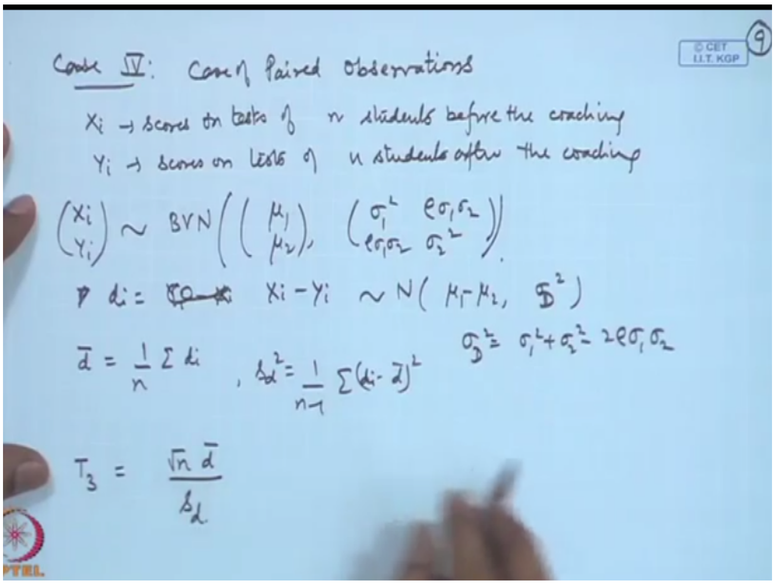

We had also considered a case of paired observations. In the confidence interval, I had described the situation that is where mu1 and mu2 are resulting from the same set of individuals or items for example it could be the certain learning procedure and we look at the ability of the candidates before conducting the learning procedure and after conducting the learning procedure after a certain time.

For example, you could say Xis are the scores on tests of n students okay before the coaching you can say and Yis are the scores on tests of n students after the coaching. In this case, we can consider say Xi, Yi this is following a bivariate normal distribution with some mean say mu1, mu2 and variances sigma 1 square, sigma 2 square and co-variances rho sigma 1, sigma 2.

So if we want to compare mu1 and mu2 we may as well consider say di=Yi-Xi or Xi-Yi say so then this will follow normal mu1-mu2 so I call it sigma D square where sigma D square is nothing but sigma 1 square+sigma 2 square-2 rho sigma 1 sigma 2. Now it is immaterial, we can actually consider our observations to be dis and we can calculate d bar that is 1/n sigma di.

And we can consider sd square as 1/n-1 sigma di-d bar whole square and we can formulate the test statistic let us call it T3=root n d bar/sd.

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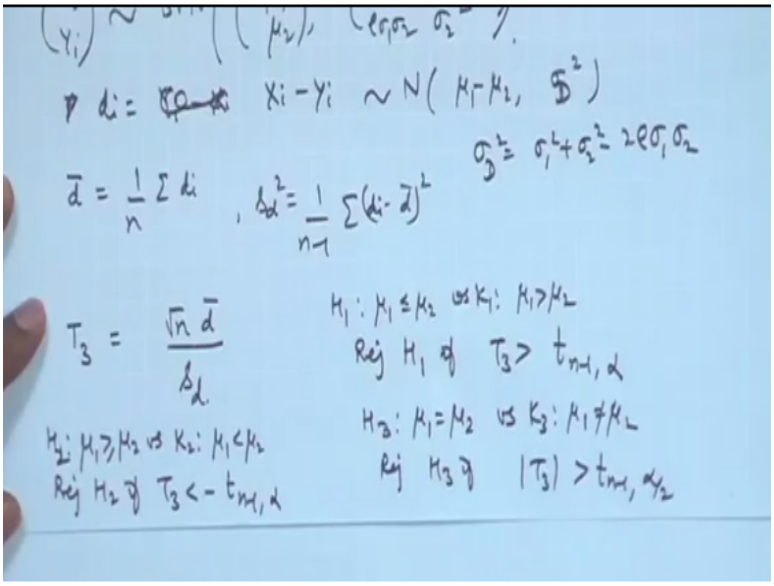

So the test procedure then for H1 that is mu1 <=mu2 versus K1 mu1>mu2. Once again you can see here it will be reject H1 if T3>tn-1, alpha. Similarly, if I consider H1 mu1 >= mu2 versus K2 mu1<mu2 then it will be reject H2 if T3<-tn-1 alpha. Similarly, if I consider the 2 sided testing problem, mu1=mu2 against mu1 != mu2, then the test procedure will reject H3 if modulus of T3 > tn-1 alpha/2.

So we have considered various cases for the comparison of the means of 2 normal populations. Let us also consider a case for comparison of the variances of 2 normal populations.

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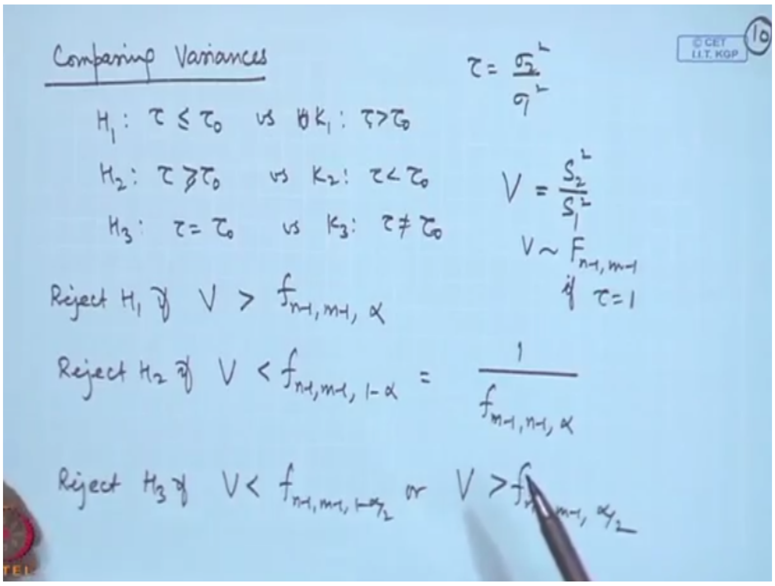

Comparing variances, so that means we may have a testing problem of the nature so let us write say tau=sigma 2 square/sigma 1 square. So we may consider say tau is <=say tau 0 against say tau>tau 0, tau<tau 0, tau=tau 0 against tau is not equal to tau 0. In all these cases, we may consider say S2 square/S1 square. Let us call it say V. Now hence sigma 1 square=sigma 2 square tau=1.

So then V will have F distribution on n-1, m-1 degrees of freedom if tau=1. Therefore, we can use this for the testing here. In the first case it will be reject H1 if now you can see here you have to reject for the large values of tau so large values of tau will correspond to the large values of V so if V>fn-1, m-1, alpha. In the second case, reject H2 if V<fn-1, m-1, 1-alpha which is of course equal to 1/fm-1, n-1, alpha.

In the third case, it will be 2 sided regions, if V<f n-1, m-1, 1-alpha/2 or V>fn-1, m-1, alpha/2. Of course, we may also consider the case when mu1 and mu2 are known. In that case, the only thing is that in place of S2 square/S1 square you can consider sigma Yj-mu2 square/sigma Xi-mu1 square and this F statistic will be replaced by fnm in rather than n-1, m-1.

So without spending too much time on that I will just skip that portion, so this is the case for the comparison of the variances. Now equivalently we may have testing problem for the proportions also.

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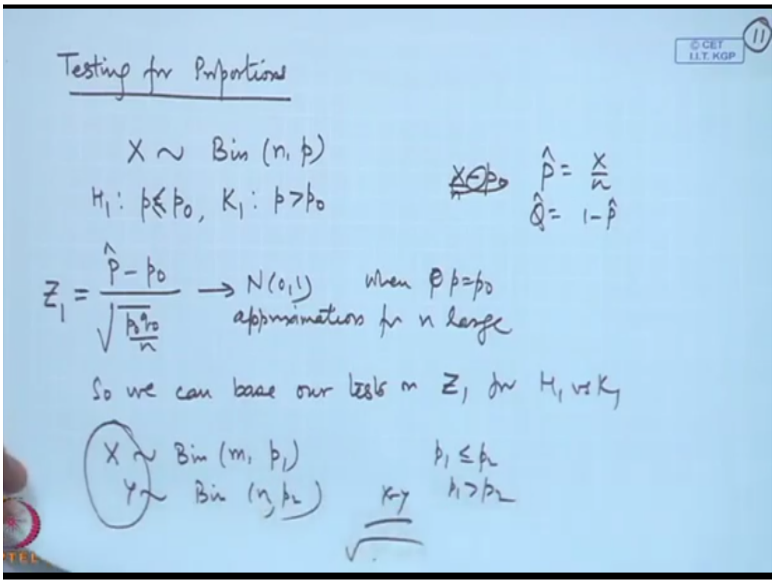

Testing for proportions, for example if I am considering say X following binomial n, p and we may like to test about say p=p0 or p <=p0 as before so we may consider the tests based on X-p0, let us write it as P hat=X/n and Q hat=1-P hat. So we may consider basing our tests on this. We can consider P hat-P0/root P0 Q0/n and we can consider the normal T for this thing.

That is when p=p0 then this is approximately normal 0, 1 okay. This is approximation for n large so let us write it say some Z1 so we can base our tests on Z1 for hypothesis H1 versus K1 or similarly we can consider p>p0 against p <=p0 etc. all those kinds of cases can be considered. We can also consider this situation X following say binomial m, p1 and Y following binomial n, p2.

And we may like to compare p1 <=p2, p1>p2 etc. So we can consider based on the differences X-Y and then we can consider the p1 q1 etc. So all those things can be done. I am not spending too much time on this problem here. Now the test that I have discussed here they are based on the Neyman Pearson theory. However, there was another approach which was considered by R.A. Fisher and others.

That is based on the likelihood ratio. In fact, Neyman Pearson came to the f1/f0 form based on the likelihood ratios only; however, the approach in a more general form can be described like this.

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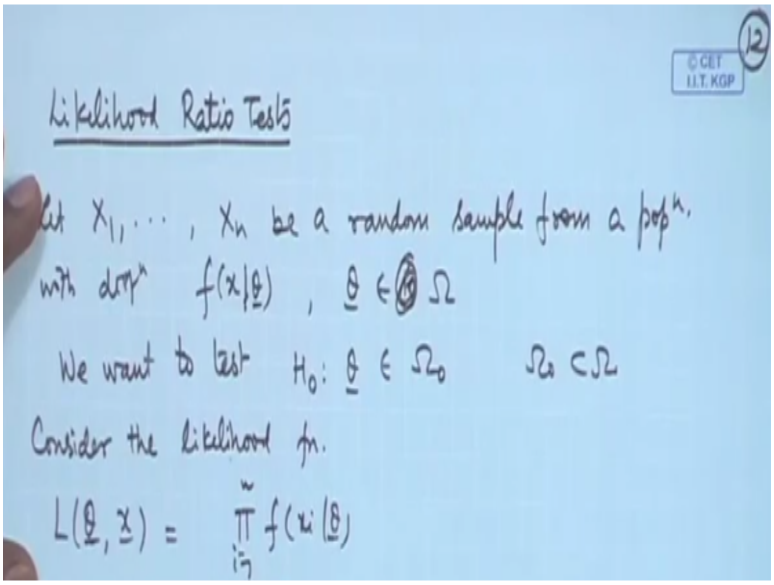

So let me mention this thing, likelihood ratio tests. Let us consider say X1, X2, Xn be a random sample from a population with some distribution. So it could be say fx theta we just write in general. Here theta belongs to some parameter space theta. We want to test H0 theta belongs to say omega 0. Let me just change the notation here this omega let me write here. So this omega 0 is the subset of omega.

As you have seen in all these problems like in the binomial problem p was lying between 0 to 1 so the parameter space was 0 to 1 but in the null hypothesis we are restricting attention to 0 to p0. If you consider the previous problems of normal populations etc for example here, you are writing sigma square=sigma 0 square but here your mu range is from – infinity to infinity and sigma square can be > 0.

So full parameter space is there but in the null hypothesis you are saying mu=mu is from – infinity to infinity but sigma square=sigma 0 square. So you are specifying a region. In the Neyman Pearson theory, it was essential to specify an alternative hypothesis but in the case of likelihood ratio test it is not required. That procedure is based on a simple argument that we consider maximization of the likelihood function under the full region and under the null hypothesis space.

And then we compare them so the logic is as follows. Consider the likelihood function L theta x=product of fxi theta.

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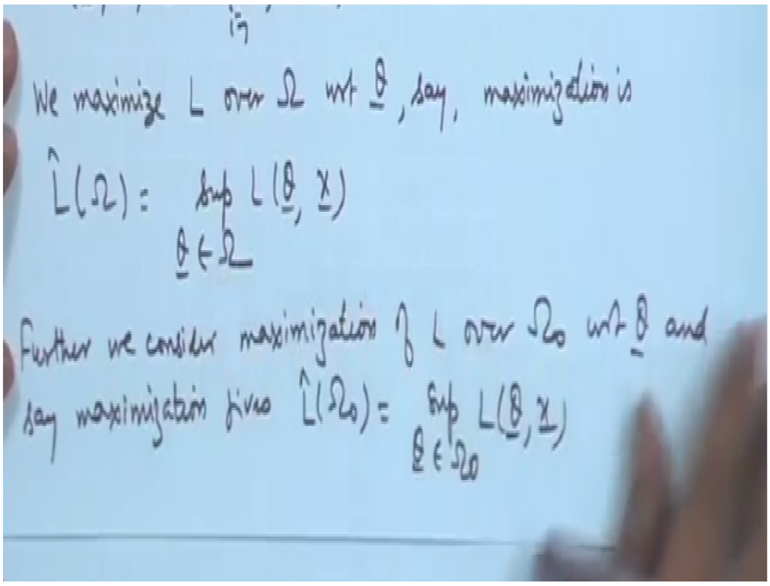

We maximize L over omega with respect to theta say maximization is L hat omega=supremum of L theta x for theta belonging to omega. Further we consider maximization of L over omega 0 with respect to theta and say maximization is L hat, I call it L hat omega 0 that is equal to supremum of L for theta belonging to omega 0.

Now you see if the hypothesis omega 0 is true that means theta belonging to omega 0 is true then the maximization of the likelihood function over this will be almost the same as the maximization over the whole space. You can of course notice from a simple mathematical argument that L hat omega 0 is always <=L hat omega because this is maximization over a subset and this is maximization over the whole space.

So we always have L hat omega 0 always <=L hat omega. So naturally if L hat omega 0 is closer to L hat omega that means we have more confidence in the hypothesis omega 0 that means the likelihood that H0 is true is more likely. However, if L hat omega 0 is much less than L hat omega then we have doubts over the correctness or being over H0 being true.

So therefore if we formulate the ratio L hat omega 0/L hat omega then for the smaller values of that we would tend to believe that H0 is not true. So this is the basic idea for formulating the likelihood ratio test.

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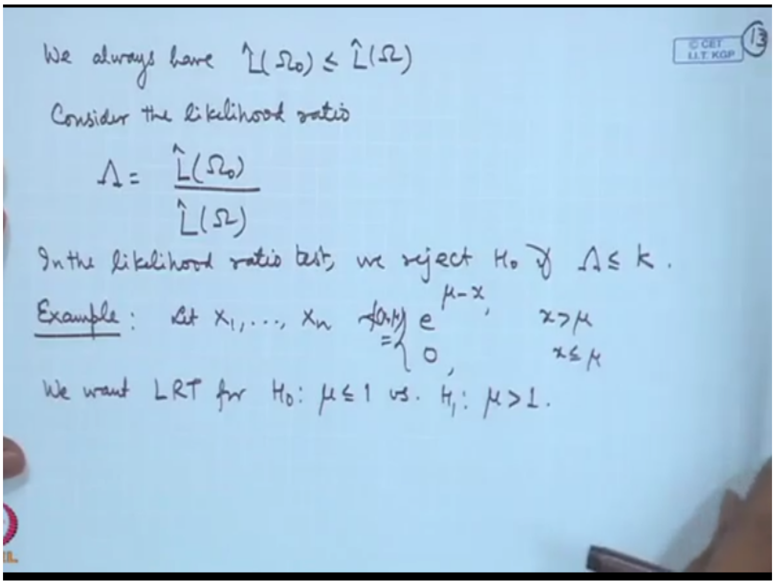

So consider the likelihood ratio so that is let us call it say some lambda that is equal to L hat omega 0. In the likelihood ratio test, we reject H0 if lambda is <= some K. Now once again the question about the choice of K comes and therefore we can choose K to fix the size. We may actually look at what is the probability of rejection? So that is known as the significance testing.

We consider the probability of this and we look at the (()) (44:57) by which we will be actually accepting. For example, if I consider say alpha=0.1 or alpha=0.5 and we look at whether we will be actually rejecting. So the minimum value of 2 which we will be considering that will be called p value of the test. Let us consider an example here. Say X1, X2, Xn follow exponential distribution with parameters say mu.

This is fx mu okay. Now let us consider say we want likelihood ratio test for say mu <= 1 against say H1 mu>1.

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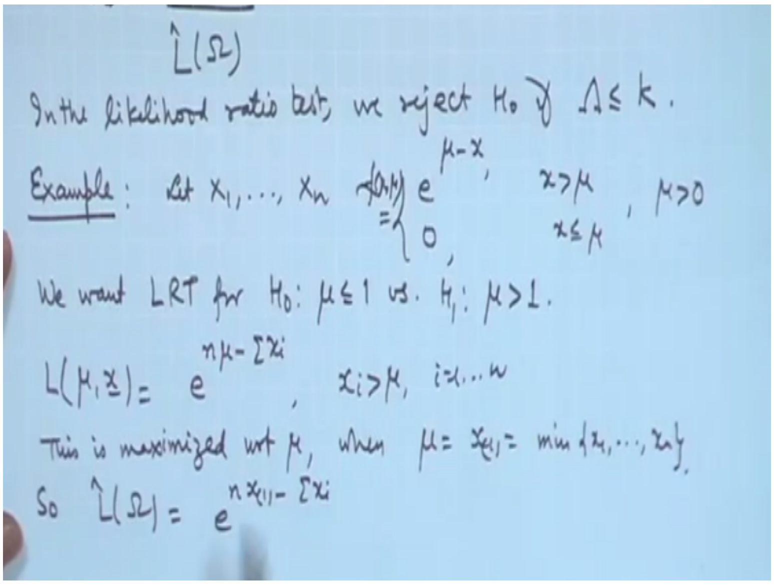

So we consider here the likelihood function that is equal to e to the power n mu-sigma xi and here it will be xi>mu for i=1 to n. So naturally this is maximized, here we can consider say mu>0 you may consider this as a typical situation where the life times of components are following exponential distribution with parameter mu but here mu denotes the minimum guarantee time.

The rate is 1 here so this is maximized with respect to mu when mu=actually the minimum of X1, X2, Xn. So you get L hat omega that is equal to e to the power n X1-sigma xi the maximum value of the likelihood function over the parameter space.

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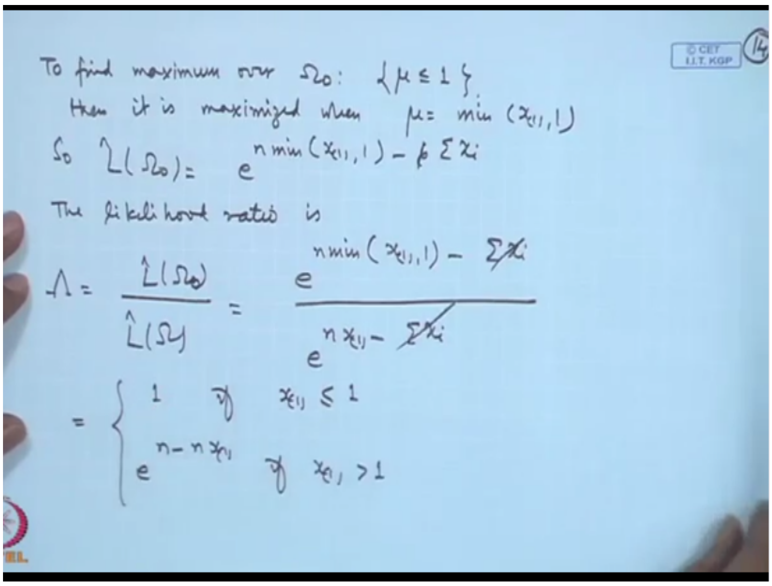

Now let us consider to find maximum over omega 0, omega 0 here is mu is <= 1. Then it is maximized when mu=minimum of x1 and 1. Because we are putting 2 restrictions mu is <=

x1 and mu is <= 1 so the maximum value that mu can take is minimum of x1 and 1. So L hat omega 0 that will become e to the power n minimum of x1 and 1-sigma xi.

So now the likelihood ratio is say lambda=L hat omega 0/L hat omega so that is equal to e to the power n minimum of x1, 1-sigma xi/e to the power n x1-sigma xi. So this term naturally cancels out. Now this is equal to 1 if x1 is <= 1 and it is equal to e to the power n-nx1 if x1 is > 1. So you can easily see that when the likelihood ratio is 1, you always cannot reject H0 because this is the best that can happen.

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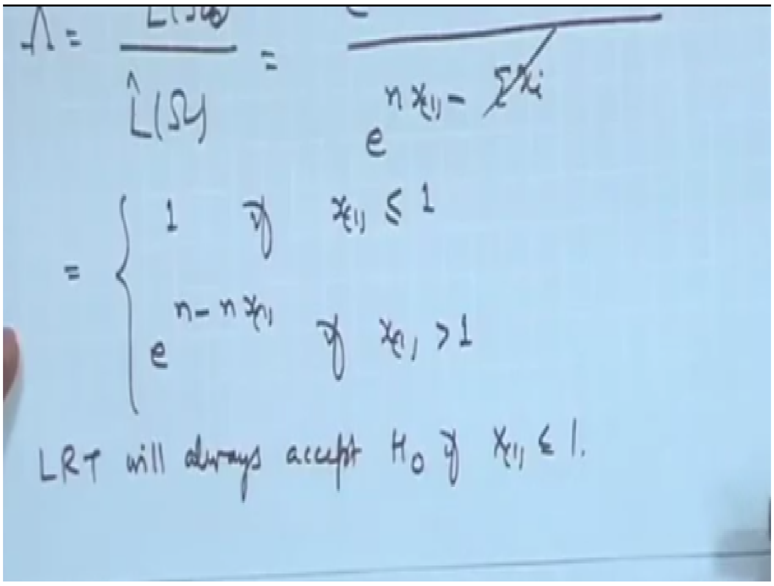

So we can say that LRT will always accept H0 if x1 is <= 1.

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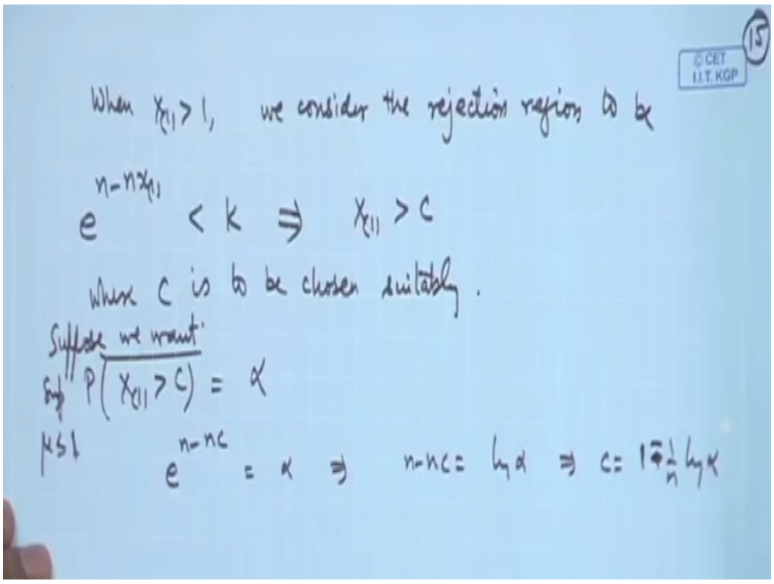

Now let us look at the other region. So when x1>1 we consider the rejection region e to the power n-nx1<K. So if I take log etc then adjust the terms then it is equivalent to something like saying X1>some c where c is to be chosen suitably. As an example we may consider say probability of X1>c=say alpha. Suppose we want this for supremum mu <= 1 suppose we consider this situation.

If we consider this situation, then this is equivalent to e to the power n-nc=alpha that means n-nc=log of alpha or we can say c=1-1/n log alpha. So you are actually rejecting for a value slightly higher than 1 okay. So this is a typical application of a likelihood ratio test and also you can see I can show you through an example for the normal distribution that how does it compare with the standard test that we obtain using Neyman Pearson theory.

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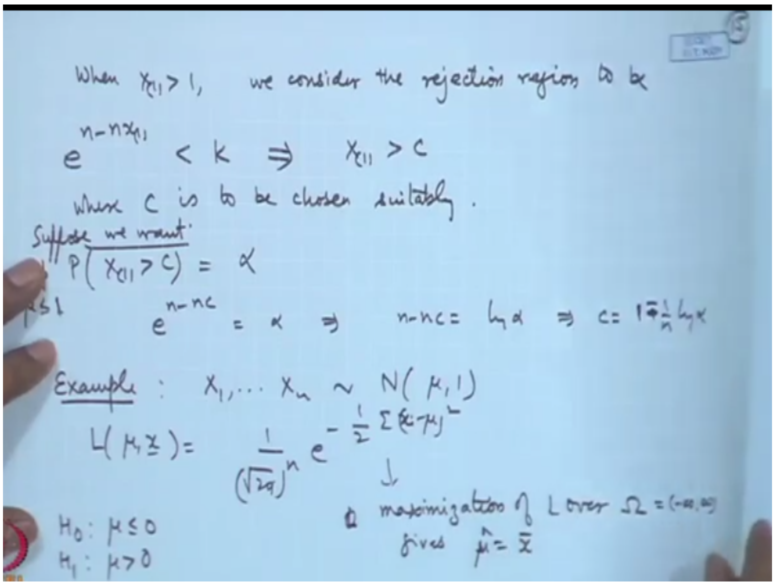

Let us consider another example say I consider X1, X2, Xn following normal mu1 situation and we consider the likelihood function=1/root 2 pi to the power n e to the power -1/2 sigma xi-mu square. Now I consider the hypothesis testing problem say mu is <= 0 against say mu>0. Now if I consider the maximization of L over omega, here omega is actually –infinity to infinity gives mu hat=say x bar.

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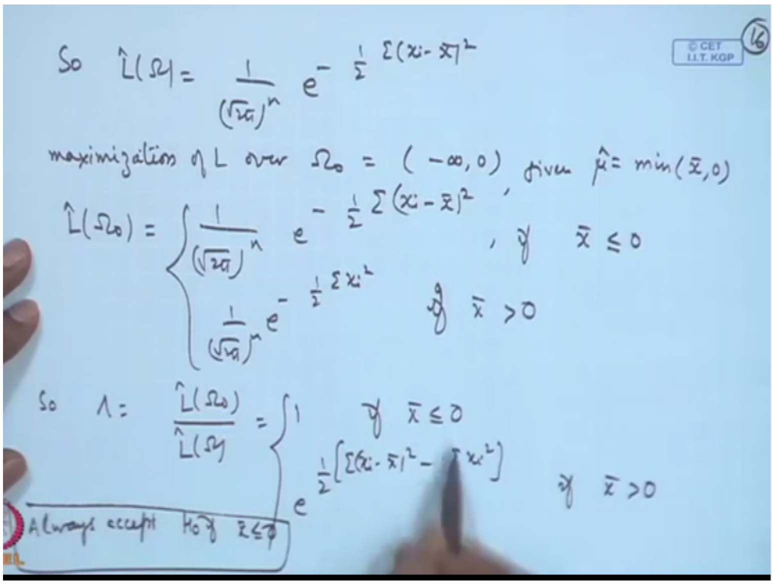

And therefore you will get L hat omega=1/root 2 pi to the power n e to the power-1/2 sigma xi-x bar square, but if we consider maximization over omega 0 where omega 0 is actually -infinity to 0 then we will get mu hat=see if x bar is < 0 then it will be x bar, but it will be 0 if x bar>0 so that will give us minimum of x bar and 0. If that is happening then L hat omega 0 that will become equal to 1/root 2 pi to the power n e to the power-1/2 sigma xi-x bar square if x bar<0.

And it is equal to 1/root 2 pi to the power n e to the power -1/2 sigma xi square if x bar>0. so we can put <= 0 here it does not matter. Now the thing is so the ratio that is L hat omega 0/L hat omega if you see that is equal to 1 if x bar is <= 0 and it is equal to this ratio e to the power 1/2 sigma xi-x bar square-sigma xi square if x bar>0. That means always accept H0 if x bar is <= 0.

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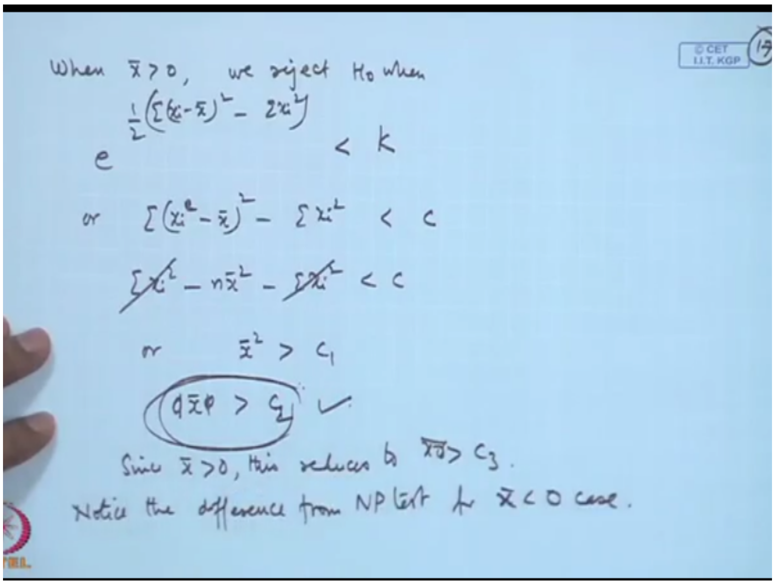

Now in the other case you will formulate the region here when x bar>0 we reject H0 when e to the power 1/2 sigma xi-x bar square-sigma xi square<K. So if I take log here and adjust this 1/2 here, it is becoming sigma xi square-x bar square-sigma xi square<some c. Now this can be further simplified here. We can consider this as sigma xi square-n x bar square-sigma xi square < c.

So this cancels out so we get actually x bar square>some c. So rejection region is turning out to be 2 sided something like modulus x bar>some c1. Let us call it c1 this as c2 here so actually we can again see here, here I am considering x bar > 0 this is equivalent to x bar > c2 okay.

Since x bar is positive this reduces to x bar > some c3 kind of thing. Now if you compare it with the Neyman Pearson test, there it would have been root n x bar>z alpha. Now here it is like this only in this particular portion, but when x bar<0 we are always accepting H0 so that is the difference from the Neyman Pearson test. So notice the difference from NP test for x bar<0 case.

But x bar> then it is but for all practical purposes you can see because alpha will be sufficiently small, therefore z alpha value will be very close to high and therefore the 2 tests will be practically the same. In the parametric methods, I have concentrated mostly on the point estimation, confidence interval and testing of hypothesis problems. So there are other cases also when we do not have the parameter specified.

That means the distribution is not specified and we consider distribution free methods; however, that will be slated for a different zone. Now we will be moving over to another topic in this statistical methods so that I will be starting from the next lecture.