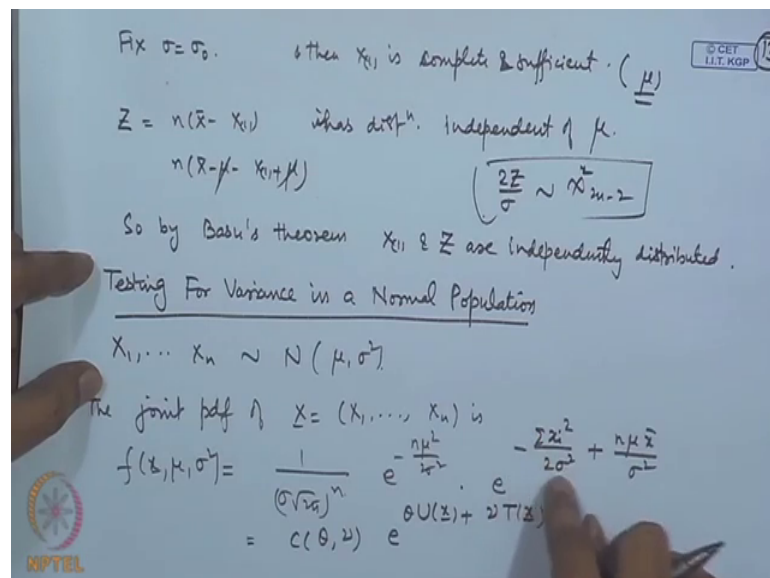


**Statistical Inference**  
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**Lecture – 49**  
**Unbiased Test for Normal Populations – III**

In the previous lecture, I have started discussing test how to obtain the UMP Unbiased Test for the variance of a Normal Population when both the parameters are unknown. So the model, let me recollect here.

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We considered a random sample from normal  $\mu$  sigma square distribution. The joint density function of  $X_1, X_2, \dots, X_n$ , I am expressing in the form of a two parameter exponential population.  $C(\theta, \nu) e^{-\theta U(x) + \nu T(x)}$  where, I am defining  $\theta$  as  $1 / (2\sigma^2)$ ,  $U$  is equal to  $\sum X_i^2$ ,  $\nu$  is equal to  $n\mu / \sigma^2$  and  $T$  is equal to  $\bar{X}$ .

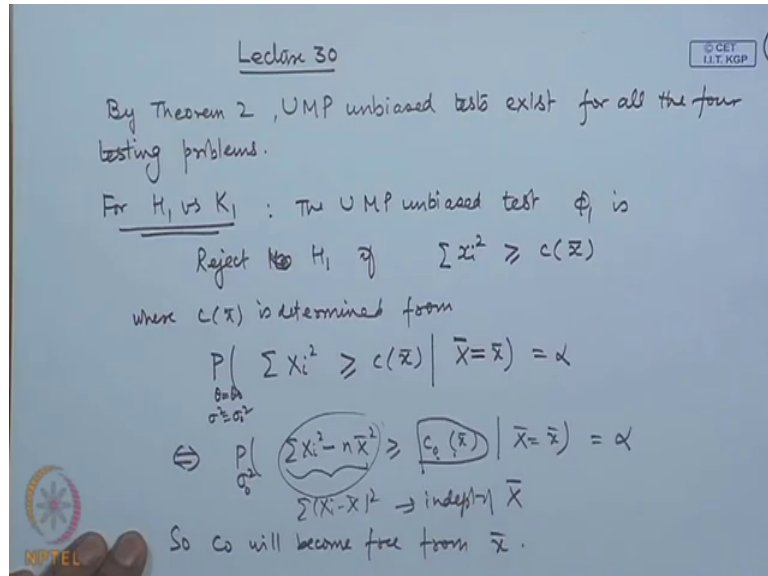
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When  $\theta = -\frac{1}{2\sigma^2}$ ,  $U = \sum X_i^2$ ,  $v = \frac{n\mu}{\sigma^2}$ ,  $T = \bar{X}$ .  
 Define  $\theta_0 = -\frac{1}{2\sigma_0^2}$   
 Then  $H_0: \theta \leq \theta_0$  vs  $K_0: \theta > \theta_0$   
 $\Leftrightarrow H_1^*: \sigma^2 \leq \sigma_0^2$  vs  $K_1^*: \sigma^2 > \sigma_0^2$ .  
 $\theta_1 = -\frac{1}{2\sigma_1^2}$ ,  $\theta_2 = -\frac{1}{2\sigma_2^2}$   
 $H_2: \theta \leq \theta_1$  or  $\theta \geq \theta_2$  vs  $K_2: \theta_1 < \theta < \theta_2$   
 $\Leftrightarrow H_2^*: \sigma^2 \leq \sigma_1^2$  or  $\sigma^2 \geq \sigma_2^2$  vs  $K_2^*: \sigma_1^2 < \sigma^2 < \sigma_2^2$ .  
 $H_3 \rightarrow H_4: \theta = \theta_0$  vs  $K_4: \theta \neq \theta_0$   
 $\Leftrightarrow H_4^*: \sigma^2 = \sigma_0^2$  vs  $K_4^*: \sigma^2 \neq \sigma_0^2$ .

I have shown that the four testing problems  $H_1$ ,  $H_2$ ,  $H_3$  and  $H_4$  they are equivalent to testing about sigma square. So, and they are having the same form that is because theta naught theta is equal to minus 1 by 2 sigma square. This is an increasing function of sigma square. Therefore, all the inequalities or equalities are maintained. That is, theta less than or equal to theta naught is equivalent to sigma square is less than or equal to sigma naught square; if I define theta naught to be equal to minus 1 by 2 sigma naught square.

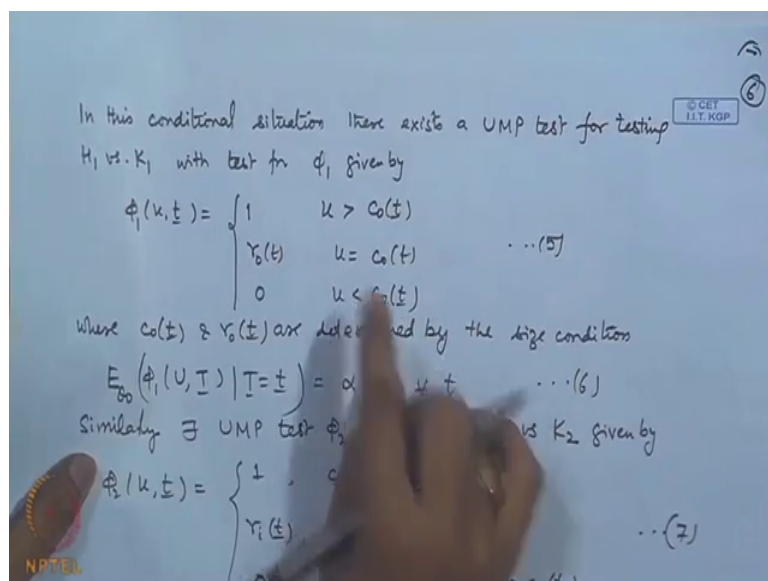
Similarly, if I define theta 1 is equal to minus 1 by 2 sigma 1 square and theta 2 is equal to minus 1 by 2 sigma 2 square, then theta less than or equal to theta 1 or theta greater than or equal to theta 2 is equivalent to sigma square less than or equal to sigma 1 square or sigma square greater than or equal to sigma 2 square. And similarly, theta 1 less than theta 2 is equivalent to sigma 1 square less than sigma square less than sigma 2 square and so on.

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Therefore the, by theorem 2 which I discussed yesterday, UMP unbiased tests, UMP unbiased tests exist for all the four testing problems. So, let me take up  $H_1$  versus  $K_1$ . So now, we are dealing with the continuous distributions.

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Therefore in the test function, the term gamma naught, this term I need not write because the probability of this  $u$  is equal to  $C$  naught  $t$  will be 0. So, we do not write this rather, we incorporate it in either this part or here. So, if I take this to be 0 for example, then this will be incorporated here.

So, the UMP unbiased test, say  $\phi_1$  is reject  $H_0$  if  $\frac{\sum (X_i - \bar{X})^2}{\sigma_0^2} \geq k$  that is,  $\sigma^2$  is greater than or equal to a function of  $\bar{X}$ ; and this  $C$  is determined from probability of  $\sigma^2 \geq C$  given  $\bar{X}$  is equal to  $\alpha$  when,  $\theta = \theta_0$  or say  $\sigma^2 = \sigma_0^2$ .

Now note here, this meets the conditional distribution of  $\sigma^2$  even given  $\bar{X}$  which is slightly inconvenient. However, here we can apply a trick here. This is equivalent to saying probability of  $\sum (X_i - \bar{X})^2$  greater than or equal to some other function say  $C$  given  $\bar{X}$  is equal to  $\alpha$  at  $\sigma^2 = \sigma_0^2$ .

Now, this  $\sum (X_i - \bar{X})^2$ , this is independent of  $\bar{X}$ . If this is independent of  $\bar{X}$ , this term will become free from; so  $C$  will become free from  $\bar{X}$ . Now this is what we had required here.

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So  $\frac{\sum (X_i - \bar{X})^2}{\sigma_0^2} \geq k \rightarrow \underline{\text{Reject } H_0}$

$\frac{\sum (X_i - \bar{X})^2}{\sigma_0^2} \sim \chi_{n-1}^2$  when  $\sigma^2 = \sigma_0^2$ .

So  $k = \chi_{n-1, \alpha}^2$

If we want to apply Theorem 3 directly.  
Then define  $W = h(U, T) = U - nT^2 = \sum X_i^2 - n\bar{X}^2 = \sum (X_i - \bar{X})^2$ .

Then  $W$  and  $U$  are independent.  
 $W$  is  $\uparrow$  in  $U$ .

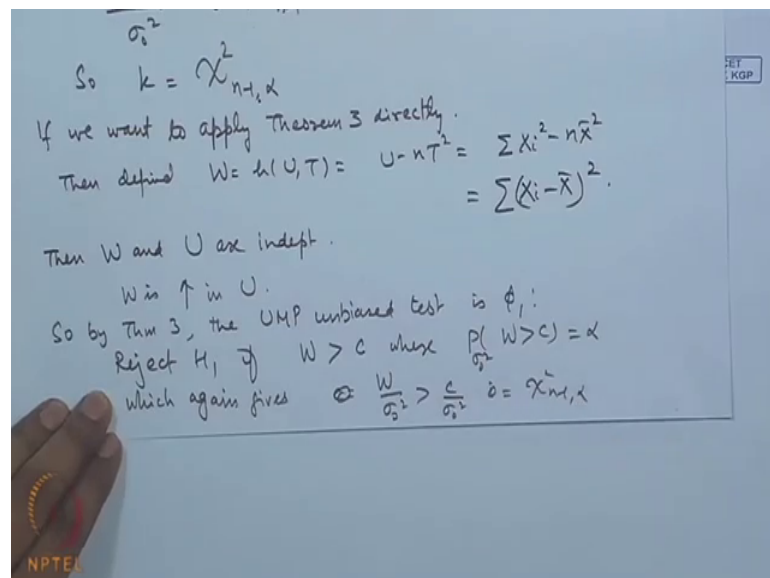
So by Thm 3, the UMP unbiased test is  $\phi_1$ :  
Reject  $H_0$  if  $W > c$  where  $P_{\sigma_0^2}(W > c) = \alpha$

So, we can say  $\sum (X_i - \bar{X})^2$  by  $\sigma_0^2$  greater than or equal to say  $k$ . So, since  $\sum (X_i - \bar{X})^2$  by  $\sigma_0^2$  this follows chi square distribution on  $n - 1$  degrees of freedom when  $\sigma^2 = \sigma_0^2$ .

So, this  $k$  will become equal to upper 100 alpha percent point of chi square distribution on  $n$  minus 1 degrees of freedom. So, we have got an exact test. So, this is the reject  $H_1$ . We are getting the level alpha test. This is UMP unbiased test; if we want to apply theorem say, 3 directly, then define  $W$  is equal to  $h(U, T)$  is equal to  $U$  minus  $nT$  square that is equal to  $\sum X_i^2$  minus  $n\bar{X}$  square that is  $\sum (X_i - \bar{X})^2$  whole square.

Then  $W$  and  $U$  are independent. So, for sigma square is equal to sigma naught square also they will be independent and  $W$  is increasing in  $U$ . So by theorem 3, the UMP unbiased test is phi 1 reject  $H_1$  if  $W$  is greater than some  $C$  where, probability of  $W$  greater than  $C$  at sigma naught square is equal to alpha; which is the same.

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Which again gives  $c$  that is,  $W$  by sigma naught square greater than  $C$  by sigma naught square that is equal to chi square  $n$  minus 1 alpha.

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The tests for  $H_2$  &  $H_3$  can also be derived in a similar way.

For  $H_2$  vs  $K_2$ , UMP unbiased test is Reject  $H_2$  if  $C_1 < W < C_2$

$$\left\{ P\left(\frac{C_1}{\sigma_1^2} < \frac{W}{\sigma_1^2} < \frac{C_2}{\sigma_1^2}\right) = \alpha, i=1,4 \right\}$$

For  $H_4$  vs  $K_4$  UMP unbiased test  $\phi_4$  is

Reject  $H_4$  if  $W < C_1$  or  $W > C_2$

or accept if  $C_1 \leq W \leq C_2$

$\frac{W}{\sigma_1^2} \sim \chi_{n-1}^2$   
 $E\left(\frac{W}{\sigma_1^2}\right) = (n-1)$

$P\left(\frac{C_1}{\sigma_1^2} \leq \frac{W}{\sigma_1^2} \leq \frac{C_2}{\sigma_1^2}\right) = 1 - \alpha$ ,  $E\left(\frac{W}{\sigma_1^2} (1 - \phi_4(W))\right) = (1 - \alpha) E\left(\frac{W}{\sigma_1^2}\right)$

$\int_{C_1/\sigma_1^2}^{C_2/\sigma_1^2} \chi_{n-1}^2(y) dy = 1 - \alpha$   
 $\Rightarrow \int_{C_1/\sigma_1^2}^{C_2/\sigma_1^2} y \chi_{n-1}^2(y) dy = 1 - \alpha$

The tests for  $H_2$  and  $H_3$  can also be derived in a similar way. Let me write for one of them. For  $H_2$  versus  $K_2$  problem, UMP unbiased test is reject  $H_2$  if  $C_1$  is less than  $W$  is less than  $C_2$  and you will have a probability of  $C_1$  by  $\sigma_1^2$  less than or equal to  $W$  by  $\sigma_1^2$  less than  $C_2$  by  $\sigma_1^2$  is equal to  $\alpha$ . Then  $\sigma_1^2$  is the true parameter value and also when  $\sigma_2^2$  is also coming.

So, these two conditions will give the value of  $C_1$  and  $C_2$  for  $H_4$  versus  $K_4$  problem. Now here, UMP unbiased test is reject  $H_4$  if  $W$  is less than  $C_1$  or  $W$  is greater than  $C_2$  or accept if  $C_1$  is less than or equal to  $W$  less than or equal to  $C_2$ . You will have probability of  $C_1$  less than or equal to  $W$  less than or equal to  $C_2$  at  $\sigma_1^2$  is equal to  $\alpha$ .

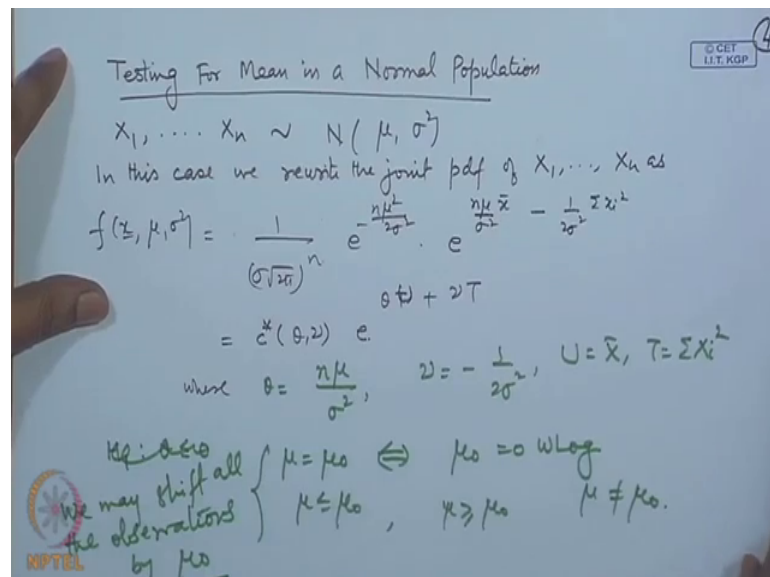
And there will be another condition that is expectation of  $W$   $1 - \phi_4$ . Let me call it  $\phi_4$ .  $\phi_4 W$  at  $\sigma_1^2$  is equal to  $1 - \alpha$  expectation  $\sigma_1^2 W$ . Now in this  $W$ , you consider the division by  $\sigma_1^2$ . So for example, here this will become  $\sigma_1^2$ , this becomes  $\sigma_1^2$ , this becomes  $\sigma_1^2$ . So here also you consider division. So,  $W$  by  $\sigma_1^2$  follows chi square  $n - 1$ .

So, expectation of  $W$  by  $\sigma_1^2$  is equal to  $n - 1$ . So this condition, second condition will become then expectation of well you can write integral  $1$  by  $n - 1$   $y$  of chi square  $n - 1$   $y$   $dy$ . This is the density function of a chi square

variable on  $n - 1$  degrees of freedom from  $C_1$  by  $\sigma^2$  to  $C_2$  by  $\sigma^2$  is equal to  $1 - \alpha$  and this condition is actually equal to chi square  $n - 1$  density from  $C_1$  by  $\sigma^2$  to  $C_2$  by  $\sigma^2$  is equal to  $1 - \alpha$ .

So, these two conditions will give the value of  $C_1$  and  $C_2$ . I have demonstrated here that we can apply theorem 3; that means, we can suitably define the function  $W$  such that we are getting the UMP unbiased test for the variance testing. Let us also consider now the testing for the mean; testing for mean in a normal population.

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Let us go back to the original expression that I wrote for the joint density of normal distribution of  $X_1, X_2, \dots, X_n$  here. Here I took  $\theta$  to be  $n\mu/\sigma^2$  and  $\nu$  to be  $-1/(2\sigma^2)$  and therefore, I was able to test for  $\sigma^2$ . If I want to test for  $\mu$  then I have to change the role of  $\theta$  and  $\nu$  here. So, then I write it here. So, model is the same; that means,  $X_1, X_2, \dots, X_n$  follows normal  $\mu, \sigma^2$ .

Now in this case, we rewrite the joint pdf of  $X_1, X_2, \dots, X_n$  as  $e^{-n\mu/(2\sigma^2)}$   $e^{n\mu\bar{x}/(2\sigma^2) - 1/(2\sigma^2)\sum x_i^2}$  and this I call  $c^*(\theta, \nu)$   $e^{\theta U + \nu T}$ . Now here, I have changed the rules. Here,  $\theta$  is equal to  $n\mu/\sigma^2$ ,  $\nu$  is equal to  $-1/(2\sigma^2)$ ,  $U$  is equal to  $\bar{X}$ ,  $T$  is equal to  $\sum X_i^2$ .

Ah Let me restrict attention to H 1 and H 4. So, H 1 would be theta less than or equal to 0. Ok if I want to test for say mu is equal to mu naught, then this is equivalent to that I can take mu not to be 0 without loss of generality. If I take mu less than or equal to mu naught r and so on. Mu greater than mu naught or mu not equal to mu naught because we can shift all the observations by mu naught.

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So we may write the testing problems as

$$H_1: \theta \leq 0 \text{ vs } K_1: \theta > 0$$

$$\Leftrightarrow H_1^*: \mu \leq 0 \text{ vs } K_1^*: \mu > 0$$

$$H_4: \theta = 0 \text{ vs } K_4: \theta \neq 0$$

$$\Leftrightarrow H_4^*: \mu = 0 \text{ vs } K_4^*: \mu \neq 0.$$

UMP unbiased tests exist for both the problems.

For  $H_1$  vs  $K_1$  
$$W = \frac{U}{\sqrt{T - nU^2}} = \frac{\bar{X}}{\sqrt{\sum X_i^2 - n\bar{X}^2}} = \frac{\bar{X}}{\sqrt{\sum (X_i - \bar{X})^2}}$$

$W$  is increasing fn. of  $U$ .

So my testing problem can be then written as. So, we may write the testing problems as; so for example, if I am looking at say H 1 theta less than or equal to 0 versus K 1 theta greater than 0 then this is equivalent to say H 1 star mu less than or equal to 0 versus K 1 star mu greater than 0. Similarly, if I consider say H 4 theta is equal to 0 versus K 4 theta is not equal to 0 then, this is equivalent to H 4 star theta, sorry mu is equal to 0 versus K 4 star mu is not equal to 0.

So, let me UMP unbiased tests will exist ok. UMP unbiased tests exist for both the problems. So now, let us consider say for H 1 versus K 1 problem. For this problem, I define W is equal to U by square root T minus nU square. That is, X bar divided by root sigma X i square minus n X bar square. So this is nothing but, X bar divided by square root sigma X i minus X bar whole square.

If you see this carefully, then W is increasing function of U and if we consider the distribution of W and T. The distribution of T when mu is equal to 0 then that is free



from  $\mu$ ; and if I consider the distribution of  $W$ , that is also free from when  $\mu$  is equal to 0 it is free from. So, let me just write it here.

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The dist<sup>n</sup> of  $W$  are Tare independent when  $\mu=0$ .  
 So by Thm 3, UMP unbiased test for  $H_1$  vs  $K_1$  is  
 Reject  $H_1$  if  $W \geq c$

$$W = \frac{\bar{X}}{\sqrt{\sum (X_i - \bar{X})^2}}$$

$\bar{X} \sim N(0, \frac{\sigma^2}{n})$  ( $\mu=0$ )  
 $\frac{\bar{X}}{\sigma} \sim N(0, 1)$   
 $\frac{\sum (X_i - \bar{X})^2}{\sigma^2} \sim \chi_{n-1}^2$   
 independent

$$\sqrt{n(n-1)} W = S = \frac{\sqrt{n} \bar{X} / \sigma}{\sqrt{\sum (X_i - \bar{X})^2 / \sigma^2 (n-1)}} \sim t_{n-1}$$

When  $\mu=0$ ,  $S \sim t_{n-1}$

The distributions of  $W$  and  $T$  are independent when  $\mu$  is equal to 0. So by theorem 3, UMP unbiased test for  $H_1$  versus  $K_1$  is reject  $H_1$  if  $W$  is greater than or equal to  $C$ . Now, in order to look at the distribution of  $W$ .  $Cv W$  is  $\bar{X}$  divided by root sigma  $X_i$  minus  $\bar{X}$  whole square. So, we may consider here  $\bar{X}$  follows normal 0 sigma square when  $\mu$  is equal to 0. So,  $\bar{X}$  by sigma follows normal 0, 1. If I look at  $\bar{X}$  divided by a root sorry, sigma  $X_i$  minus  $\bar{X}$  whole square by sigma square that follows chi square  $n-1$  and these two are independent. These two are independent.

So, if I look at the ratio  $\bar{X}$  by sigma divided by square root sigma  $X_i$  minus  $\bar{X}$  whole square by sigma square into  $n-1$ , that will follow  $t$  distribution on  $n-1$  degrees of freedom. Now, there is a small mistake here this will be divided by  $n$ . So here I will have to put a square root  $n$ . So, this is square root  $n$ ; that means, it is equal to square root  $n$  into  $n-1$   $W$ . So, we can modify, we can define this as say let me call it say  $S$ . So, when  $\mu$  is equal to 0,  $S$  follows  $t$  distribution on  $n-1$  degrees of freedom.

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$$W = \frac{\bar{X}}{\sqrt{\sum (X_i - \bar{X})^2}}$$

$$\sqrt{n(n-1)} W = S = \frac{\sqrt{n}\bar{X}/\sigma}{\sqrt{\sum (X_i - \bar{X})^2 / \sigma^2 (n-1)}} \sim t_{n-1}$$
 When  $\mu=0$ ,  $S \sim t_{n-1}$   
 $W \geq c \Leftrightarrow S \geq k$ ,  $P_{\mu=0}(S \geq k) = \alpha \downarrow t_{n-1, \alpha}$

So the region  $W$  greater than or equal to  $C$  is equivalent to  $S$  greater than or equal to some  $K$  where probability of  $S$  greater than or equal to  $K$  when  $\mu$  is equal to 0 should be equal to  $\alpha$ ; that means,  $K$  value is nothing, but  $t_{n-1, \alpha}$ . That is the upper 100  $\alpha$  percent point of the  $t$  distribution on  $n$  minus 1 degrees of freedom. So, the exact test has been derived.

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Then the best is Reject  $H_0$  if  

$$|\sqrt{n(n-1)} W| \geq c$$
 For  $H_0$  vs  $H_1$ , we define  $W = \frac{U}{\sqrt{T}}$  (this linear in  $U$ )  
 The dist<sup>n</sup> of  $W$  is indept of  $T$  when  $\mu=0$ . (the dist<sup>n</sup> of  $W$  is symmetric about 0 when  $\mu=0$ )  
 The conditions (7), (8), (9) are therefore satisfied for the rejection region  
 $|W| \geq c \Leftrightarrow |t| \geq k$   
 $P(|W| \geq c) = \alpha$   
 If we define  $t = \frac{\sqrt{n(n-1)} W}{\sqrt{1-nW^2}} \sim t_{n-1} (\mu=0)$   
 We can then choose  $k = t_{n-1}(\alpha/2)$

If I use the notation which I have developed here then, the test is reject  $H_0$  if root  $n$  into  $n$  minus 1  $W$  is greater than or equal to  $t_{n-1, \alpha}$ . So, this is the exact test.

We may include equality or we may not include any equality here at this point, it does not make any difference.

If you look at this function here that I have defined,  $U$  divided by square root  $T$  minus  $n$   $U$  square. This is not a linear function of  $T$ ; a linear function of  $U$ ; although it is increasing in  $U$  but it is not linear. So, if I want to test the hypothesis,  $H_4$  versus  $K_4$ , I cannot use this. So, further I define another function for  $H_4$  versus  $K_4$ , we define  $W$  equal to  $U$  divided by square root of  $T$ .

Now, this is linear in  $T$ , linear in  $U$ , increasing in  $U$  and the distribution of  $W$  is independent of  $T$  when  $\mu$  is equal to 0. So, the conditions that I wrote in  $H_4$  versus  $K_4$  test for the test function  $\phi_4$ . Let us recollect those conditions. The conditions I wrote as the form of the  $\phi_4$  function the condition, that expectation of  $\phi_4$  should be equal to  $\alpha$  at  $\theta$  naught also, expectation of  $\theta$  naught  $W \phi_4 W$ . There should be  $\alpha$  times expectation of  $\phi_4 W$ . These conditions 7, 8, 9 they should be satisfied here.

So, the conditions 7, 8, 9 are therefore, satisfied. Ok we note here, the distribution of  $W$  is symmetric about 0 when  $\mu$  is equal to 0. That is important here. The condition 7, 8, -9 are therefore, satisfied for the rejection region modulus  $W$  greater than or equal to  $C$  and probability of modulus  $W$  greater than or equal to  $C$  is equal to  $\alpha$ . So, if we define say a small  $t$  is equal to square root  $n$  into  $n$  minus 1  $W$  divided by square root  $1$  minus  $nW$  square then, modulus  $t$  is increasing in modulus  $W$ .

So, this region is then equivalent to modulus  $t$  greater than or equal to  $K$  and the distribution of  $t$  is nothing but  $t$  distribution on  $n$  minus 1 degrees of freedom when  $\mu$  is equal to 0. So, we can choose then this  $K$  as  $t_{n-1, \alpha/2}$ . This is the famous  $t$  test which was initially derived by Gossett in 1907. Of course, he did not consider it as a UMP unbiased test, he considered it as a likelihood ratio test only. But here, we are able to derive the exact test when  $\sigma$  is unknown. So, this is testing for the mean.