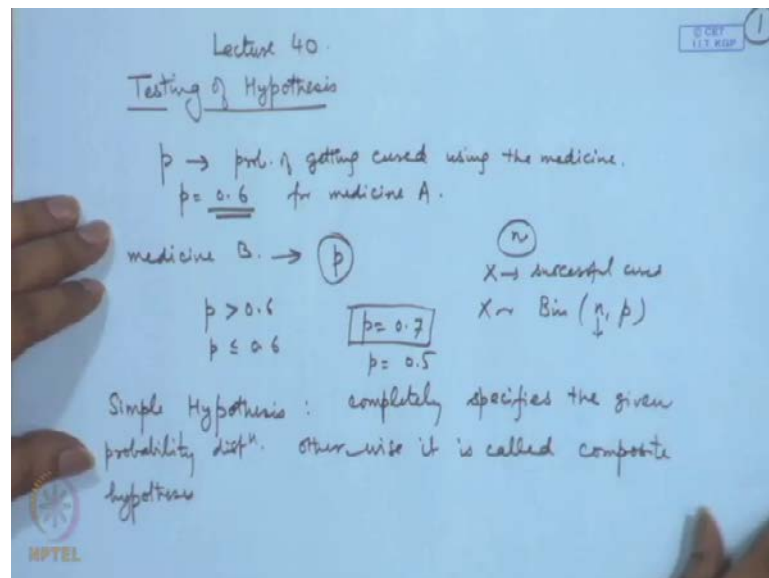


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Lecture No. # 41
Basic Concepts of Testing of Hypothesis

Today I will consider the third problem related to this statistical inference. Are here we have discussed, the problem of point estimation in which we specify a value for the unknown parameter of the population. Another one in the previous lecture I have introduced that is called the problem of interval estimation, where in place of giving a single value; we give an interval for the specified parameter. The other type of problem of inference occurs, when we want to test whether our parameter value satisfies certain condition. For example, if we are considering the cure rate using a certain medicine, then how many patients get cure? Suppose, there is a medicine which we have been using, and it is known that approximately 60 percent of the patients get cure for that.

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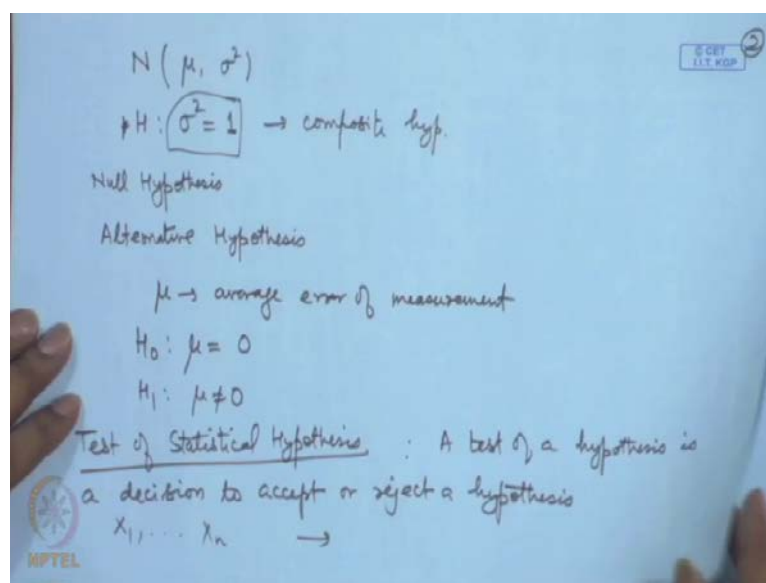
So, if we use the parameter p to denote the success rate or the probability of getting cure using the medicine, now a new medicine is introduced in the market. So, here it is given that p is equal to 0.6 for say medicine A. Now, a new medicine B is introduced, and the

success rate with this is say p . Then we want to know, whether p is greater than 0.6 or p is less than or equal to 0.6. Suddenly this is a problem of interest to the under manufacturer, and the person who is going to market it. Now, here the problem of inferences based on certain assumption about the probability distribution, because if we consider say n patients to which the medicine has been given, and x is the number of successful cures **successful cures**.

Then we can say that x follows binomial n, p . And then we want to test the hypothesis, whether p is greater than 0.6 or p is less than or equal to 0.6 or say p is equal to 0.7 or p is 0.5, etcetera. We can make any a statement of this nature, this is called a hypothesis. Now, the they can be several I have written several a statements here, p is equal to 0.7, p is equal to 0.5, p is greater than 0.6, p is less than or equal to 0.6. We classify this hypothesis into different forms.

If we consider here n is known and p is unknown, and if we write a statement like p is equal to 0.7, then the probability distribution is completely specified. Whereas, if we write p is greater than 0.6, then the probability distribution is not completely specified; it only says p is some value greater than 0.6. So, this gives a simple hypothesis - in a simple hypothesis completely specifies the given probability distribution, otherwise it is called composite hypothesis. So, you consider that the testing of hypothesis problem can be classified as the problem to test as simple hypothesis or to test composite hypothesis. See, we may have a situation like this.

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Suppose we are considering normal distribution with parameter μ , and σ^2 . We want to test whether σ^2 is equal to 1. Now, if I say σ^2 is equal to 1 this is not actually a simple hypothesis, because this is only specifying the value of σ^2 ; μ is not specified here. So, this is actually a composite hypothesis; usually a notation H or H_0 , etcetera is used to denote a hypothesis statement. For example, here we may write H_0 , here we may write H_1 , here we may write H_2 , here we may write H_3 , etcetera.

So, a hypothesis usually we use a notation H for denoting the hypothesis. Now, there is another classification of the nature of the hypothesis, we say something is a null hypothesis, and there is an alternative hypothesis. Now, what is a null hypothesis? We frame this problem here that we want to test, whether the new medicine is more effective, than the previously used medicine. So, we have framed a hypothesis whether p is greater than 0.6, and then we say whether it is more effective R_0 . So, R_0 is a statement that is corresponding to p is less than or equal to 0.6, we may also say here we may put greater than or equal to, and here we may put less. Of course, it does not matter here or we may put one hypothesis as p is equal to 0.7 or p is equal to 0.5.

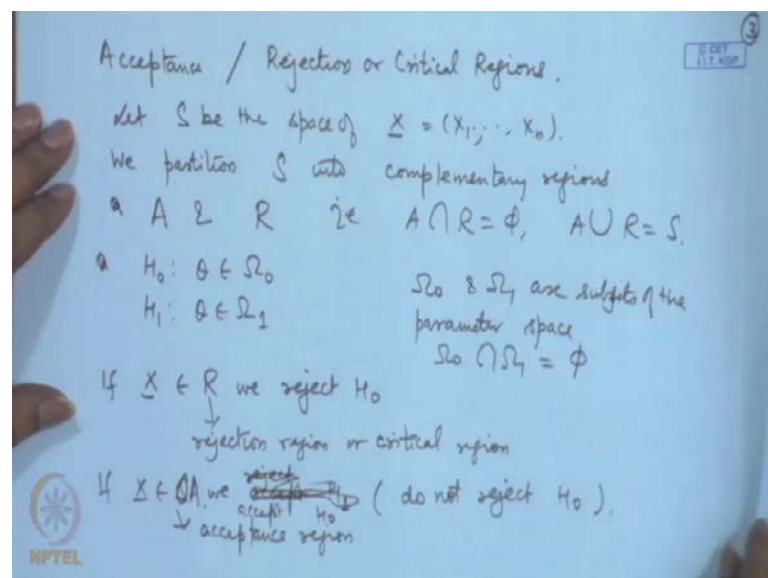
So, we may call this as H_0 , and this as H_1 . Now, one initial hypothesis which we want to check, that is certain original assumption about the parameter of the population, that we call or we term it as a null hypothesis. Now, when the null hypothesis is not likely

to be true, in that case something else is going to be true; that we designate as an alternative hypothesis.

So, we have. So, we may have something like, we are considering certain we are measuring certain thing. Now, that measuring device may introduce errors in the measurements, and then we want to check whether the average errors are eliminated or not. So, if my μ is the average error of measurement, tell me may like to check whether this average is 0 or it is not 0; if it is 0, then we will say our measuring device performs consistently or it is performing well.

Now, when we introduce the problem of testing of hypothesis, ultimately we have to check whether the hypothesis is consistent with our given data or not. When we test with respect to our given data, it is called the test of hypothesis, test of statistical hypothesis. So, a test of a hypothesis is a decision to accept or reject a hypothesis. So, for example, we take a sample X_1, X_2, X_n ; based on that we make a decision basically what we will do? We will partition the entire sample space into two regions, when the value our sample point belongs to one portion of the sample space. We will say accept one hypothesis, if it is in the other case we will say accept the other hypothesis.

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Based on that we frame what is called acceptance, and rejection or critical regions. Let S be the space of X is equal to X_1, X_2, X_n ; we partition S into complementary regions say A and R that is A intersection R is ϕ , and A union R is equal to S . Suppose, we are

considering the hypothesis testing problem H_0 versus H_1 belonging to Ω_0 and Ω_1 respectively, where Ω_0 and Ω_1 are subsets of the parameter space, and certainly $\Omega_0 \cap \Omega_1$ must be equal to \emptyset , they must be disjoint.

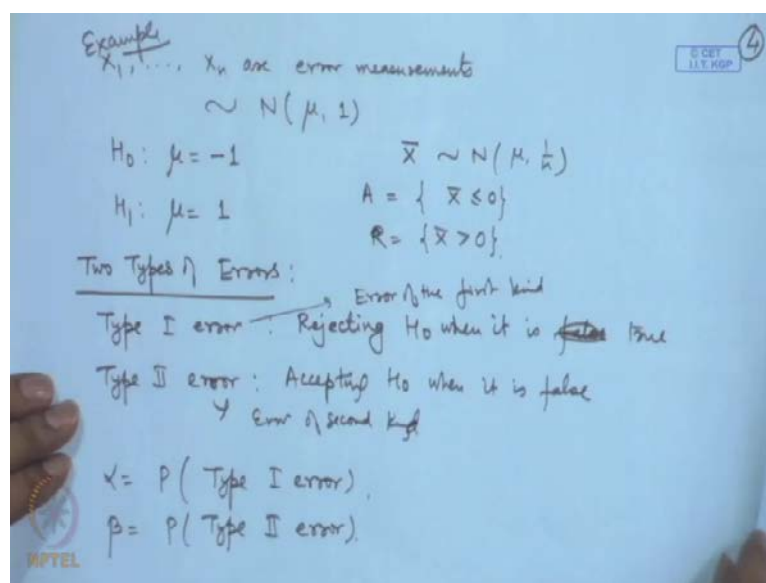
If X belongs to R , we reject H_0 . So, R is called the rejection region or critical region; if X belongs to S , we accept H_0 or we say do not reject H_0 .

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This is called the **acceptance region**, this is A , this is called the acceptance region. So, we actually I am written wrongly we accept H_0 , then X belongs to A , we accept H_0 or we say do not reject H_0 . Here, I would like to mention one point, the decision to accept or reject hypothesis is based on the sample.

So, when we observe a sample based on which, if we can say our null hypothesis is not consistent with the value of the test statistics or value of the criteria that we are deciding; then we simply say that the H_0 or the null hypothesis is rejected. However, when our hypothesis turns out to be consistent with the criteria for that is criteria, in that case we do not use our that we accepted is not where other say that there is no sufficient evidence to reject H_0 . So, roughly speaking we say that H_0 is accepted, but we do not say it that way, this is something like what we say in a testing of hypothesis problem.

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Let me introduce the one problem; let us consider that same where our X_1, X_2, \dots, X_n are error measurements, and we are assuming that they follow say normal μ , one distribution; here, I am assuming that sigma square is equal to 1. We want to test whether μ is equal to say minus 1 against μ is equal to plus 1; it is something like saying that whether the is (()) are negatively waving or they are waving positively. Let us consider, here we can consider \bar{X} - \bar{X} follows normal $\mu, 1$ by n ; we can make a decision based on \bar{X} .

So, we give the acceptance region as \bar{X} less than or equal to 0, and the rejection region as \bar{X} greater than 0. Naturally our decision is based on sample, and therefore there is a chance of errors. There are two types of errors that are committed: One is called type one error, that is rejecting H_0 - when it is false, when it is true. And type two error accepting H_0 , when it is false. So, this is called the error of the first kind, and this is called the error of the second kind.

Usually we use a notation α is equal to the probability of type one error, and β is probability of the type two error.

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For the above example.

$$\begin{aligned}\alpha &= P(\text{Rejecting } H_0 \text{ when it is true}) \\ &= P(\bar{X} > 0) \quad \bar{X} \sim N(-1, \frac{1}{n}) \\ &= P(\sqrt{n}(\bar{X}+1) > \sqrt{n}) \quad \sqrt{n}(\bar{X}+1) \sim N(0,1) \\ &= P(Z > \sqrt{n}).\end{aligned}$$

Let $n=9 \rightarrow P(Z > 3) = 0.0013$

$$\begin{aligned}\beta &= P(\text{Accepting } H_0 \text{ when it is false}) \\ &= P(\bar{X} \leq 0) = P(\sqrt{n}(\bar{X}-1) \leq -\sqrt{n}) \quad \bar{X} \sim N(1, \frac{1}{n}) \\ &= P(Z \leq -\sqrt{n}) = 0.0013\end{aligned}$$

Let me calculate these probabilities for this example, for the above example alpha that is the probability of type one error, that is probability of rejecting H_0 , when it is true. Now, when are we rejecting, we are rejecting when \bar{X} is greater than 0. So, probability of \bar{X} is greater than 0, when it is true - **true** means μ is equal to minus 1; now when μ is equal to minus 1 \bar{X} follows normal minus 1, $1/n$. So, this value, then you can write as probability of $\bar{X} + 1$ into \sqrt{n} greater than $1/\sqrt{n}$. So, this will have $\sqrt{n}(\bar{X} + 1)$, this will follow normal 0, 1. So, this value turns out to be probability of Z greater than \sqrt{n} , suppose n is equal to 9 here; then this value will turn out to be probability of Z greater than 3; that is 0.0013 in the case of a standard normal distribution.

So, the probability of type one error is 0.0013 here. Let us consider say beta here, that is the probability of type two error; that is probability of accepting H_0 when it is false, that is equal to probability of \bar{X} less than or equal to 0, when it is false that is μ is equal to 1. So, now, when μ is equal to 1, \bar{X} follows normal 1, $1/n$; that means, $\bar{X} - 1$ into \sqrt{n} will follow normal 0, 1. So, this is probability of $\sqrt{n}(\bar{X} - 1)$ less than or equal to minus \sqrt{n} , that is equal to probability of Z less than or equal to minus \sqrt{n} . Now, in this particular case when I have taken n to be 9; this is again 0.0013. So, in this case both probability of type one error, and probability of type two error; they are 0.0013 here.

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A Test of Statistical Hypothesis divides the sample space into two regions \rightarrow acceptance region \Leftrightarrow 2 rejection region

$\boxed{\phi(\underline{x})} \rightarrow P_{H_0} \text{ of rejecting } H_0$

$$E_{\theta} \phi(X) = P_{\theta}(\text{Rejecting } H_0)$$

$$= \beta_{\phi}^*(\theta) \rightarrow \text{Power function of the test}$$

When $\theta \in \Omega_1$, $\beta_{\phi}^*(\theta) = 1 - \beta_{\phi}(\theta)$
 $= \text{Power of the test.}$

$$\alpha(\theta) = P_{\theta}(X \in R) = P_{\theta}(\text{Rejecting } H_0), \theta \in \Omega_0$$

$\sup_{\theta \in H_0} \alpha(\theta) = \alpha^* \rightarrow \text{Size of the test.}$

So, what is a test of statistical hypothesis? A test of statistical hypothesis divides the sample space into two regions, that is the acceptance region, and the rejection region

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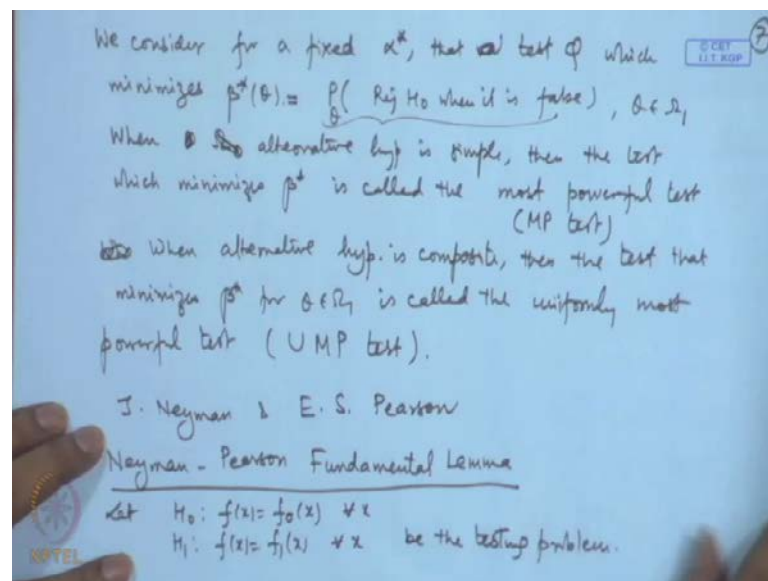
So, based on this what we are doing? We are actually determining a function say $\phi(X)$, this is called a test function, this we can call probability of rejecting H_0 . So, we are actually assigning a function here and, we are calculating expected value of $\phi(X)$ that is equal to probability of rejecting H_0 , when θ is a parameter value. Now remember here, when θ is belonging to the null hypothesis space, then this is the coming the probability of type one error, and when θ belongs to the alternative hypothesis set, then this is becoming 1 minus the probability of type two error.

So, we give it a new name, we call it β^* of θ ; this is called the power function of the test. So, ϕ here... So, when θ belongs Ω_1 , then $\beta^* \phi \theta$ is actually 1 minus $\beta \phi \theta$, this is called the power of the test. Now, you can notice here, that the probabilities α and β that have been calculated, they are based on the complementary regions; here \bar{X} is greater than 0, and \bar{X} is less than or equal to 0, so they are based on the complementary regions.

In an ideal test both α , and β must be equal to 0, but the simultaneous minimization is not possible. If we decrease α say, then β will increase; if we

increase alpha, then beta will decrease. Therefore, as a compromise solution what we do, one of the errors and then we try to minimize the other one; this gives us the concept of the most powerful test. So, what we do, we fix let us call it alpha star, that is equal to probability of type one error, that is when \bar{X} belongs to the rejection region; that is the probability of rejecting H_0 when θ belongs to the null hypothesis set. So, consider the maximum value of this; let us call it alpha star, this is called the size of the test.

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So, what we do, that we consider **we consider** for a fixed alpha star that value that test phi which minimizes beta star theta. So, when omega naught, see this beta star theta is actually probability of rejecting H_0 when it is false; when theta belongs to omega one here. So, this is called the power of the test. So, when alternative hypothesis is simple, then the test which minimizes beta star is called the most powerful test or MP test. Otherwise when **when** alternative hypothesis is composite, then the test that minimizes beta star for theta belonging to omega 1 is called the uniformly most powerful test, that is we called U M P test.

So, in a given problem our aim is to find out the most powerful test or the uniformly most powerful test. This problem of finding out the most powerful test has been solve by statistician, and a solution which is given for the simple versus simple case was introduced in 1920's by Jorgen Neyman, and E.S Pearson, and the result is famously

called Neyman Pearson Fundamental Lemme. This result which was introduced for testing simple versus simple case was later on extended to the case of composite hypothesis also, and the solutions for the cases we had the uniformly most powerful test or the uniformly most powerful test within a certain class of test, we are also derived.

In this particular lecture, I will be only giving the Neyman Pearson Fundamental Lemme, and then based on this how various tests have been derived. So, we will give the form of the test for testing the parameters of the normal population only, and we will not discuss the general methodology for finding out the test; there are other methodologies also such as the likelihood ratio test etcetera. However, we will not be concentrating on those things in this particular lecture here. Let me introduce the name part of the Neyman Pearson Lemme.

So, let us consider say hypothesis H_0 , say $f(x)$ is equal to $f_0(x)$, against H_1 $f(x)$ is equal to $f_1(x)$. Of course, this means that the density, whether the density is f_0 or the density is f_1 . So, this is the testing problem.

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The MP test at level α is given by

Reject H_0 if $f_1(x) > k f_0(x)$
 Accept H_0 if $f_1(x) \leq k f_0(x)$
 where k is determined by the size condition.

$X_1, \dots, X_n \sim N(\mu, 1)$

$H_0: \mu = -1 \rightarrow f_0$ $\mu \in \mathcal{R}_1$
 $H_1: \mu = 1 \rightarrow f_1$

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

$f(z) = \frac{1}{(\sqrt{2\pi})^n} e^{-\frac{1}{2} \sum (x_i - \mu)^2}$

$\frac{f_1(z)}{f_0(z)} = e^{\frac{1}{2} \sum (x_i + 1)^2 - \frac{1}{2} \sum (x_i - 1)^2} > k$
 or $\sum (x_i + 1)^2 - \sum (x_i - 1)^2 > k_1$

Then the Neyman Pearson Lemme says that the most powerful test at level α is given by $\phi(x) = 1$, other we can say reject H_0 ; if $\phi(x)$ is **sorry** $f_1(x)$ is greater than K times $f_0(x)$ accept H_0 ; if $f_1(x)$ is less than K times $f_0(x)$, where K is determined by the size condition - size α condition. Let me solve one problem. Let us consider the normal example X_1, X_2, \dots, X_n following normal $\mu, 1$; and

our hypothesis testing problem is whether μ is equal to minus 1, against whether μ is equal to plus 1. Let us write down the density function here, $f(x)$ is equal to $\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2}$ is equal to 1 to n.

So, if we consider $f_1(x)$ by $f_0(x)$ that is equal to $e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i + 1)^2}$ square minus half $\sigma^2 \sum_{i=1}^n (x_i - 1)^2$... f_1 is corresponding to μ is equal to 1. So, this will be with the minus here, and this will be with the plus sign here. So, we are saying it is greater than K , now we can simplify this, if we take the logarithm here; this will imply $\sum_{i=1}^n (x_i - 1)^2$ square minus $\sum_{i=1}^n (x_i + 1)^2$ square greater than some constant say K_1 .

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$$+2\sum_{i=1}^n x_i - 2\sum_{i=1}^n 1 > k_2$$
 or $\sum_{i=1}^n x_i > k_3$ or $\bar{X} > k_4$
 where k_3 is determined by the size condition
 $P(\bar{X} > k_4) = \alpha$
 $\mu = -1$
 $\bar{X} \sim N(-1, \frac{1}{n})$
 $\sqrt{n}(\bar{X} + 1) \sim N(0, 1)$
 $P(\sqrt{n}(\bar{X} + 1) > \sqrt{n}(k_4 + 1)) = \alpha$
 Test is Reject H_0 if $Z = \sqrt{n}(\bar{X} + 1) > z_{\alpha}$
 else accept H_0 .
 This is MP test for testing H_0 against H_1 .

Now this can be further simplified, we can write it as minus twice $\sum_{i=1}^n x_i$ plus twice again minus twice $\sum_{i=1}^n x_i$ greater than some k_2 or we consider $\sum_{i=1}^n x_i$ is less than k_3 . Let us check the steps here, $f(x)$ is equal to $\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2}$. So, if we write $f_1(x)$ here, f_1 will become equal to $\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - 1)^2}$, and f_0 will become equal to $\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i + 1)^2}$.

So, if we consider f_1 by f_0 here, then this will become plus here, and this will become minus here; this is plus, this is minus here. So, here we will get plus, and this

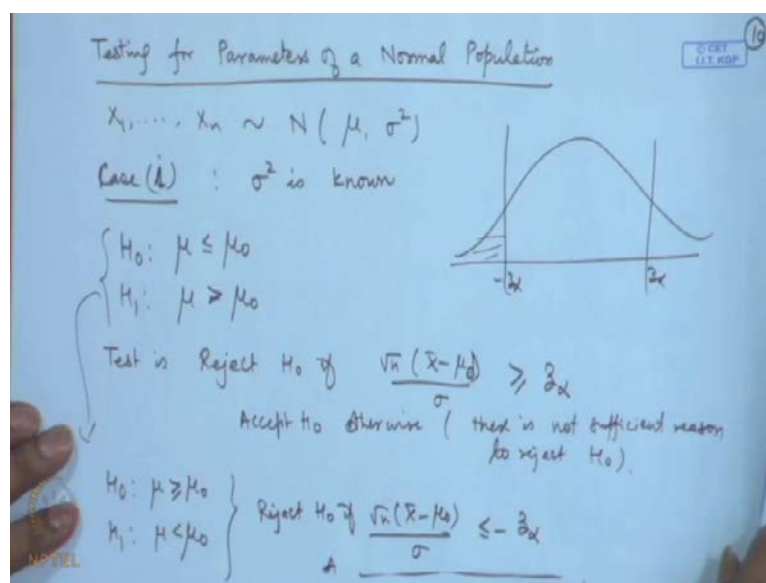
will become **become** plus. So, this is greater than k_3 , where k_3 is determinant by the size condition. So, here we **we** make use of the fact that probability of... So, we can write it as \bar{X} greater than say k_4 . So, \bar{X} greater than k_4 , this should be equal to α , when μ is equal to μ_0 that is the probability of rejecting H_0 ; this is the rejection region. We are saying reject H_0 , if **if** this statement is true.

Now, again \bar{X} follows normal $\mu_0, 1/\sqrt{n}$. So, we will get $\sqrt{n}(\bar{X} - \mu_0)$ following normal $0, 1$. So, this statement can then be written as $\sqrt{n}(\bar{X} - \mu_0) > k_4 - \mu_0\sqrt{n}$, that is equal to α . So, this is nothing but Z . So, we can write Z is equal to $\sqrt{n}(\bar{X} - \mu_0)$ greater than z_α . So, the test is reject H_0 , if $\sqrt{n}(\bar{X} - \mu_0)$ is greater than z_α else accept H_0 . So, this is nothing but the most powerful test for testing H_0 , against H_1 . Now note here, in the null hypothesis we are saying μ is equal to μ_0 , and in the alternative hypothesis μ is equal to μ_1 .

So, actually roughly speaking you can say that in the alternative hypothesis, the average value is higher than the value in the null hypothesis. And therefore, the rejection region also reflects that, we are rejecting actually for higher value of \bar{X} , because \bar{X} is actually an estimated for μ here. It is actually a consistent, and **(())** estimated; and here it turns out that \bar{X} is greater than we reject H_0 . Likewise in case of in place of here μ_0 , and μ_1 if I had written here say μ_0 , and here I had written μ_1 ; where μ_0 is less than μ_1 , that form of the test is statistics would have been the same. Except for the fact that here one would have been replaced by $\bar{X} - \mu_0$.

So in fact, this observation led to the solution of the composite hypothesis also; that means, in place of say $\mu = \mu_0$ against $\mu = \mu_1$, if we consider say $\mu \leq \mu_0$ against $\mu > \mu_1$, etcetera. Then the uniformly most powerful tests are found out.

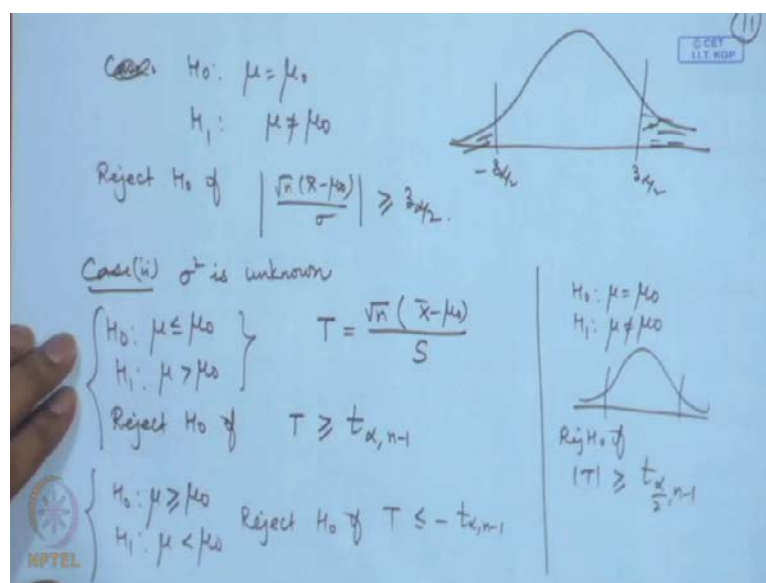
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And let me introduce those testing problems here testing for parameters of a normal population. So, X_1, X_2, \dots, X_n follows normal μ, σ^2 distribution here. We are considering say case one when say σ^2 is known, we are considering say hypothesis say μ is less than or equal to μ_0 , against μ is greater than μ_0 . Here the test is then reject H_0 , if the root n \bar{X} minus μ_0 by σ is greater than or equal to z_α ; the alternative region will become the acceptance region; accept H_0 otherwise or you can say that there is no region, not sufficient region to reject H_0 .

See, this case could have been that in the null hypothesis we have greater than or equal to this, and in the alternative hypothesis we have the... When if you look at the curve here of the normal distribution, then this is z_α ; here you will have minus z_α . So, if it is (()) side, the smaller side then the test will get reversed. You will say reject H_0 , if root n \bar{X} minus μ_0 by σ is less than or equal to minus z_α , and the other region is complementary region will be the acceptance region.

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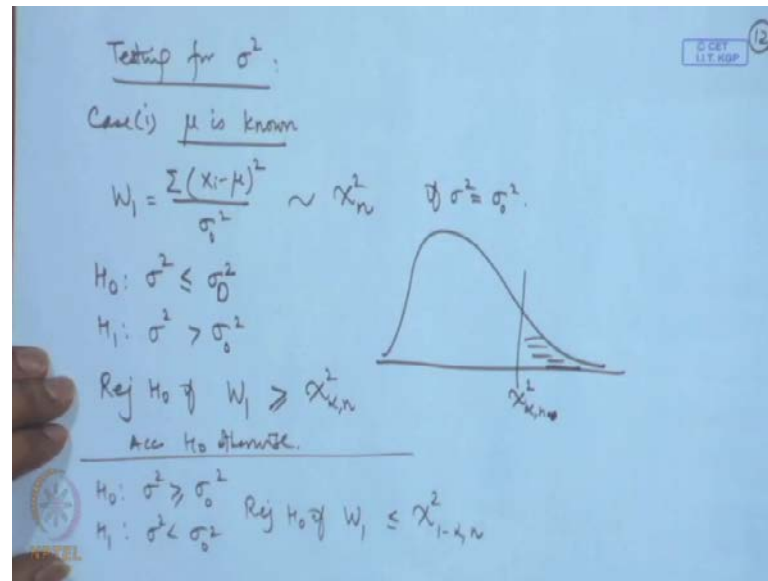


Now, we may also have the case when the alternative hypothesis is on both the sides; for example, you may discuss μ is equal to μ_0 or say μ is not equal to μ_0 . In that case on both the regions, we will be considering rejection. So, if we consider the reason of the α into two portion, then this will come α by 2, and α by 2 here and α by 2 here. So, we will then consider reject H_0 , if modules of root $n \bar{X}$ minus μ_0 by σ is greater than or equal to $z_{\alpha/2}$.

Let us also consider the case, when σ^2 is unknown **when σ^2 is unknown**; here our decision making will be dependent upon square root $n \bar{X}$ minus μ_0 by S , let us call T . Then we will have the test statistics as reject H_0 , if T is greater than or equal to $T_{\alpha, n-1}$. On the other hand, if we are considering say $H_0: \mu \geq \mu_0$ against $H_1: \mu < \mu_0$; in that case we will say reject H_0 , if T is less than or equal to minus $t_{\alpha, n-1}$. However, if I have $H_0: \mu = \mu_0$ against $H_1: \mu \neq \mu_0$, then as in the normal distribution T distribution is also symmetric distribution. So, you will have reject H_0 , if modules of T greater than or equal to $T_{\alpha/2, n-1}$.

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Let us also consider the test for sigma square; testing for sigma square here, and again we may have two cases: mu is known, if mu is known then we can consider sigma x i minus mu square. And we can consider this divided by sigma naught square, let us call it say W 1, then this follows chi square on n degrees of freedom when sigma square is equal to sigma naught square. So, if we consider the hypothesis says sigma square is less than or equal to sigma 1 square sigma naught square, against H 1 sigma square greater sigma naught square, then our rejection region will be... If we consider the chi square curve here, then on the larger side chi square alpha n minus 1.

So, here n reject H naught, if W 1 is greater than or equal to chi square alpha on n degrees of freedom, accept H naught otherwise. Similarly, we can consider the complementary region, and here we will say reject H naught if W 1 is less than or equal to chi square 1 minus alpha n.

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$H_0: \sigma^2 = \sigma_0^2$
 $H_1: \sigma^2 \neq \sigma_0^2$
 Then $\text{Rej } H_0 \text{ if } W_1 \leq \chi^2_{1-\frac{\alpha}{2}, n} \text{ or } W_1 \geq \chi^2_{\frac{\alpha}{2}, n}$

Example: The life (in years) of a battery is normally distributed.
 A random sample of 16 batteries produced a sample variance
 $S^2 = 3$.
 $H_0: \sigma^2 = 2$
 $H_1: \sigma^2 > 2$ at $\alpha = 0.05$

and (ii) μ is unknown
 $W_2 = \frac{(n-1)S^2}{\sigma_0^2} \sim \chi^2_{n-1}$ when $\sigma^2 = \sigma_0^2$
 $\frac{15 \times 3}{2} = 22.5$ $\chi^2_{15, 0.05} = 24.9958$

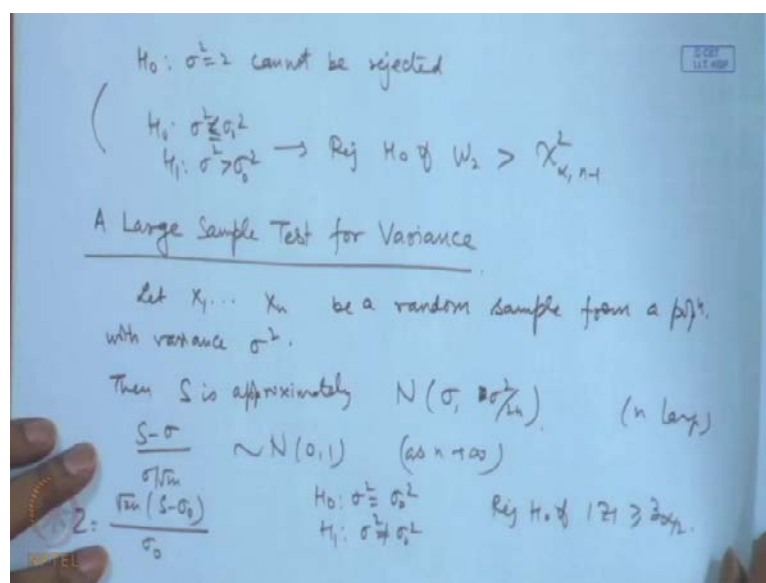
In the case of two sided region, suppose we are considering sigma square is equal to sigma naught square, against sigma square is not equal to sigma 1 square. Then reject H naught, if W 1 is less than or equal to chi square 1 minus alpha by 2 n or W 1 is greater than or equal to chi square alpha by 2 n.

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The life in years of a battery is normally distributed. A random sample of say 16 batteries produced a sample variance say sigma square is equal S square is equal to 3. We want to test the hypothesis sigma square is equal to 2, against say H 1 sigma square is greater than 2 at alpha is equal to 0.05 level of significance. Here, we apply the method here described that we calculate W, and that is sigma here.

Mu is not known here. So, we have to consider the procedure for mu unknown, let me give the procedure for mu unknown. Case two mu is unknown, when mu is unknown then we consider the quantity W 2 is equal to n minus 1 S square by sigma square, there follows chi square n minus 1. So, when sigma square is equal to sigma naught square. So, the test will be based on this; that is rejection regions, and acceptance regions. So, using this we calculate 15 into 3 by 2 that is equal to 22.5, and the value of chi square on 15 degrees of freedom and 0.05 is equal to 24.9958.

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So, here we say that $H_0: \sigma^2 = 2$ cannot be rejected, because here the general rejection region for $H_0: \sigma^2 = \sigma_0^2$ is equal to $\sigma^2 > \sigma_0^2$, against $H_1: \sigma^2 > \sigma_0^2$ is greater than $\sigma^2 > \sigma_0^2$. This rejection region would have been reject H_0 , if W_2 is greater than $\chi^2_{\alpha, n-1}$. So, here we cannot reject the null hypothesis.

(No audio from 46:34 to 46:49)

We also we will large sample test for variance. So, let X_1, X_2, \dots, X_n be a random sample from a population with variance say σ^2 , then S is the approximately normal $\sigma^2/(2n)$, for n large. So, $S - \sigma^2/(2n)$ by $\sigma^4/(4n)$ root $2n$ this is approximately normal $0, 1$ as n tends to infinity.

So, we can consider here, the test based on root $2n$ $S - \sigma^2/(2n)$ by $\sigma^4/(4n)$ let me call z , then if I consider the hypothesis $\sigma^2 = \sigma_0^2$ against $\sigma^2 > \sigma_0^2$, then, we can consider reject H_0 , if $|z| \geq z_{\alpha/2}$.

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Example: Let a sample of size $n=10$ give $S=6.9$.

Test $H_0: \sigma \leq 7$
 $H_1: \sigma > 7$

$Z = \frac{\sqrt{10}(6.9-7)}{7} = -0.0639$

So we cannot reject H_0 .

$H_0: \sigma \geq 7$
 $H_1: \sigma < 7$ } H_0 cannot be rejected

$H_0: \sigma = 7$
 $H_1: \sigma \neq 7$ } H_0 is not rejected

$\alpha = 0.05$
 $z_{\alpha/2} = 1.645$

$\alpha = 0.025$
 $z_{\alpha/2} = 1.96$

Let me consider one example for this problem: Let a sample of size n is equal to 10 give S is equal to 6.9, we want to test the hypothesis whether sigma is less than or equal to 7 or sigma is greater than 7. So, z equal to root 20 6.9 minus 7 by 7 that is minus 0.0639; if we consider say alpha is equal to say 0.05, then z of 0.025 is equal to 1 point... z is equal to 0.05, that is equal to 1.645. So, we cannot reject H_0 . If we consider say yours of the say H_0 sigma greater than or equal to 7, against H_1 sigma less than 7; in that case, again H_0 cannot be rejected. See, if we consider H_0 sigma is equal to 7, against H_1 sigma is equal not equal to 7; here you will consider two sided alpha by 2. So, z alpha by 2 is equal to 1.96. So, again H_0 is not rejected. So, actually we can say that sigma is approximately 7 here.

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Suppose we have $X \sim P(\lambda)$

$H_0: \lambda = 2$
 $H_1: \lambda = 1$

$f(x, \lambda) = \frac{e^{-n\lambda} \lambda^{\sum x_i}}{\prod (x_i!)}$

$\frac{f_1(x)}{f_0(x)} = \frac{e^{-n}}{\prod x_i!} \div \frac{e^{-2n} 2^{\sum x_i}}{\prod x_i!}$

$= \frac{e^n}{2^{\sum x_i}}$

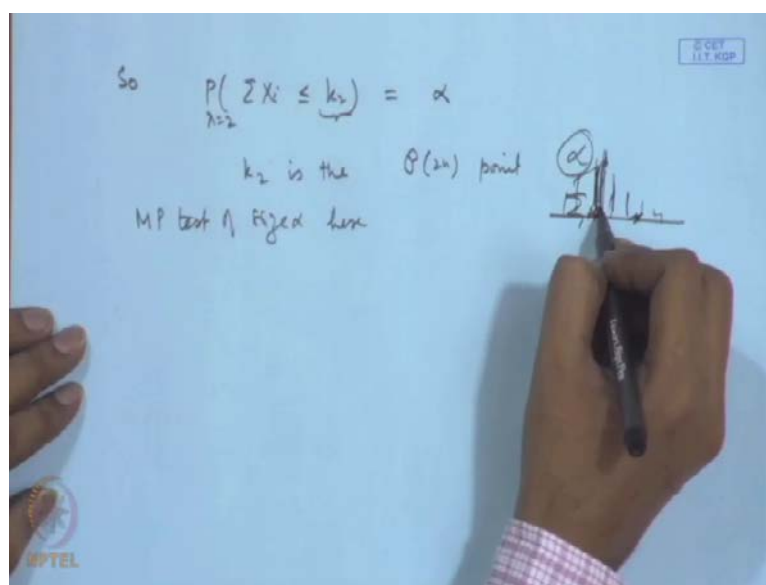
Rej H_0 if $\frac{e^n}{2^{\sum x_i}} \geq k$

$\Rightarrow n - \sum x_i \log 2 \geq \log k$
 or $\sum x_i \leq k_2$

Let me give 1 or 2 more example here. Suppose, we have X following Poisson λ distribution, we want to test whether λ is equal to 2, against λ is equal to 1. And we have a random sample X_1, X_2, \dots, X_n from this population. So, we consider here, the density function $f(x, \lambda)$ that is equal to $e^{-n\lambda}$ to the power $\sum x_i$ by product x_i factorial. If we consider f_1 by f_0 that is equal to e^{-n} to the power $\sum x_i$ divided by product x_i factorial divided by e^{-2n} to the power $\sum x_i$ divided by product of x_i factorial. Now, this term cancels out, you left with e^n and $2^{\sum x_i}$ to the power $\sum x_i$.

So, rejection region is if e^n divided by $2^{\sum x_i}$ is greater than or equal to k . So, here you can write it as $n - \sum x_i \log 2 \geq \log k$ let me write it as k_1 or $\sum x_i \leq k_2$. Once again, here you notice that in the alternative hypothesis the value of λ is smaller than the value in the null hypothesis. And therefore, the rejection region is for the lower value. here you notice here that $\sum x_i$ follows Poisson, and λ that is $2n$ when H_0 is true.

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So, probability of $\sum x_i$ less than or equal to k_2 , when λ is equal to 2 that is equal to α ; that means, k_2 is the Poisson $2n$ point; that is the point on the Poisson $2n$ distribution, that is the probability up to this is equal to α , up to this the probability some up to α here.

So, this will be the most powerful test of size α here. Now, here you may notice in Poisson is a discrete distribution; there may be a case that up to a certain point the value α will be achieved, and after that the value will exceed α . So that means, at one point the value will be below α , and after that the **point** value will be above α .

So, at that point we do the randomization, and we locate that point with certain probability say γ , here you reject and $1 - \gamma$ you accept. You choose the γ in such a way that the total actually becomes equal to α here. In the next lecture, I will consider the two sample problems for the normal distributions, and we will consider testing about the equality of means, the equality of variances, etcetera. And we will consider certain examples based on that, **that** will be the part of the next lecture.