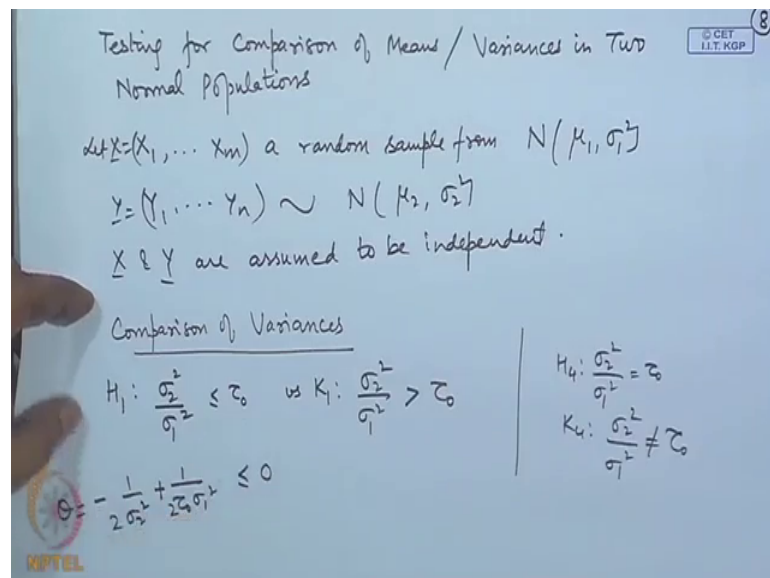


Statistical Inference
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Lecture – 50
Unbiased Test for Normal Populations – IV

Now I will consider two sample problems.

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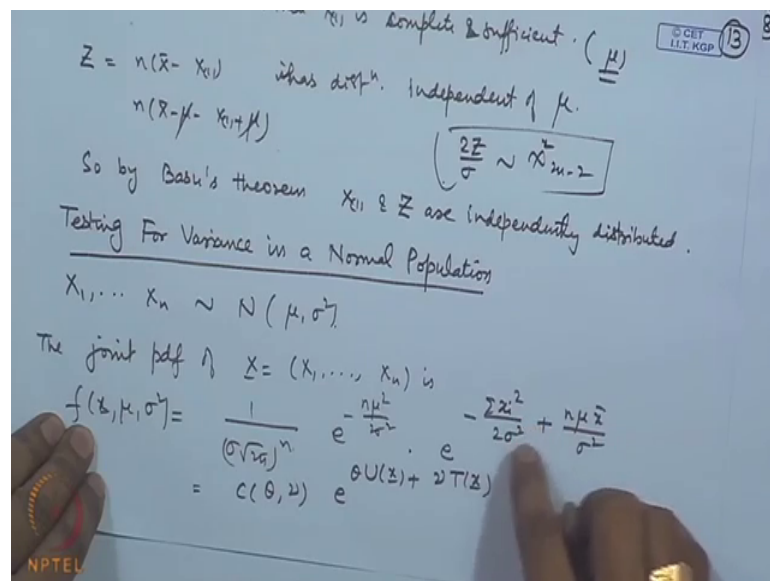
That means we consider testing for comparison of means and variances in two normal populations. Remember, here our aim is to consider the UMP unbiased test. Therefore, we will write the joint density in the form of a multi parameter exponential family. So, let us consider say X_1, X_2, \dots, X_m , a random sample from normal μ_1 sigma 1 square ; and Y_1, Y_2, \dots, Y_n a random sample from normal μ_2 , sigma 2 square.

So, I assume that X and R are independently collected; the two random samples are independent. Now let us take the first problem, comparison of say variances ; that means, I need to test something like sigma 1 square is equal to sigma 2 square against sigma 1 square is not equal to sigma 2 square. Sigma 1 square is less than or equal to sigma 2 square or sigma 1 square is greater than sigma 2 square etcetera. That is the comparison.

Now, keeping into view that the sigma parameter in the normal distribution, is actually a scale parameter. When we are considering the scale, it will be beneficial if I consider the

ratio; that means, the hypothesis $\sigma_1^2 = \sigma_2^2$. I can express as $\sigma_2^2 / \sigma_1^2 = 1$ or $\sigma_2^2 = \sigma_1^2$. Similarly, if I say $\sigma_1^2 < \sigma_2^2$, I can express it as $\sigma_2^2 / \sigma_1^2 > 1$, greater than or equal to 1 etcetera ; that means, I take the ratio. Because in the form of the density, that I have expressed in the normal distribution.

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You can see; here this is appearing in the denominator, so taking the difference will not be easy. In fact, it will be extremely inconvenient. Therefore, if I take the ratio, I will be able to express it in a proper form. So now, let us look at the hypothesis testing problem such as say H_1 . I will write slightly general hypothesis, $\sigma_1^2 = \tau$ against say $K_1 \sigma_2^2 / \sigma_1^2 < \tau$ and similarly, we may consider say $H_4 \sigma_2^2 / \sigma_1^2 = \tau$ against $K_4 \sigma_2^2 / \sigma_1^2 > \tau$.

So, in order to write it in the form of a required desired multi parameter exponential family, let us write down the joint.

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The joint pdf of X & Y is

$$f(x, y, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2) = \frac{1}{(\sigma_1 \sqrt{2\pi})^m (\sigma_2 \sqrt{2\pi})^n} e^{-\frac{m\mu_1^2}{2\sigma_1^2} - \frac{n\mu_2^2}{2\sigma_2^2}} e^{-\left[\frac{\sum x_i^2}{2\sigma_1^2} - \frac{\sum y_j^2}{2\sigma_2^2} + \frac{m\mu_1 \bar{x}}{\sigma_1^2} + \frac{n\mu_2 \bar{y}}{\sigma_2^2} \right]}$$

$$= c(\theta, \eta) e^{\left[\left(\frac{1}{2\sigma_1^2 \tau_0} - \frac{1}{2\sigma_1^2} \right) \sum y_j^2 - \frac{1}{2\sigma_1^2} \left(\sum x_i^2 + \frac{1}{\tau_0} \sum y_j^2 \right) + \frac{m\mu_1}{\sigma_1^2} \bar{x} + \frac{n\mu_2}{\sigma_2^2} \bar{y} \right]}$$

$$\theta = \frac{1}{2\sigma_1^2 \tau_0} - \frac{1}{2\sigma_1^2}, \quad U = \sum y_j^2$$

$$\nu_1 = -\frac{1}{2\sigma_1^2}, \quad T_1 = \sum x_i^2 + \frac{1}{\tau_0} \sum y_j^2$$

$$\nu_2 = \frac{m\mu_1}{\sigma_1^2}, \quad T_2 = \bar{x}, \quad \nu_3 = \frac{n\mu_2}{\sigma_2^2}, \quad T_3 = \bar{y}$$

So $H_1: \frac{\sigma_1^2}{\tau_0} \leq \tau_0 \Leftrightarrow H_1^*: \theta \leq 0$ $H_4: \frac{\sigma_1^2}{\sigma_2^2} = \tau_0$
 $\Leftrightarrow H_4^*: \theta = 0$

The joint pdf of X and Y ; so, that is equal to $f(x, y, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2)$ square, that is equal to so, there will be some terms. Basically, if I write it in full, it will become 1 by σ_1 1 root 2π to the power m . σ_2 2 root 2π to the power n , e to the power minus $m\mu_1^2$ square by $2\sigma_1^2$ square minus $n\mu_2^2$ square by $2\sigma_2^2$ square and then e to the power minus $\frac{\sum x_i^2}{2\sigma_1^2}$ square by $2\sigma_1^2$ square minus $\frac{\sum y_j^2}{2\sigma_2^2}$ square by $2\sigma_2^2$ square plus $\frac{m\mu_1 \bar{x}}{\sigma_1^2}$ plus $\frac{n\mu_2 \bar{y}}{\sigma_2^2}$ here.

Straightforwardly, this is a four parameter exponential family as I have described in the example in one of the previous lecture where I was applying the Gosset's theorem. But the problem here is that, if I straightforwardly write it as with four parameter exponential family, I can test about either σ_1^2 or about σ_2^2 or about μ_1 or about μ_2 , which is not our aim.

So, we reparameterize it; so, this coefficients I put it as c of θ , η and this I write as e to the power $\left[\left(\frac{1}{2\sigma_1^2 \tau_0} - \frac{1}{2\sigma_1^2} \right) \sum y_j^2 - \frac{1}{2\sigma_1^2} \left(\sum x_i^2 + \frac{1}{\tau_0} \sum y_j^2 \right) + \frac{m\mu_1}{\sigma_1^2} \bar{x} + \frac{n\mu_2}{\sigma_2^2} \bar{y} \right]$.

Here, I am taking θ to be $\frac{1}{2\sigma_1^2 \tau_0} - \frac{1}{2\sigma_1^2}$ square. So, U is equal to $\sum y_j^2$. ν_1 is equal to $-\frac{1}{2\sigma_1^2}$ square. So, T_1 is equal to $\sum x_i^2 + \frac{1}{\tau_0} \sum y_j^2$. ν_2 is equal

to $m\mu_1$ by σ_1^2 . So, T_2 is equal to \bar{X} . μ_3 is equal to $n\mu_2$ by σ_2^2 so, T_3 is equal to \bar{Y} .

So, if I am considering the testing problem say H_1 that is, σ_2^2 by σ_1^2 less than or equal to τ_0 , we can express it as 1 by $\tau_0 \sigma_1^2$ and I divide here. So, 1 by σ_2^2 and I put 2 here. So, this will become plus this will become minus. So, if I read take σ_2^2 in the denominator here and I bring it to the left hand side, this becomes less than or equal to 0 .

So, this θ term that I am having this is equivalent to less than or equal to 0 . So, this will be equal to θ is equal to 0 . So, H_1 σ_2^2 by σ_1^2 less than or equal to τ_0 . This is equivalent to say H_1 θ less than or equal to 0 . And similarly, this H_4 that is σ_2^2 by σ_1^2 is equal to τ_0 . this is equivalent to H_4 θ is equal to 0 . So, we can derive the UMP unbiased tests.

However, those UMP unbiased tests, if I use theorem 2, there will be conditional tests of U given T_1, T_2, T_3 ; U given T_1, T_2, T_3 U is this. So, this conditional distribution will be quite complicated even when I am taking say σ_2^2 by σ_1^2 is equal to τ_0 . So, this will be quite complicated form here. So what we do? We apply theorem 3. To apply theorem 3, I define function W as an increasing function of U and the distribution of W should be free from T_1, T_2, T_3 .

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Define $W = h(U, T_1, T_2, T_3) = \frac{m-1}{n-1} \cdot \frac{\sigma_1^2}{\sigma_2^2} \cdot \frac{U - n\tau_0^2}{\left(\tau_1 - \frac{U}{n} - m\tau_0^2\right)}$

$= \frac{\sum (x_i - \bar{x})^2 / (m-1) \sigma_1^2}{\sum (x_i - \bar{x})^2 / (m-1) \sigma_1^2} \sim F_{m-1, m-1}$

So W is \uparrow in U .

The distⁿ of W does not depend on $\mu_1, \mu_2, \sigma_1^2, \sigma_2^2$

When $\theta=0$, T is sufficient & complete

So by Basu's Thm. W and T are indep^t when $\theta=0$

So by Thm 3, a UMP unbiased test for H_1 vs K_1 is

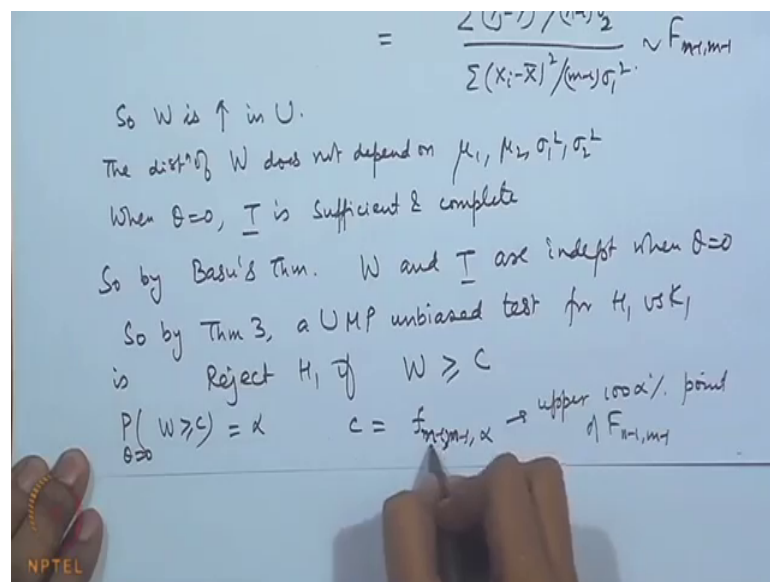
Reject H_0 if $W \geq c$

So, we consider like this. Define W is equal to h of U, T_1, T_3 that is equal to $m - 1$ by $n - 1$ σ_1^2 square by σ_2^2 square $U - n T_3$ square divided by $T_1 - U$ by $\Delta \tau$ naught minus $m T_2$ square. It is actually equal to $\sigma_2^2 \sum (Y_j - \bar{Y})^2$ divided by $n - 1$ σ_1^2 square divided by $\sigma_2^2 \sum (X_i - \bar{X})^2$ divided by $m - 1$ σ_1^2 square. So, W is increasing in U . The distribution of W does not depend on $\mu_1, \mu_2, \sigma_1^2, \sigma_2^2$. Actually this is F distribution on $m - 1, n - 1$ degrees of freedom.

So, since the distribution of W does not depend upon the parameters and when θ is equal to 0 T is sufficient. When θ is equal to 0, T is that is, T_1, T_2, T_3 that is sufficient and complete. So, by an application of Basu's theorem W and T are independent when θ is equal to 0. Remember that for testing H_1 and H_4 both, I need the independence when θ is equal to 0, that is satisfied here.

So, by theorem 3 a UMP unbiased test for H_1 versus K_1 is Reject H_1 if W is greater than or equal to C and probability of W greater than or equal to C when θ is equal to 0 that is equal to α .

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So, C is given by the point on f distribution, that is upper 100α percent point of F distribution on $n - 1, m - 1$ degrees of freedom.

Now, this should be $n - 1 - m - 1$. Firstly, it is $n - 1$ in the numerator because the way I have defined here, this function in the numerator the degrees of freedom for chi square is $n - 1$ and in the denominator it is $m - 1$. So, we are getting an exact test here using the theory of unbiased tests here for testing the comparison of the variances like I have put here $\sigma_2^2 \leq \sigma_1^2$ here. If I consider say $\sigma_1^2 = \sigma_2^2$ versus the inequality then this function will not be useful because this is not linear in τ linear in U . So, we need to define another function which is related to this.

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For H_4 vs K_4 , we define

$$W^* = h(U, T) = \frac{(U - nT_3^2) / \tau_0}{\left(T_1 - mT_2^2 - \frac{1}{\tau} nT_3^2 \right)}$$

$$= \frac{\frac{1}{\tau_0} \sum (y_j - \bar{y})^2}{\sum (x_i - \bar{x})^2 + \frac{1}{\tau_0} \sum (y_j - \bar{y})^2}$$

W^* is linear in U (\uparrow). When $\theta = 0$.

The distⁿ of W^* does not depend on ν_1, ν_2 & ν_3 when $\theta = 0$.

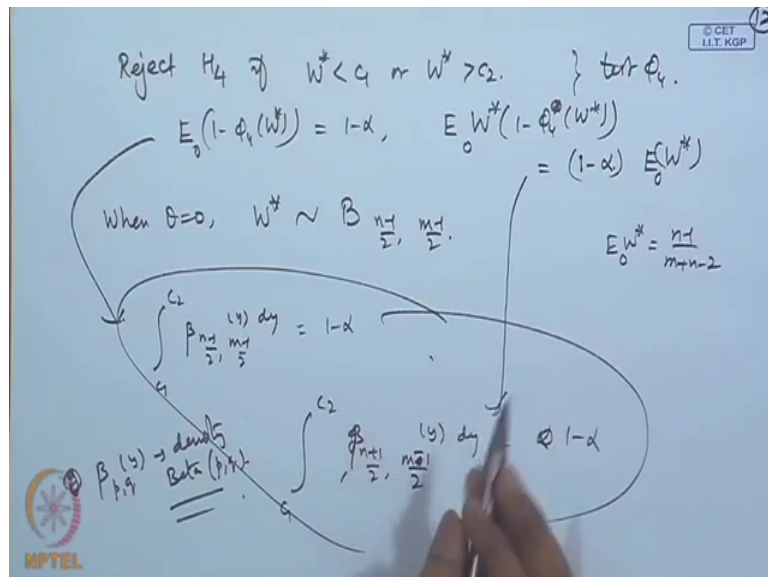
So W^* & T are indep^t when $\theta = 0$.

So UMP unbiased test for H_4 vs K_4 is given by

For H_4 versus K_4 , we define say W^* is equal to $h(U, T)$ that is equal to $U - nT_3^2$ divided by τ_0 divided by $T_1 - mT_2^2 - \frac{1}{\tau} nT_3^2$. That is equal to $\frac{1}{\tau_0} \sum (y_j - \bar{y})^2$ divided by $\sum (x_i - \bar{x})^2 + \frac{1}{\tau_0} \sum (y_j - \bar{y})^2$.

Now W^* is linear in U and of course it is increasing. Then, $\theta = 0$, the distribution of W^* does not depend on ν_1, ν_2 and ν_3 . The parameters that I defined here when I wrote it in this particular fashion, ν_1 was $n - 1 - 2\sigma_1^2$, ν_2 was this and ν_3 was $n - m - 2\sigma_2^2$. So, that is true here that the distribution of this thing does not depend on this when $\theta = 0$. So, W^* and T are independent when $\theta = 0$.

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So, UMP unbiased test for H_4 versus K_4 is given by, Reject H_4 if W is less than W^* is less than C_1 or W^* is greater than C_2 . Now to determine C_1 and C_2 the conditions are; let me call this test say ϕ_4 . Then you have expectation of $1 - \phi_4(W^*)$ at $\theta = 0$ that is equal to $1 - \alpha$ and expectation of $W^* (1 - \phi_4(W^*))$ at $\theta = 0$ that is equal to $(1 - \alpha) E_0 W^*$.

Now, when $\theta = 0$ the distribution of W^* is actually a beta distribution on $n - 1/2$ and $m - 1/2$ degrees of freedom. That is, this function when I am assuming σ_2^2 by σ_1^2 is equal to τ , then this is actually having because it is actually in the numerator a chi square divided by sum of 2 chi squares and they are independent. So, this is a beta distribution actually, $n - 1/2$ and $m - 1/2$.

So, this condition is actually then determined from if I write the density of beta, say $B(y)$ from C_1 to C_2 this should be equal to $1 - \alpha$ and the second condition, we can simplify because expectation of W^* is actually $\frac{n - 1/2}{m + n - 1}$. If we utilize that, then this condition can be transformed to $\int_{C_1}^{C_2} B(y) dy = \alpha$ and $\int_{C_1}^{C_2} B(y) dy = 1 - \alpha$.

Now, this is actually the density of y ; that means, I am using this beta say $B(y)$, this is density of a beta distribution with parameters p and q . Then these 2 conditions can be used to determine the coefficients C_1 and C_2 . For convenience, we are generally taking

alpha by 2 point and 1 minus alpha by 2 point on the f m minus 1 n minus 1 degrees of .
 Now, let me consider comparison of two means of normal populations.

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Comparing Means of Two Normal Populations

$\mu_1 = \mu_2$, $\mu_1 < \mu_2$, $\mu_1 > \mu_2$

Assume $\sigma_1^2 = \sigma_2^2 = \sigma^2$ (unknown).

The joint pdf of X & Y is written as:

$$C(\theta, \mu_1, \mu_2, \sigma^2) e^{\theta U + \nu_1 T_1 + \nu_2 T_2}$$

where $\theta = \frac{(\mu_2 - \mu_1) mn}{\sigma^2(m+n)}$, $\nu_1 = \frac{m\mu_1 + n\mu_2}{(m+n)\sigma^2}$, $\nu_2 = -\frac{1}{2\sigma^2}$

$U = \bar{Y} - \bar{X}$, $T_1 = m\bar{X} + n\bar{Y}$, $T_2 = \sum X_i^2 + \sum Y_j^2$.

$H_0: \theta = 0 \Leftrightarrow H_0^*: \mu_1 = \mu_2$
 $H_1: \theta < 0 \Leftrightarrow H_1^*: \mu_1 < \mu_2$
 $H_4: \theta \neq 0 \Leftrightarrow H_4^*: \mu_1 \neq \mu_2$

Comparing means of two normal populations; it means we want to test whether mu 1 is equal to mu 2, mu 1 less than or equal to mu 2 or mu 1 is greater than. We assume here that sigma 1 square is equal to sigma 2 square is equal to sigma square, this is of course, unknown here, the joint density function of X and Y as we wrote earlier.,

Now, this has to be written for modified form; that means, when sigma 1 square is equal to sigma 2 square, the terms will be combined. Let me go back to the original form here, in this term sigma 1 square, sigma 2 square are same. So, here sigma x i square and sigma y j square will get combined and this one also will have common denominator so, this term will also get combined. Now when they get combined and I want to get mu 1 minus mu 2 for comparison of mu 1 mu 2. So, we rewrite in the following fashion.

So, let me give this form here is written as because I am not writing the original term again and again. I have already written it several times. So, I am considering this a function of mu 1, mu 2 and sigma square e to the power theta U plus nu 1 T 1 plus nu 2 T 2 where, so this is theta nu now. Nu 1, nu 2 theta nu 1, nu 2, where theta I am defining to be mu 2 minus mu 1 divided by sigma square m plus n into mn. Then, nu 1 is equal to m mu 1 plus n mu 2 divided by m plus n sigma square nu 2 is equal to minus 1 by 2 sigma

square. U is equal to \bar{Y} minus \bar{X} , T_1 is equal to $m\bar{X}$ plus $n\bar{Y}$, T_2 is equal to $\sum X_i^2$ plus $\sum Y_j^2$.

So, if I consider the hypothesis $H_1: \theta \leq 0$, this is equivalent to H_1^* . Say $\mu_1 \leq \mu_2$. Similarly if I consider $\theta = 0$ this is equivalent to $\theta = 0$ that is $\mu_1 = \mu_2$. So, once again we have the UMP unbiased tests here.

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UMP unbiased tests can be derived for H_1 vs K_1 & H_4 vs K_4 using Thm 3.

For $H_1: \theta \leq 0$ vs $K_1: \theta > 0$, we define

$$W = h(U, T) = \frac{U}{\sqrt{T_2 - \frac{T_1^2}{m+n} - \frac{mn}{m+n} U^2}} = \frac{(\bar{Y} - \bar{X})/\sigma}{\sqrt{[\sum (X_i - \bar{X})^2 + \sum (Y_j - \bar{Y})^2]/\sigma^2}}$$

h is \uparrow in U

When $\theta = 0$, the distⁿ of W does not depend on μ_1, μ_2 .

So when $\theta = 0$, T_1, T_2 is complete & suff. Basis's thm

When $\theta = 0$

$$\bar{X} \sim N(\mu_1, \sigma^2/m)$$

$$\bar{Y} \sim N(\mu_2, \sigma^2/n)$$

$$\bar{Y} - \bar{X} \sim N(\mu_2 - \mu_1, \sigma^2 \cdot \frac{1}{m} + \frac{1}{n})$$

$$\bar{Y} - \bar{X} \sim N(0, \frac{mn}{m+n} \sigma^2)$$

So, UMP unbiased tests can be derived for H_1 versus K_1 and H_4 versus K_4 using theorem 3.

So, if I consider the problem $H_1: \theta \leq 0$ versus $K_1: \theta > 0$ we define the function W that is as. U divided by T_2 minus T_1 square by m plus n minus mn by m plus n U square. Now this function is actually \bar{Y} minus \bar{X} divided by square root of $\sum X_i^2$ minus \bar{X} whole square plus $\sum Y_j^2$ minus \bar{Y} whole square; h is increasing in U that can be easily checked here when θ is equal to 0.

Now, let us look at the distribution theory here. What are the distributions here? \bar{X} will follow normal μ_1 sigma square by m . \bar{Y} follows normal μ_2 sigma square by n . The distribution of \bar{Y} minus \bar{X} is normal μ_2 minus μ_1 sigma square by 1

m plus 1 by n . So, when θ is equal to 0 \bar{Y} minus \bar{X} will follow normal 0, m plus n by mn sigma square.

The distribution of \bar{Y} minus \bar{X} is free from θ also the distributions of $\sum_{i=1}^m (X_i - \bar{X})^2$ by sigma square, this follows chi square distribution on m minus 1 degrees of freedom. The distribution of $\sum_{j=1}^n (Y_j - \bar{Y})^2$ by sigma square that follows chi square distribution on n minus 1 degrees of freedom. So, these are all having distributions independent of θ . So when θ is equal to 0, the distribution of W does not depend on; what is ν_1 and ν_2 here? μ_1 involves μ_i 's and sigma square ν_2 involve sigma square.

If we consider this function, if I take divided by sigma and here, this thing divided by sigma square, so you can easily see that the distribution of W is also free from sigma. So, this does not depend on ν_1 and ν_2 . So, when θ is equal to 0 T_1, T_2 is a complete sufficient statistic here. So, when θ is equal to 0. T_1, T_2 is complete and sufficient. So, Basu's theorem is applicable here.

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$W = h(U, I) = \frac{\sqrt{T_2 - \frac{T_1^2}{m+n} - \frac{mn}{m+n} U^2}}{\sqrt{(\sum_{i=1}^m (X_i - \bar{X})^2 + \sum_{j=1}^n (Y_j - \bar{Y})^2) / \sigma^2}}$

$\sum_{i=1}^m \frac{(X_i - \bar{X})^2}{\sigma^2} \sim \chi_{m-1}^2$

$\sum_{j=1}^n \frac{(Y_j - \bar{Y})^2}{\sigma^2} \sim \chi_{n-1}^2$

When $\theta = 0$,
 the distⁿ of W does
 not depend on μ_1, μ_2 .
 So when $\theta = 0$, T_1, T_2 is complete & suff.
 So Basu's thm gives that when $\theta = 0$, W & T_1, T_2 are indep.

When $\theta \neq 0$
 $\bar{X} \sim N(\mu_1, \sigma^2/m)$
 $\bar{Y} \sim N(\mu_2, \sigma^2/n)$
 $\bar{Y} - \bar{X} \sim N(\mu_2 - \mu_1, \sigma^2(\frac{1}{m} + \frac{1}{n}))$
 When $\theta = 0$
 $\bar{Y} - \bar{X} \sim N(0, \frac{mn}{m+n} \sigma^2)$

Basu's theorem gives, that when θ is equal to 0, W and T_1, T_2 are independent and therefore, we are in a position to write down the UMP.

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So UMP unbiased test for H_1 vs K_1 is
 Rej H_0 if $W \geq c$.

$$t = \frac{(\bar{y} - \bar{x}) / \sqrt{\frac{1}{m} + \frac{1}{n}}}{\sqrt{\frac{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2}{m+n-2}}} \sim t_{m+n-2} \text{ when } \theta = 0.$$

$t \geq k \rightarrow t_{m+n-2, \alpha}$

Rej H_0 if $\frac{\sqrt{\frac{mn}{m+n}} \frac{\bar{y} - \bar{x}}{S_p}}{t_{m+n-2, \alpha}} \geq t_{m+n-2, \alpha}$

$$S_p^2 = \frac{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2}{m+n-2}$$

So, UMP unbiased test for H_1 versus K_1 is Reject H_0 if W is greater than or equal to C . Now let us look at the distribution part of W .

So, we have already seen here that $\bar{Y} - \bar{X}$ follows normal $0, m+n$ by $m+n$ by $mn \sigma^2$ when θ is equal to 0 . So, we adjust this term here, we get here $\bar{Y} - \bar{X}$ divided by $\sqrt{\frac{1}{m} + \frac{1}{n}}$ divided by $\sqrt{\frac{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2}{m+n-2}}$.

Let us define this as say T . Then, this is T distribution on $m+n-2$ degrees of freedom then θ is equal to 0 . Therefore, I can choose this term W as $t \geq k$ and t will be $m+n-2, \alpha$. The upper handed α percent point of the t distribution on $m+n-2$ degrees of freedom. So you can see here, this is the pooled sample variance formula here that we are getting here.

In fact, we can write this term as $\sqrt{\frac{mn}{m+n}} \frac{\bar{y} - \bar{x}}{S_p}$, where S_p^2 is actually $\frac{\sum (x_i - \bar{x})^2 + \sum (y_j - \bar{y})^2}{m+n-2}$. So, we are comparing the test is Reject H_0 if this is greater than $t_{m+n-2, \alpha}$. We have an exact UMP unbiased test.

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For H_4 vs K_4 , we take

$$W^* = \frac{U}{\sqrt{T_2 - \frac{T_1^2}{m+n}}} \quad \text{linear in } U.$$

$$= \frac{\bar{Y} - \bar{X}}{\sqrt{\sum X_i^2 + \sum Y_j^2 - \frac{1}{m+n} (\sum X_i + \sum Y_j)^2}}$$

is free from $\mu_1, \mu_2, \sigma_1^2, \sigma_2^2$ (when $\mu_1 = \mu_2$)

So distⁿ of W^* is indep^t of T_1, T_2 .

W^* has distⁿ symmetric about 0 when $\mu_1 = \mu_2$.

So UMP unbiased test is $|W^*| \geq C$ (Rej H_0)

Now, let us also look at the H 4 problem. For H 4 versus K 4, this function will not be useful because this function is not linear in U. So, I modify. We can consider W star is equal to U divided by square root T 2 minus T 1 square by m plus n. This is linear in U and this function if you see, actually it is Y bar minus X bar divided by square root sigma Xy square plus sigma Yj square minus 1 by m plus n sigma X i plus sigma Yj whole square.

So, this term is free from mu 1, mu 2, sigma 1 square, sigma 2 square when mu 1 is equal to mu 2. So, distribution of W star is independent of T 1, T 2. So, and also W star has distribution symmetric about 0 when mu 1 is equal to mu 2. So, UMP unbiased test is based on W star greater than or equal to C, that is the Rejection.

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$$W = \frac{W^*}{\sqrt{1 - \frac{mn}{m+n} W^{*2}}} \quad \uparrow \text{ in } W^*.$$

So we can again write the rejection region as

$$|t| \geq t_{m+n-2, \alpha/2}.$$

$$t = \frac{(\bar{Y} - \bar{X}) \sqrt{\frac{mn}{m+n}}}{S_p}$$

When $\sigma_1^2 \neq \sigma_2^2$ (unknown) the problem of comparing means is called Behren's Fisher problem.

NPTEL

Now, what we can do? We can consider say W that is, W star divided by root 1 minus mn by m plus n W star square. This is increasing in W star. So, we can again write the rejection region as modulus of t which I define in the previous case. I am sorry this is t . So, in terms of this t which was having n plus n minus 2 degrees of freedom, we can write here t greater than or equal to t m plus n minus 2 alpha by 2 where this t is actually \bar{Y} minus \bar{X} bar root mn by m plus n divided by the S_p .

In this today's lecture, I have been able to give UMP unbiased tests for parameters testing problem for one sample problem from normal distributions. Also, for the comparison of parameters for two sample problems; that means, when we are having two normal populations then for comparison of the variances I am having UMP unbiased test for the comparison of the means I am having unbiased test. UMP unbiased test, one point which should be noted, when I was considering comparison of the means I have taken σ_1^2 is equal to σ_2^2 .

When I gave the derivation it was clear that it was helping because in the denominator and the exponent in the joint density that σ^2 term was getting combined. So, the terms were adjusted ; however, if I do not make this assumption that σ_1^2 is equal to σ_2^2 then, I will not be able to adjust these terms. So, when σ_1^2 is not equal to σ_2^2 , that is unknown the problem of comparing means this is called Behren's Fisher problem.

In fact, it can be shown that there is no exact test, no exact UMP unbiased test for this problem. Approximate tests are available which are actually you can say approximately t distribution is there which are provided by Smith, Satterwhite and Welch etcetera. We are not discussing it here because in this particular course I have actually given you the derivations of the exact test. The theory that I have developed is using the name and Pearson theory.

The concept is started from the simple versus simple hypothesis. We had considered the most powerful test for a fixed size, then we extended that theory to UMP unbiased test. Initially, we consider the families of distribution with monotone likelihood ratio; later on we restricted attention to one parameter exponential family, for I define for a special kind of hypothesis H_1 , H_2 , H_3 and H_4 for H_1 and H_2 you are having UMP test for H_3 and H_4 we got UMP unbiased test.

Whereas, when we considered multi parameter exponential family, all of the testing problems reduce to we are getting the UMP unbiased test. In the next lectures, I will introduce another method of derivation of the test called Likelihood Ratio Testing Procedures which is also a natural procedure I will be describing those tests in detail in the following lectures.