

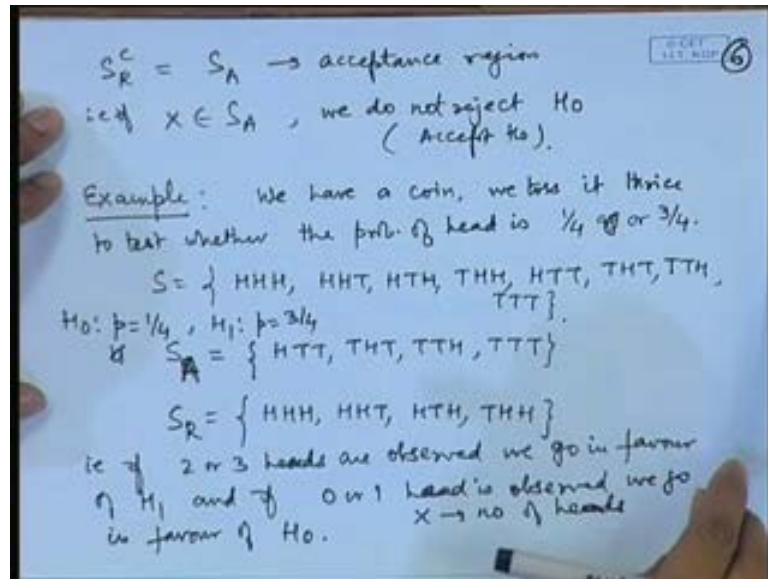
Probability and Statistics
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Module No. # 01
Lecture No. # 34
Testing of Hypothesis – II

So, we continue our discussion of the problem of Testing of Hypothesis. So, I framed it in the following terminology, we should have a null hypothesis, we should have an alternative hypothesis. And then, we take a random sample and we split the sample space into two portions; one portion is called the rejection region and another is called the acceptance region. As a consequence, we are likely to commit errors of two types; we call them, type 1 error and type 2 error and we have the respective probabilities. I mentioned that, in the case of composite hypothesis, the probabilities of type 1 error and type 2 errors will be the functions of the parameters.

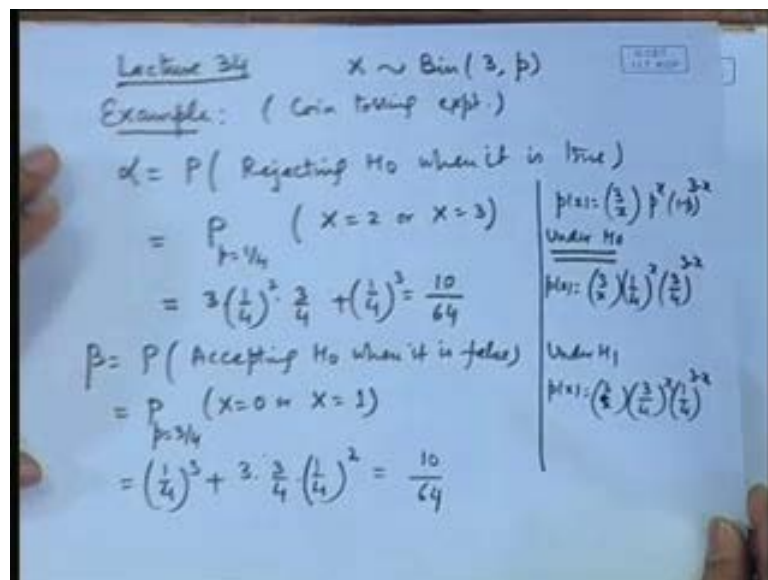
So, the most desirable would have been to have both the type 1 error and type 2 error probabilities to be as small as possible, but as in a two-dimensional decision spaces or you can say that, two-dimensional space is not ordered therefore, it is not possible to minimize both of them. So, a practical approach is to keep the value alpha to a fixed level and then find that, test procedure for which beta is minimized or $1 - \beta$ is maximized.

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Let me explain these through one example. We discuss the problem of say, checking the unbiasedness or say certain probability related to a probability of head of in a coin tossing experiment. So, we have a coin and we tossed it thrice and we want to test the hypothesis, whether p is equal to 1 by 4 against p is equal to 3 by 4. So, I have given here one region, that acceptance region is that, when either zero or one head is observed and we reject H_0 , when two or three heads are observed. Let us calculate the probabilities of type 1 error and type 2 error for this problem.

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So, coin tossing experiment, so here alpha that is the probability of type 1 error rejecting H_0 when it is true. So, we can restrict attention to the random variable x that is the number of heads. So, here x follows binomial $3, p$. Because, in the three tosses of the coin you may have at the most three heads, so, zero, one, two, three. So, it is a binomial distribution, the head occurs with the probability p .

So, then it is true means p is equal to $1/4$ under this we are rejecting, when x is either 2 or x is equal to 3. So, this is basically reducing to the probability of x equal to 2 or x equal to 3, so now this probabilities can be evaluated because, we know the distribution of x that is $P(X=x) = \binom{3}{x} p^x (1-p)^{3-x}$. Now, under H_0 this $P(X=x)$ function will be equal to $\binom{3}{x} (1/4)^x (3/4)^{3-x}$. So, when I substitute x is equal to 2 here, I get $\binom{3}{2} (1/4)^2 (3/4)^1$ plus when I put x equal to 3 here, this is simply reducing to $(1/4)^3$. So, that is equal to $10/64$. Let us, look at beta that is a probability of accepting H_0 when it is false that is probability of p is equal to $3/4$, when x equal to 0 or x is equal to 1. Now, under H_1 that is when p is equal to $3/4$, $P(X=x) = \binom{3}{x} (3/4)^x (1/4)^{3-x}$. So, when x is equal to 0, this value is simply $(1/4)^3$ plus when x equal to 1, it is $3 \times (3/4) \times (1/4)^2$. So, that is equal to $10/64$.

So, in this particular situation you can see alpha is $10/64$ and beta is equal to $10/64$, the probabilities is of. Now, you see we suppose we try to reduce alpha, we may try to reduce alpha by taking another test.

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Rej H_0 if $X=3$
Acc H_0 if $X=0, 1, 2$.

$$\alpha^* = P(X=3) = \frac{1}{64}$$

$p = 1/4$

$$\beta^* = P(X=0 \text{ or } X=1 \text{ or } X=2)$$

$p = 3/4$

$$= \left(\frac{1}{4}\right)^3 + 3 \cdot \left(\frac{3}{4}\right) \left(\frac{1}{4}\right)^2 + 3 \cdot \left(\frac{3}{4}\right)^2 \cdot \frac{1}{4} = \frac{37}{64}$$

$H_0: \theta \in \Omega_0$
 $H_1: \theta \in \Omega_1$ } $\Omega_0 \cup \Omega_1 \in \Omega$ \rightarrow parameter space

So, suppose I say reject H_0 if x is equal to 3, accept H_0 if x is equal to 0, 1 or 2. Now, let us see what is the value of alpha? Let me call it alpha star that is the probability of x is equal to 3, when p is equal to 1 by 4; so, when p is equal to 1 by 4 we noted down that, the distribution here 3×1 by 4 to the power x 3 by 4 to the power 3 minus x , if we substitute x is equal to 3 here, I get 1 by 4 cube, that is 1 by 64. So, naturally you can see here, that this test is having alpha is equal to 10 by 64, this is having 1 by 64; so, this is having a much smaller probability of type 1 error, but now let us see what happens to the probability of type 2 error, beta star that is probability of x is equal to 0 or x equal to 1 or x equal to 2 under p is equal to 3 by 4.

So, when p is equal to 3 by 4, the probability distribution of x is given by 3×3 by 4 to the power x 1 by 4 to the power 3 minus x . So, this will be equal to 1 by 4 cube plus 3 into 3 by 4 into 1 by 4 square plus 3 c 2 that is 3 into 3 by 4 square into 1 by 4. So, that is equal to now you see here, this value turns out to be 9 and 27, 27 plus 9 is 36, this is becoming 37 by 64, so compare this. Earlier, you had the probability of type 2 error as 10 by 64, but as a consequence of reducing the probability of type 1 error, the probability of type 2 error has shouted up, it has become 37 by 64. So, this is the problem which I was mentioning that, if we try to reduce 1 type of error, the other type of error increases very much.

Therefore, a compromise solution is that, we keep a maximum level for one type of error; that means, we say we pre assign that, the probability of say type 1 error should not go beyond a point and then, among all the other test procedures which have the same maximum level of type 1 error we find we choose that one which has the smallest type 2 error. So, that gives us the concept of the most powerful test procedure.

So, there is a theory called. So, in the most general terms the theory would be represented like this, that we have $H_0: \theta \in \Omega_0$ against $H_1: \theta \in \Omega_1$. So, our parameter space is Ω , the full parameter space; you have the hypothesis testing problem as $\theta \in \Omega_0$ against $\theta \in \Omega_1$. So, let me put $\Omega_0 \cup \Omega_1 = \Omega$ or it is not necessary, it may be actually a subset also, because in case we are dealing with a simple hypothesis in that case the full parameter space need not be necessarily this one.

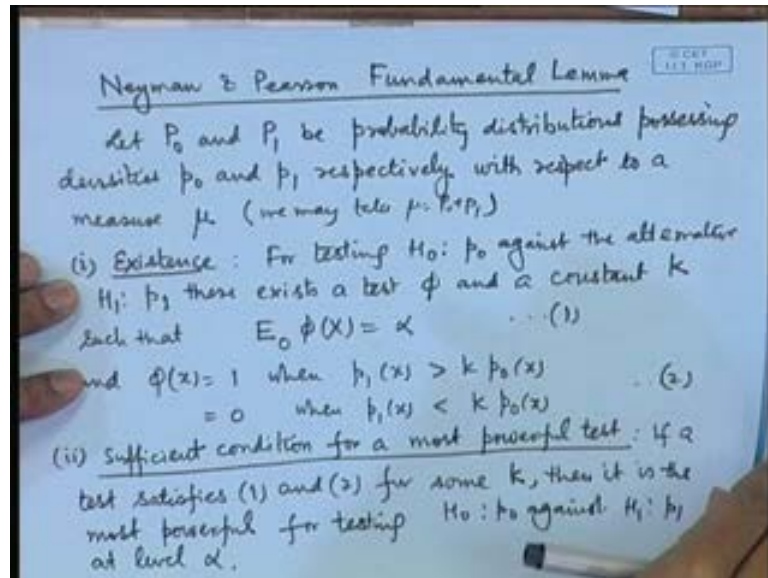
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$\alpha = 1/4$
 $\beta = 3/4$
 $\beta^* = P(X=0 \text{ or } X=1 \text{ or } X=2)$
 $= \left(\frac{1}{4}\right)^3 + 3 \cdot \left(\frac{3}{4}\right) \cdot \left(\frac{1}{4}\right)^2 + 3 \cdot \left(\frac{3}{4}\right)^2 \cdot \frac{1}{4} = \frac{37}{64}$
 $\Omega \rightarrow \text{parameter space}$
 $H_0: \theta \in \Omega_0$
 $H_1: \theta \in \Omega_1$
 $\Omega_0 \cup \Omega_1 \subset \Omega$
 $\phi(x) = \begin{cases} 1 & \text{if } x \in S_R \\ 0 & \text{if } x \in S_A \end{cases}$
 $\alpha(\theta) = P(X \in S_R | \theta \in \Omega_0)$
 $\beta(\theta) = P(X \in S_A | \theta \in \Omega_1)$

So, the procedure that we are trying to tell here is that, we are devising a function $\phi(x)$ based on the sample. So, we are saying $\phi(x)$ is equal to 1, if x belongs to say S_R , it is equal to 0, if x belongs to S_A . But, in some cases as I mention we may go for randomization also, we may put some value p here for certain region. So, the probability of type 1 error, that is probability that x belongs to S_R , when θ belongs to Ω_0 , so we take the maximum of this. So, supremum of $\alpha(\theta)$, that let us call it

say alpha naught or alpha star we choose that and then, we try to minimize beta theta, that is probability of x belonging to S A, when theta belongs to omega 1.

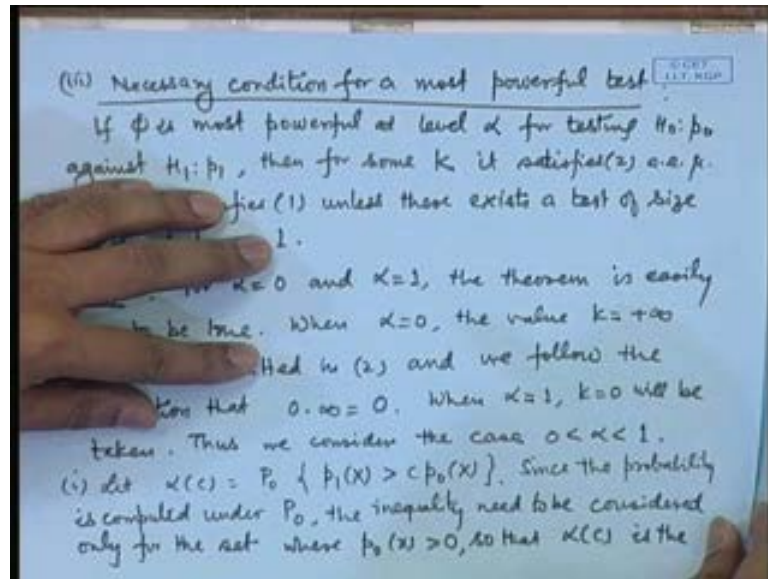
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So, this optimization problem has been dealt with and the basic result in this regard is by Neyman and Pearson and the result is known as popularly Neyman and Pearson fundamental lemma also it is called NP lemma, this fundamental lemma which was given in 1927 by statisticians (()) and Ebony Pearson this initially dealt with the cases, when we are having simple versus simple case.

So, the theorem is as follows: let p_0 and p_1 be probability distributions possessing densities p_0 and p_1 respectively with respect to a measure μ ; we may take say μ is equal to $p_0 + p_1$ also. So, the first part is existence: For testing $H_0: p_0$ against the alternative $H_1: p_1$, that is p_1 there exists a test ϕ and a constant k such that, expectation of $\phi(X)$ is equal to α and $\phi(X)$ is equal to 1, when $p_1(X)$ is greater than $k p_0(X)$; it is equal to 0, when $p_1(X)$ is less than $k p_0(X)$. Second is sufficient condition for a most powerful test: if a test satisfies 1 and 2 for some k , then it is the most powerful for testing $H_0: p_0$ against $H_1: p_1$ at level α .

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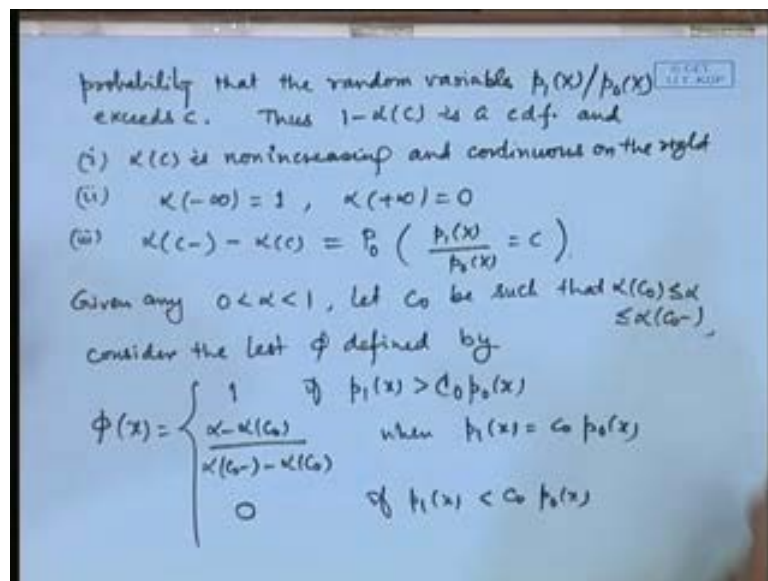
The third is necessary condition for a most powerful test: if ϕ is most powerful at level α for testing $H_0: p_0$ against $H_1: p_1$, then for some k it satisfies (2) or most everywhere μ . It also satisfies (1) unless there exists a test of size α and power 1. So, we see here first of all that, this lemma is very powerful in the sense that, if I am having a simple hypothesis versus a simple hypothesis testing problem, then the first thing it tells is that, there is a test with a given size, then secondly, if that test is of that form and it has that given size, then it is the most powerful. Conversely, if there is a most powerful test then, that must be of this particular form. So, in that sense it is a very important result or you can say a very powerful result, which actually gives you the optimal solution in the case of simple versus simple hypothesis testing problems.

So, let me look at the proof of this and then, we will look at certain applications here, for α is equal to 0 and α is equal to 1, the theorem is easily seen to be true. When α is equal to 0, the value k is equal to plus infinity has to be admitted in (2) and we follow the convention that, 0 into infinity is equal to 0 . When α is equal to 1, k equal to 0 will be taken. Let us, look at these two choices; when α is equal to 0 ; that means, I want the probability of type 1 error to be 0 , when will that happen; that means, probability of rejecting; that means we should never reject, if we do not reject then, this value should be infinity otherwise, so if this is infinity, then right hand side is infinite; that means, always this condition will be true, that is $p_1(x)$ is less than infinite and therefore, you will always be accepting H_0 .

So, the probability of type 1 error will become 0. So, this condition is also satisfied and the whole thing is true basically, because in this case when you will look at the probability of type 2 error that is probability of accepting H_0 that will become 1, because you are always accepting, so the power is 1. So, naturally it is the most powerful test, also we see the case of alpha is equal to 1, alpha is equal to 1 will happen when I take k equal to 0. So, if I take k equal to 0 this side is 0; that means, $p_1(x)$ is greater than 0 is always satisfied therefore, you are always rejecting H_0 ; when you are always rejecting H_0 , then the probability of type 1 error is 1. Now, in this case what is happening to the probability of type 2 error, if you are always rejecting H_0 , then the probability of accepting H_0 will become 0 because, you are never accepting that, because you are always rejecting, so you are never accepting.

So, this gives you beta is equal to 0. So, these are the trivial cases. Now, let us look at the conventional cases. So, let us define a function $\alpha(c)$ is equal to $\alpha(c)$, that is the probability under H_0 , when $p_1(x)$ is greater than $c p_0(x)$.

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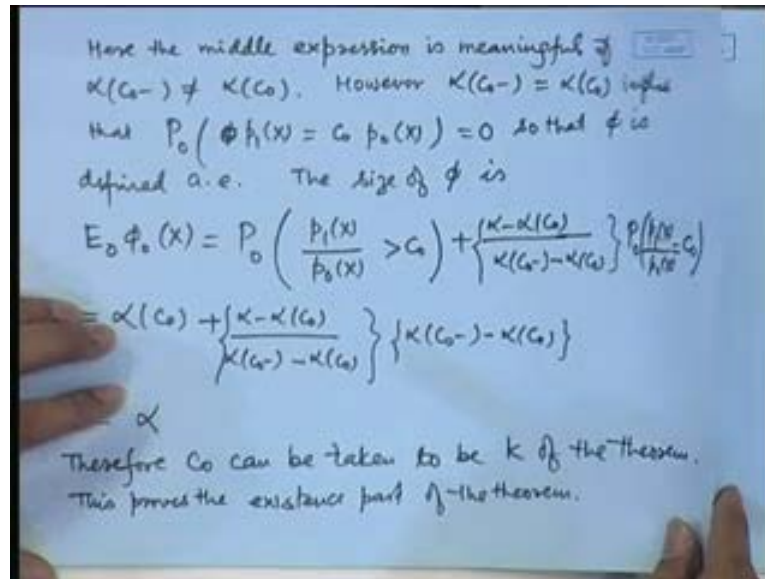


Since the probability is computed under p_0 , the inequality need to be considered only for the set, where $p_0(x)$ is strictly positive, so that $\alpha(c)$ is the probability that the random variable $p_1(x)$ by $p_0(x)$ exceeds c . Thus, $1 - \alpha(c)$ is a cumulative distribution function and we have the following properties; that is $\alpha(c)$ is non-increasing and continuous on the right, that is the properties of the cdf. So, if 1

minus αc is non decreasing, then αc will be non increasing. Secondly α of minus infinity will be 1 that is the limit of αc as c tends to minus infinity, because 1 minus αc is $c d f$ and α plus infinity will become equal to 0. The third is that, αc minus minus αc that is the left hand limit at c minus αc that is the probability that, $p 1 x$ by p naught x is equal to c . So, given any α such that, α is between 0 and 1, let c naught be such that, αc naught is less than or equal to α less than or equal to αc naught minus. Consider the test ϕ defined by: so, we define ϕx is equal to 1, if $p 1 x$ is greater than c naught p naught x and we define α minus αc naught divided by αc naught minus minus αc naught, this denotes the left hand limit at c naught, when $p 1 x$ is equal to c naught p naught x . So, this is the randomization as I was mentioning earlier that, when there is equality we put some value, because finally, we want to achieve the power α , the size α and it is 0, if $p 1 x$ is strictly less than c naught p naught x .

Now, you compare this conditions with the original function we defined here the ϕS equal to 1, when $p 1 x$ is greater than $k p$ naught and it is equal to 0, when $p 1 x$ is less than $k p$ naught. So, if you compare this greater and less conditions are exactly matching here. So, only we have introduce one quantity for equality that is the randomization point, which may be required in the case of discrete distributions. So, and of course as I mentioned this is meaningful only, when αc naught is not equal to αc naught minus, because if it is a continuous distribution this will be 0. So, you do not need to define this thing; that means, this is not useful because, the probability of this event will be actually 0 only in the case of discrete distribution, when the c naught is having a positive probability for the function $p 1 x$ by p naught x then this value will be of use.

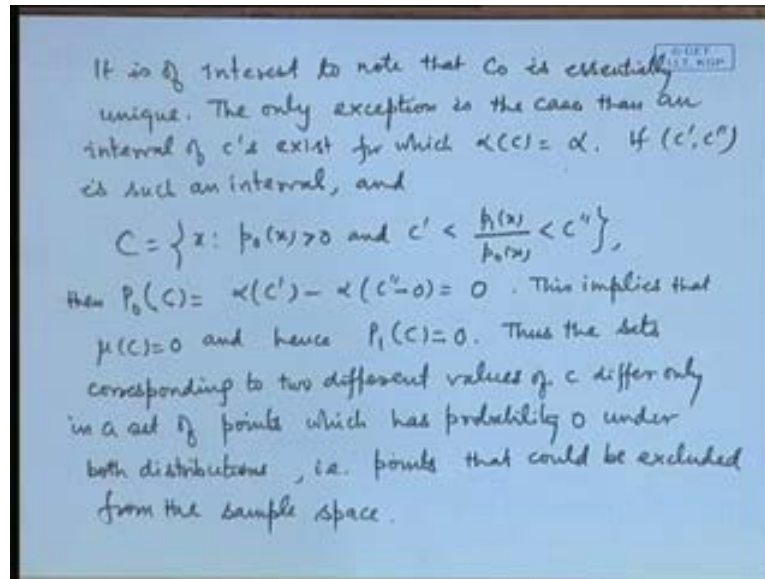
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Let me write that comment here, **here** the middle expression is meaningful if $\alpha(c_0^-)$ is not equal to $\alpha(c_0)$; however, $\alpha(c_0^-) = \alpha(c_0)$ implies that, $P_0(\phi_1(X) = c_0 p_0(X)) = 0$, so that ϕ is defined almost everywhere. Now, let us look at the size of ϕ that is the probability of rejecting, when H_0 is true; that is probability of $p_1(X)$ by $p_0(X)$ greater than c_0 plus $\frac{\alpha - \alpha(c_0)}{\alpha(c_0^-) - \alpha(c_0)}$ times $\frac{p_1(X)}{p_0(X)} - c_0$ divided by $\alpha(c_0^-) - \alpha(c_0)$. So, by the definition here this is $\alpha(c_0^-) + \frac{\alpha - \alpha(c_0)}{\alpha(c_0^-) - \alpha(c_0)} (\alpha(c_0^-) - \alpha(c_0))$ and this value is again $\alpha(c_0^-) - \alpha(c_0)$. So, this term cancels with this and this cancels with this, so this is actually reducing to α .

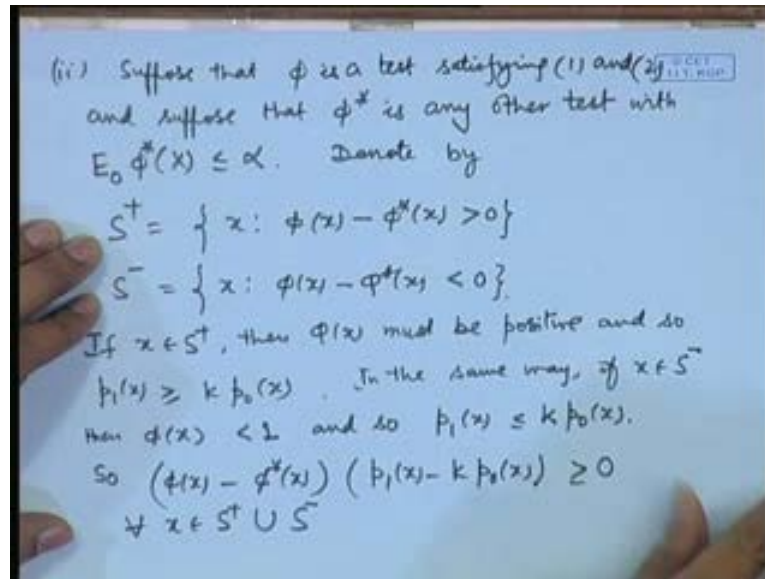
Therefore c_0 can be taken to be k of the theorem. So, this proves the existence part of the theorem, because we have exhibited that, there exists a test which has size equal to α of a given type, because we fix the type also here in the existence part, that there exists a test of this type. So, of course, this was not complete because, this not take care of the equality part. So, we defined that part here and it is having this power α . So, this k value is well defined here. This proves the existence. Let me pay some attention to this value c_0 here.

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Now, it is of interest to note that, c naught is essentially unique. The only exception is the case that an interval of c exists for which αc may be equal to α . So, if c prime to c double prime is such an interval, and c is equal to x such that, p naught x is greater than 0 and c prime is less than p 1 x by p naught x is less than c double prime, then p naught c is equal to αc prime minus αc double prime minus 0 is actually equal to 0. This implies that μc is equal to 0 and hence p 1 c is equal to 0. Thus the sets corresponding to two different values of c differ only in a set of points which has probability 0 under both distributions, that is points that could be excluded from the sample space.

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Now, let us pay attention to the sufficiency part. So, suppose that ϕ is a test satisfying 1 and 2 and suppose that ϕ^* is any other test with say expectation of ϕ^* less than or equal to α .

Let us use the S^+ notation for the set of those points for which $\phi - \phi^*$ is greater than 0 and S^- is the set of those points for which $\phi - \phi^*$ is less than 0. Now these two are test functions. So, both ϕ and ϕ^* take values 0 or 1 or between 0 and 1. So, if x belongs to S^+ , then what we are getting is that $\phi(x)$ is strictly greater than $\phi^*(x)$, then $\phi(x)$ must be positive. Now, if it is positive then, the way we have defined our test function here if you remember here the definition of the test function that, it is positive if it is 0 then only it is less; that means, in other cases it has to be greater than or equal to. So, we will have this then $\phi(x)$ must be strictly positive and so we will have $p_1(x) \geq k p_0(x)$.

Let me repeat this argument, if x belongs to S^+ then $\phi(x)$ is strictly greater than $\phi^*(x)$. Now, $\phi^*(x)$ is a non-negative function therefore, this $\phi(x)$ has to be strictly greater than 0, if $\phi(x)$ is strictly greater than 0, then by our definition of the test function $p_1(x)$ has to be greater than or equal to $k p_0(x)$. In the same way, if x belongs to S^- then here $\phi(x)$ will be strictly less than $\phi^*(x)$ $\phi^*(x)$ can take values between 0 and 1 therefore, $\phi(x)$ is less than 1 and so now less than 1 condition by the definition here is satisfied for ϕ function for $p_1(x) \leq k p_0(x)$.

So, let us look at this we are having $\phi(x) - \phi^*(x) > 0$, when x belongs to S^+ and for that $p_1(x) - k p_0(x) \geq 0$. So, if I multiply these two terms, I will get non negative quantity on the other hand, if x belongs to S^- , then this is negative and this is also $p_1(x) - k p_0(x) \leq 0$. So, the product will become greater than or equal to 0. So, what we are getting is that, $(\phi(x) - \phi^*(x)) (p_1(x) - k p_0(x)) \geq 0$, for all x belonging to $S^+ \cup S^-$.

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Therefore

$$\int (\phi - \phi^*) (p_1 - k p_0) d\mu$$

$$= \int_{S^+ \cup S^-} (\phi - \phi^*) (p_1 - k p_0) d\mu \geq 0$$

or $\int (\phi - \phi^*) p_1 d\mu \geq k \int (\phi - \phi^*) p_0 d\mu$

$$= k \{E_0 \phi(X) - E_0 \phi^*(X)\}$$

$$\geq 0$$

$\Rightarrow \phi - \phi^* \geq 0$

$\Rightarrow \phi$ is more powerful than ϕ^* .

ϕ^* denotes the power

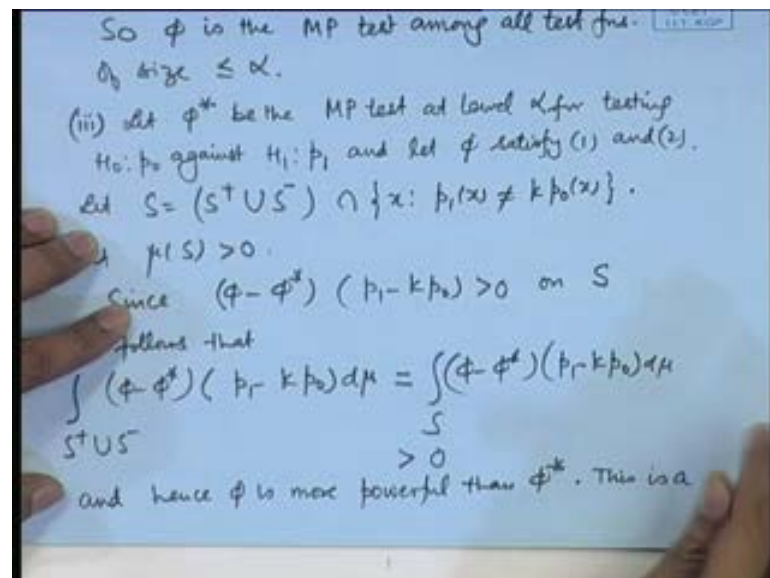
Now, let us use this, if we consider $(\phi(x) - \phi^*(x)) (p_1(x) - k p_0(x)) d\mu$. So, this is a generalized term; that means, if we are dealing with the discrete distribution this will be summation otherwise, it is an integral; So, this integral will be equal to integral over the region. So, we have exhausted all the regions, because over S^+ this term was positive and over S^- , it is negative. So, if we go out of S^+ and S^- , then this will be equal to 0. So, in that case this integral value integrand will become 0. So, we can ignore that. So, we are looking at only the portion where it is non-negative and this is greater than or equal to 0.

So, this we can simplify we can write it as, $(\phi(x) - \phi^*(x)) p_1(x) d\mu \geq k \int (\phi(x) - \phi^*(x)) p_0(x) d\mu$. Now, you look at the right hand side just $(\phi(x) - \phi^*(x)) p_0(x)$, this value is nothing but, the expectation of ϕ under H_0 and expectation of ϕ^* under H_0 , that is we can write it as

k times expectation naught ϕ x minus expectation naught ϕ^* x . Now, expectation naught ϕ x is α and this value we have chosen to be less than or equal to α . So, this is greater than or equal to 0. Now, **what is the right hand side sorry** what the left hand side is? This value is the probability of rejecting, when H_1 is true; that means it is the power function. So, we use the notation say, β^* for the power. So, let me say β^* denotes the power function, then this is $\beta \phi$ minus $\beta \phi^*$ this is greater than or equal to 0 this means that, ϕ is more powerful than ϕ^* .

Now, in this one what we did; we started with a test function ϕ , which satisfies the conditions 1 and 2 that means it has size α and ϕ^* we took to be any other test function, which is having size less than or equal to α ; that means, equal to α case is also covered and then, we are able to prove that the power of ϕ is more than or equal to the power of ϕ^* ; now, this ϕ^* is any arbitrarily chosen test for which the size is less than or equal to α ; that means, among all the test functions which have size less than or equal to α , the power of ϕ is the maximum; that means, ϕ is the most powerful test.

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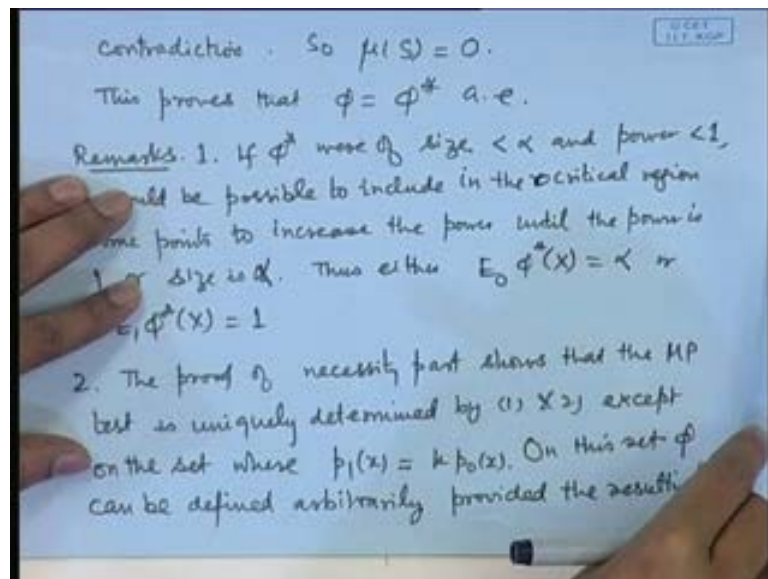


So, ϕ is the most powerful test among all test functions of size less than or equal to α . So, this theorem is very powerful in that sense that, for a simple versus simple situation it gives you a test procedure with a pre assigned size, which is the most powerful. So, you have actually an optimal solution in this situation, but there is

something more to this here, if there is a test which is most powerful, then it will satisfy conditions 1 and 2. So, this is another important thing that, there will not be any other test also. So, in that sense it is a necessary and sufficient condition.

Let me prove that also. So, let ϕ^* be the most powerful test at level α for testing H_0 against H_1 and let ϕ satisfy 1 and 2. Let us take say, S is equal to $S_+ \cup S_-$ the set of the values for which $p_1(x)$ is not equal to $k p_0(x)$. Let $\mu(S)$ is positive. Now, we have already seen that, on S_+ and S_- the quantity $\phi - \phi^*$ and $p_1 - k p_0$ will be greater than 0. So, as already observed that, $\phi - \phi^*$ into $p_1 - k p_0$ is greater than 0 on S , it follows that $\int_S (\phi - \phi^*)(p_1 - k p_0) d\mu$ that is equal to $\int_S (\phi - \phi^*)(p_1 - k p_0) d\mu$ this is strictly greater than 0. So, this means that, ϕ is more powerful than ϕ^* . So, this is a contradiction because I started with ϕ^* to be the most powerful.

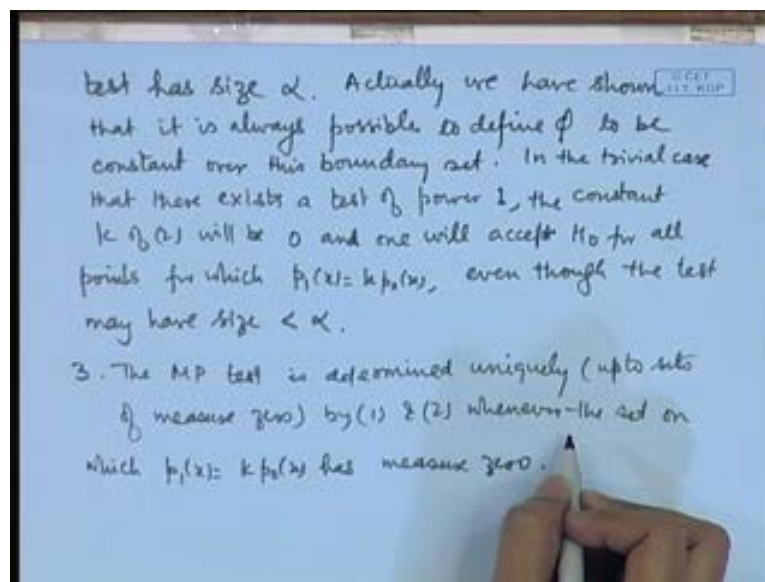
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This is a contradiction, so $\mu(S)$ must be equal to 0; that means, the set where you have this $\phi - \phi^*$ $p_1 - k p_0$ is actually greater than 0 that set must have measure 0. This proves that, ϕ and ϕ^* are same almost everywhere. So, in this third part what we have done is that, if there is a most powerful test it must be the same as a test which satisfies the conditions 1 and 2; that means, and that is almost everywhere; that means, over a set of measure 0 you may modify the things here.

So, in essence this Neyman Pearson fundamental lemma gives you entire conditions under which you can derive a most powerful test uniquely up to almost everywhere. Let me give a few remarks here; if ϕ were of size say less than α and power less than 1, it would be possible to include in the critical region some points to increase the power until the power is 1 or size is 1, either of the things will happen. Thus, either you will have expectation of ϕ is equal to α or expectation $1 - \phi$ is equal to 1; that means, either the size will become 1 or the sorry this is size is α either the size will become α or the power will become 1. The proof of necessity part shows that, the most powerful test is uniquely determined by 1 and 2 except on the set, where $p_1(x)$ is actually equal to $k p_0(x)$; that means on this portion we can define it arbitrarily, but the size has to remain α .

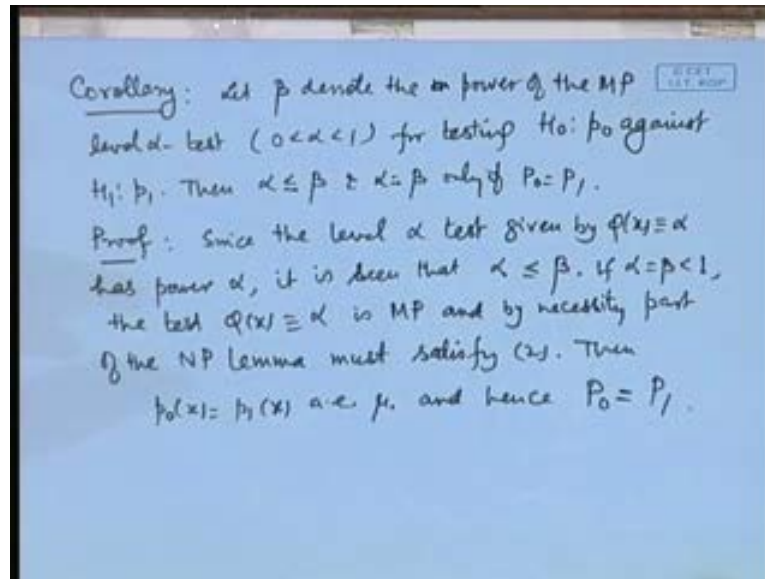
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So, on this set ϕ can be defined arbitrarily provided the resulting test has size α . Actually we have shown that, it is always possible to define ϕ to be constant over this boundary set. In the trivial case, that there exists a test of power 1, the constant k of 2 will be 0 and 1 will accept H_0 for all points for which $p_1(x)$ is equal to $k p_0(x)$, even though the test may have size less than α .

Third remark is that, the most powerful test is determined uniquely up to sets of measure 0 by 1 and 2 whenever the set on which $p_1(x)$ is equal to $k p_0(x)$ has measure 0.

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We have a corollary here then, let beta denote the most the power of the most powerful level alpha test for testing $H_0: p_0$ against $H_1: p_1$. Then alpha is less than or equal to beta and alpha is equal to beta only if p_0 is equal to p_1 .

Let me see a proof of this since the level alpha test given by $\phi(x) \equiv \alpha$; that means, throughout this has power alpha, it is seen that alpha has to be less than or equal to beta. If alpha is equal to beta is less than 1, the test $\phi(x) \equiv \alpha$ everywhere is MP and by necessity part of the NP lemma it must satisfy 2. If it satisfies 2, then $p_0(x) \equiv p_1(x)$ almost everywhere μ and hence you must have a p_0 is equal to p_1 ; that means, basically there is no testing problem if the null and alternative hypotheses are same, then the testing problem is dissolved actually; that means, there is no inference problem left here.

So, today we have seen a powerful tool to derive the most powerful test for simple versus simple hypothesis testing problems. So, we will see some applications in the next lectures this entire theory for the testing of hypothesis, because in most of the other cases we will have a composite hypothesis, a simple versus composite or a composite versus composite hypothesis, there have been extensions of this Neyman Pearson fundamental lemma, the whole theory was developed in 1930s by Neyman and Pearson. So, that will be the part of the course on statistical inference in this particular course in the remaining portion, I will be taking up the applications of the Neyman Pearson lemma for looking at

the simple versus simple problems as well as, applications to specific parameter testing problems in the normal distributions, the test for the proportions in both in 1 sample and 2 sample problems and we will also look at the chi square for test for goodness of fit. So, that will be the coverage for the next lectures.