

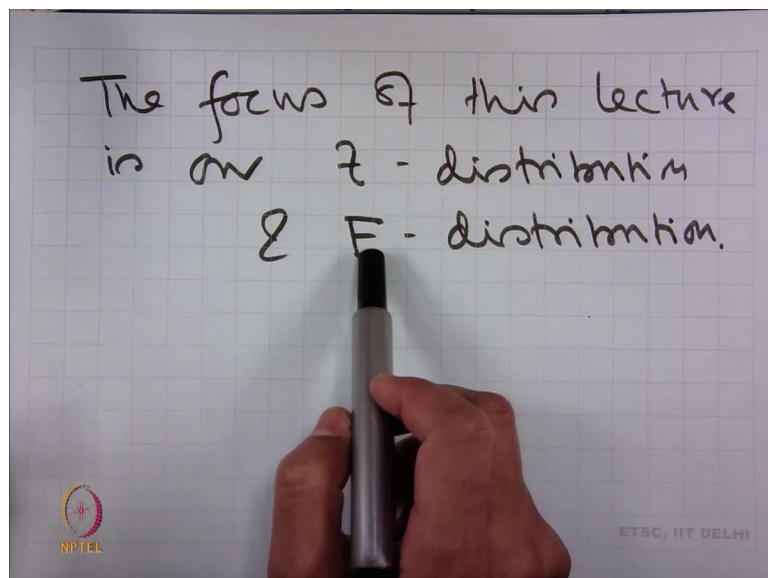
Statistical Inference
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Lecture – 06
Statistical Inference

Welcome students to the 6th lecture of the MOOC series on Statistical Inference. In the last lecture, we were looking at the chi square distribution which is obtained as a square of standard normal variate. If there is one such normal which is x , then we got that x square is distributed as chi square with one degrees of freedom, which is essentially gamma distribution with half and half.

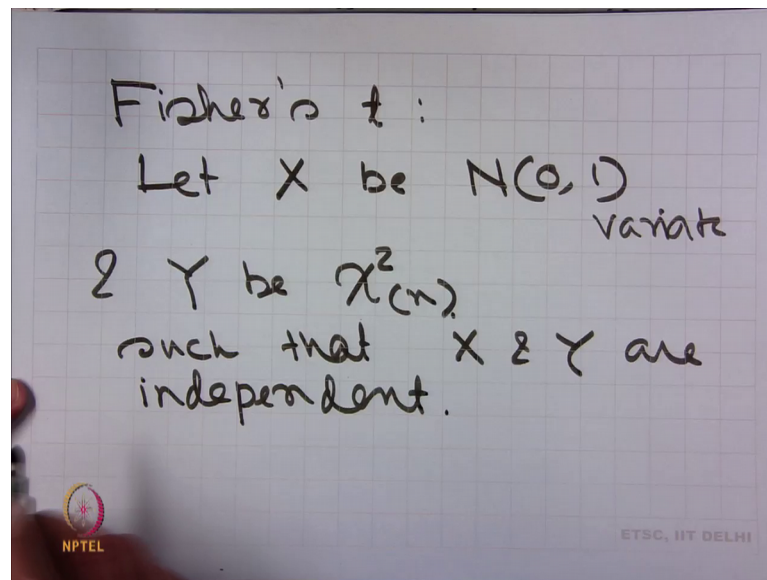
We also found that if we look at the sum of square of n independent normal variates, then that will distribute as chi square with n degrees of freedom which is gamma with half and n by 2. In this lecture, we will look at some more types of random variables in particular.

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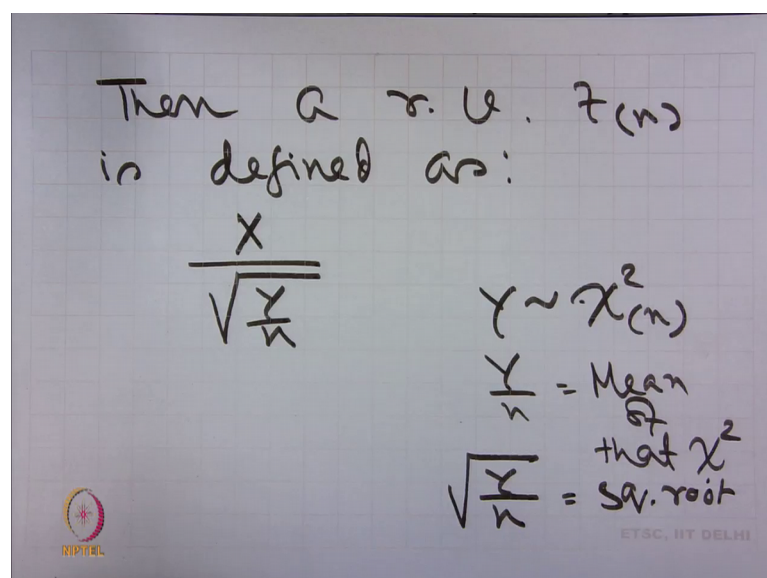
The focus of this lecture is on t distribution and F distribution. These are very important for statistical inference with respect to population.

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And we will see that how they are used in inferencing about population, but before that in this lecture, I will just derive their pdf. R. A. Fisher's has defined t to be a random variable which is the quotient of 2 independent distribution, where the numerator is a normal 0 1, and the denominator is a function of chi square. So, let me define it first, such that X and Y are independent.

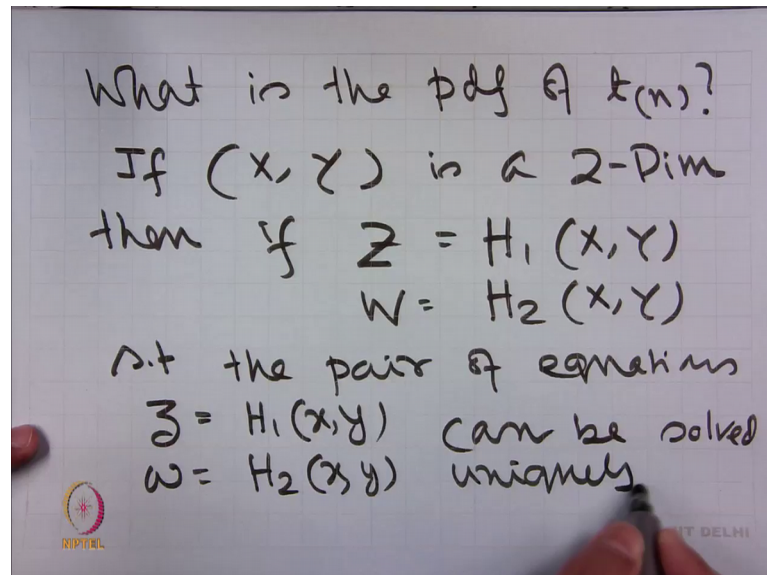
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Then a random variable t with n degrees of freedom is defined as X upon root over Y by n . X is a normal variable Y is a chi square variable; therefore, Y by n is mean of that chi

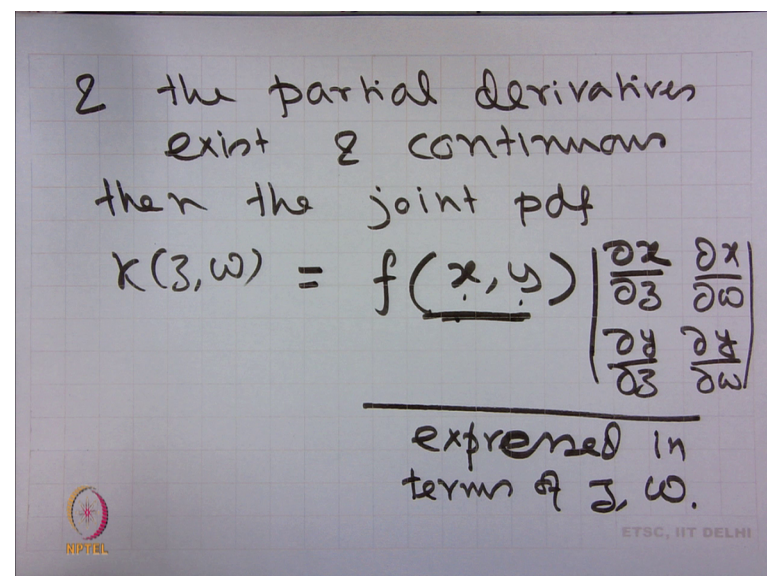
square and root over Y by n is equal to square root of that. So, essentially t distribution is the ratio of a standard normal divided by a root mean chi square distribution.

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So, what is the pdf of; in order to obtain the pdf of t , I will in order to obtain the distribution of t_n , I will appeal to that theorem that we have done in our lecture 5; that if X, Y is a 2 dimensional random variable, then if Z is equal to H_1 of X, Y and W is equal to H_2 of X, Y such that the pair of equations z is equal to H_1 of x, y and w is equal to H_2 of x, y can be solved uniquely.

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And the partial derivatives exist and continuous, then the joint pdf $k(z, w)$ of z, w is given by $f(x, y)$ multiplied by the Jacobean which is the determinant of and this whole thing expressed in terms of z and w . And that is possible because the transformation is one to one. So, given z, w we can uniquely determine the x and y . If we remember this, then we shall use the same theorem for obtaining the pdf of the t distribution with n degrees of freedom.

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$$\text{Let } Z = \frac{X}{\sqrt{\frac{Y}{n}}} \quad \left| \begin{array}{l} \text{Our} \\ \text{variable} \\ \text{of interest} \end{array} \right.$$

$$W = Y$$

$$\therefore Y = W$$

$$\therefore X = Z \sqrt{\frac{W}{n}} = Z \sqrt{\frac{W}{n}}$$

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So, let z is equal to X upon root over Y by n . Note that this is our variable of interest. In order to use it we take a dummy variable W is equal to y , ok. Because we need to do transformation to a 2D plane, and then as I have shown with respect to the obtaining the chi square distribution which is summation of 2 independent normal variables square if you remember we have transformed it to R, θ then you have integrated out θ .

So, same thing we are going to do here. Therefore, y is equal to W therefore, X is equal to Z into root over Y by n is equal to z into root over W by n . Therefore, given Z, W we can uniquely determine X and Y and vice versa.

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$$\begin{aligned} \therefore |J| &= \begin{vmatrix} \frac{\partial x}{\partial z} & \frac{\partial x}{\partial w} \\ \frac{\partial y}{\partial z} & \frac{\partial y}{\partial w} \end{vmatrix} \\ &= \begin{vmatrix} \sqrt{\frac{w}{n}} & \frac{1}{2} \frac{z}{n w^{\frac{1}{2}}} \\ 0 & 1 \end{vmatrix} \\ &= \sqrt{\frac{w}{n}} \end{aligned} \quad \begin{aligned} x &= z \sqrt{\frac{w}{n}} \\ y &= w \\ \frac{\partial y}{\partial z} &= 0 \end{aligned}$$

Therefore, what is going to be the determinant or the Jacobian. This is the determinant of $\frac{\partial x}{\partial z}$, $\frac{\partial x}{\partial w}$, $\frac{\partial y}{\partial z}$ and $\frac{\partial y}{\partial w}$; which is equal to x is Z root over W by n . Therefore, $\frac{\partial x}{\partial z}$ is equal to root over W by n . $\frac{\partial x}{\partial w}$ is half z by n z by n into half w to the power minus half. And we know that Y is equal to W therefore, $\frac{\partial y}{\partial z}$ is equal to 0, and $\frac{\partial y}{\partial w}$ is equal to 1. Therefore, this determinant is coming out to be root over W by n .

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$$\begin{aligned} \therefore k(z, w) &= f(x, y) \left| \sqrt{\frac{w}{n}} \right| \\ &\quad \begin{aligned} &\xrightarrow{\text{expressed in } (z, w)} \\ &y = w \\ &x = z \sqrt{\frac{w}{n}} \end{aligned} \\ \therefore f(x, y) &= \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} * \frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} e^{-\frac{y}{2}} y^{\frac{n}{2}-1} \\ &\quad * \sqrt{\frac{w}{n}} \quad \begin{aligned} &-\infty < z < \infty \\ &0 < w < \infty \end{aligned} \end{aligned}$$

This is important because this will need in obtaining the pdf of z, w . Therefore, pdf of z, w is f of x, y multiplied by the determinant which is w by n expressed in z, w . Now x and y are independent, therefore, f of x, y is equal to the product of their individual density function, which is 1 over $\sqrt{2\pi}$ e to the power minus x square by 2 , this comes from x multiplied by y is a chi square with n degrees of freedom. Therefore, it is pdf is $\lambda^\alpha \Gamma(\alpha) e^{-\lambda x} x^{\alpha-1}$. In fact, x becomes y here, so, e to the power minus y by 2 y to the power $n/2 - 1$.

It is worth noting that z will go from minus infinity to infinity, because z is a standard normal distribution divided by something which is positive, and w goes from 0 to infinity. Now this we have to write in terms of z and w , and our transformation was that y is equal to w and x is equal to $z \sqrt{w}$ by n . So, we are replacing these things here, and this has to be multiplied by the Jacobian $\sqrt{w}$ by n . So, this whole thing will give me the pdf of z, w .

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$$\begin{aligned}
 \therefore k(z, w) &= \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} \times \frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} e^{-\frac{w}{2}} y^{\frac{n}{2}-1} \sqrt{\frac{w}{n}} \\
 &\quad \left(\frac{1}{\sqrt{2\pi}} e^{-\frac{w}{2}} w^{\frac{n}{2}-1} \right) \left(\frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} e^{-\frac{z^2}{2}} \right) \sqrt{\frac{w}{n}} \\
 &= \frac{1}{2^{\frac{n+1}{2}} \sqrt{\pi} \Gamma(\frac{n}{2}) n^{\frac{1}{2}}} w^{\frac{n}{2}-1+\frac{1}{2}} e^{-\frac{w}{2} \left(1 + \frac{z^2}{n} \right)}
 \end{aligned}$$

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Let me write it again therefore, $k(z, w)$ is equal to 1 over $\sqrt{2\pi}$ e to the power minus x square by 2 into 1 over $2^{\frac{n}{2}} \Gamma(\frac{n}{2})$ e to the power minus y by 2 y to the power $n/2 - 1$ into $\sqrt{w}$ by n . And we have to replace x with $z \sqrt{w}$ by n and y with w . Therefore, this becomes 1 over $\sqrt{2\pi}$ e to the power minus w by 2 , w to the power $n/2 - 1$, and from here we get e to the power minus z square into w by n by 2 into $\sqrt{w}$ by n .

So, this is slightly complicated expression, but this I am doing for you to understand the trick of obtaining the pdf of a function of 2 random variables. So, let us simplify it to some extent what we get? 1 upon 2 to the power n by 2 into half; So, 2 to the power n plus 1 by 2 into root over π , into gamma or n by 2 into this routine let me take out it is n 2 the power half. So, we have taken out all the constants.

Now, let us look at the variables. So, it is w to the power n by 2 minus 1 plus half multiplied by e to the power minus w by 2 . From here it is w by 2 from here also it is w by 2 . Multiplied by e to the power minus w by 2 into, from here I am getting 1 from here I am getting 1 , from here I am getting z square by n .

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The image shows a handwritten mathematical expression on a grid background. The expression is:

$$\frac{1}{2^{\frac{n+1}{2}} \sqrt{\pi} \left(\frac{n}{2}\right)! n^{\frac{1}{2}}} \omega^{\frac{n+1}{2} - \frac{z^2}{n}} e^{-\frac{\omega}{2} \left(1 + \frac{z^2}{n}\right)}$$

Below the expression, there are handwritten notes in red ink:

We get the pdf of z by integrating out ω .

Below the notes, there are two lines of handwritten inequalities:

$$-\infty < z < \infty$$

$$0 < \omega < \infty$$

In the bottom left corner, there is a small logo for NPTEL. In the bottom right corner, there is a small text "ETSC, IIT DELHI".

So, this is the joint pdf of z and w , which we can write it as 1 over 2 to the power n plus 1 by 2 root over π gamma n by 2 n to the power half, w to the power n plus 1 minus 2 by 2 , e to the power minus w by 2 into 1 plus z square by n where minus infinity less than z less than infinity, and 0 less than w less than infinity.

Once you obtain the pdf of z and w , we need to find out the pdf of z from there. How do I get it? By integrating out w , right? If we consider this carefully we can see that this actual is coming out to be a gamma integral. So, let us forget about that constant first.

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$$\text{Let } I = \int_0^{\infty} \omega^{\frac{n+1}{2}-1} e^{-\frac{\omega}{2}(1+\frac{z^2}{n})} d\omega$$

$$= \int_0^{\infty} \omega^{\frac{n+1}{2}-1} e^{-\frac{1}{2}(1+\frac{z^2}{n})\omega} d\omega$$

$$\frac{\left(\frac{n+1}{2}\right)}{\left(\frac{1}{2}(1+\frac{z^2}{n})\right)^{\frac{n+1}{2}}}$$

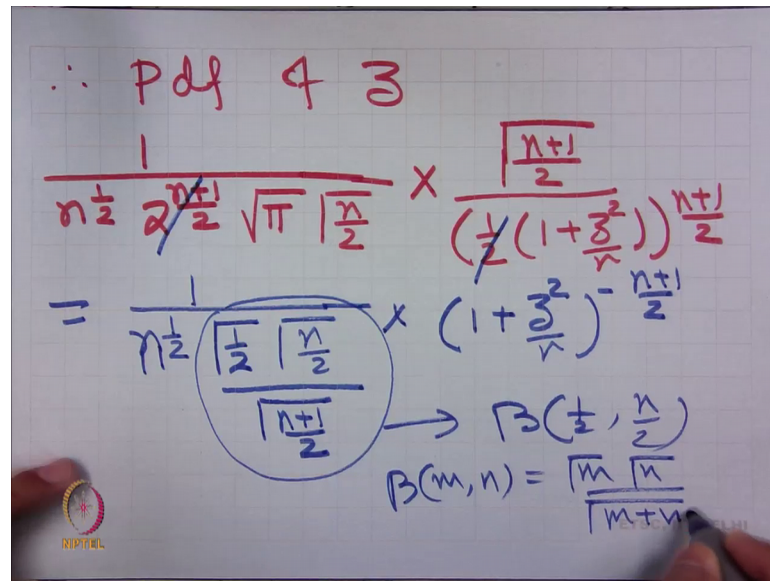
$$\left| \int_0^{\infty} e^{-\lambda x} x^{\alpha-1} dx = \frac{\Gamma(\alpha)}{\lambda^{\alpha}} \right.$$

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Let us look at this and let us try to find out what is the integral. I am trying to convert it into the gamma form we know that it is e to the power minus λx , x to the power α minus 1. So, I have put it into something minus 1 into e to the power minus half into $1 + z^2$ by n ω $d\omega$. And we know that e to the power minus λx into x to the power α minus 1 dx that integrates to $\Gamma(\alpha)$ upon λ^{α} .

So, we are going to use the same thing. Here α is equal to $n + 1$ by 2, and here λ is equal to this whole thing. Therefore, this integration is coming out to be $\Gamma(n + 1 \text{ by } 2)$ divided by half into $1 + z^2$ upon n whole to the power $n + 1$ by 2, ok.

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$$\therefore \text{pdf of } z$$

$$\frac{1}{n^{\frac{1}{2}} 2^{\frac{n+1}{2}} \sqrt{\pi} \left(\frac{n}{2}\right)!} \times \frac{\left(\frac{n+1}{2}\right)!}{\left(\frac{1}{2}\left(1+\frac{z^2}{n}\right)\right)^{\frac{n+1}{2}}}$$

$$= \frac{1}{n^{\frac{1}{2}} \left(\frac{1}{2}\right)^{\frac{n}{2}} \left(\frac{n}{2}\right)!} \times \left(1+\frac{z^2}{n}\right)^{-\frac{n+1}{2}}$$

$$\frac{\left(\frac{1}{2}\right)^{\frac{n}{2}} \left(\frac{n}{2}\right)!}{\left(\frac{n}{2}\right)!} \rightarrow B\left(\frac{1}{2}, \frac{n}{2}\right)$$

$$B(m, n) = \frac{\Gamma(m) \Gamma(n)}{\Gamma(m+n)}$$

So, this is the integral of this part, therefore pdf of z is first we have to write that constant; which is 1 upon n to the power half 2 to the power n plus 1 by 2 root over π gamma n by 2 . Now, multiplied by gamma n plus 1 by 2 upon half into 1 plus z square by n whole to the power n plus 1 by 2 ; This 2 to the power n by 2 cancels with this 2 to the power n plus 1 by 2 .

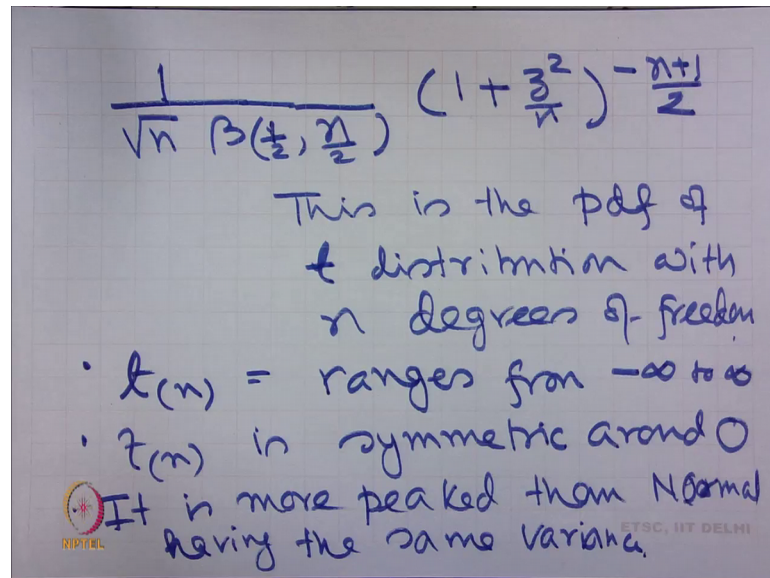
Therefore, what we obtain is n 2 the power half root π we know is that it is gamma half, gamma n by 2 into 1 plus z square by n whole to the power minus n plus 1 by 2 . This divided by gamma n plus 1 by 2 . This whole thing is gamma half gamma n by 2 upon gamma n plus 1 by 2 ; actually follows beta half n by 2 . Because we know that beta m comma n is equal to gamma m gamma n upon gamma m plus n .

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$$\frac{1}{\sqrt{n} B(\frac{1}{2}, \frac{n}{2})} \left(1 + \frac{z^2}{n}\right)^{-\frac{n+1}{2}}$$

This is the pdf of
t distribution with
n degrees of freedom

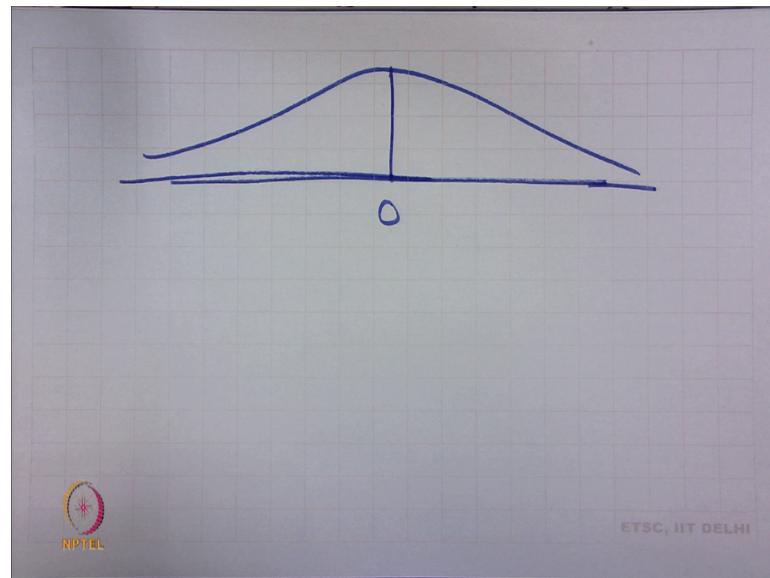
- $t(n)$ = ranges from $-\infty$ to ∞
- $t(n)$ is symmetric around 0
- It is more peaked than Normal having the same variance.



Therefore, this can be written as 1 over root over n, beta half comma n by 2 multiplied by 1 plus z square by n whole to the power minus n plus 1 by 2. So, this is the pdf of t distribution with n degrees of freedom.

Why n degrees? Because in the denominator we had a chi square distribution which is of n degrees of freedom properties t_n or t with n degrees of freedom ranges from minus infinity to infinity; t_n is symmetric around 0 which is also true for normal. But basically t is more peaked than normal having the same variance. What I mean that the shape of the distribution is symmetric around 0, but if its shape will vary with the degrees of freedom and therefore, the variance will also keep changing.

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So, if we take a t distribution with certain variance, and consider the corresponding normal distribution with mean 0 and having the same variance, then we will find that t is more peaked than the normal distribution.

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F-Distribution.

Let X_1 & X_2 be two independent χ^2 distⁿ

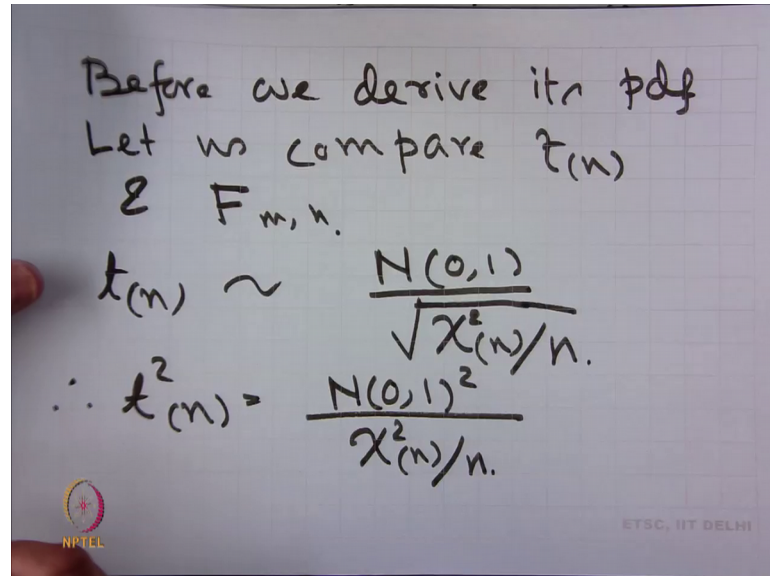
$$\begin{array}{l|l} \exists \begin{array}{l} X_1 \sim \chi^2_{(n_1)} \\ X_2 \sim \chi^2_{(n_2)} \end{array} & \begin{array}{l} \text{Then} \\ \frac{X_1/n_1}{X_2/n_2} \\ \sim F(n_1, n_2) \end{array} \end{array}$$

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Another important distribution that I like to cover today is called F distribution. What is an F distribution? Let X_1 and X_2 be 2 independent chi square distribution; such that X_1 is chi square with n_1 degrees of freedom, and X_2 is chi square with n_2 degrees of freedom. Then X_1 upon n_1 divided by X_2 upon n_2 is called F distribution with n_1 and n_2 degrees of freedom.

2 degrees of freedom. So, basically we are looking at a ratio of 2 mean chi square distribution.

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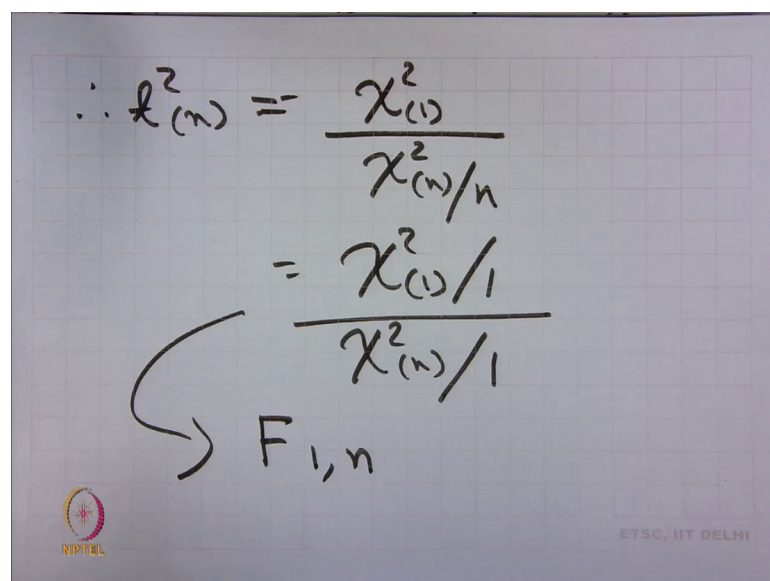
Before we derive its pdf
Let us compare $t_{(n)}$
& $F_{m,n}$.

$$t_{(n)} \sim \frac{N(0,1)}{\sqrt{\chi^2_{(n)}/n}}$$
$$\therefore t^2_{(n)} = \frac{N(0,1)^2}{\chi^2_{(n)}/n}$$

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Before I go for let us compare t_n and F . T_n is defined as normal 0 1 divided by root over chi square n by n . Therefore, t square with n degrees of freedom is equal to normal 0 1 square divided by chi square n by n . We have already seen that normal 0 1 square is basically chi square with one degrees of freedom.

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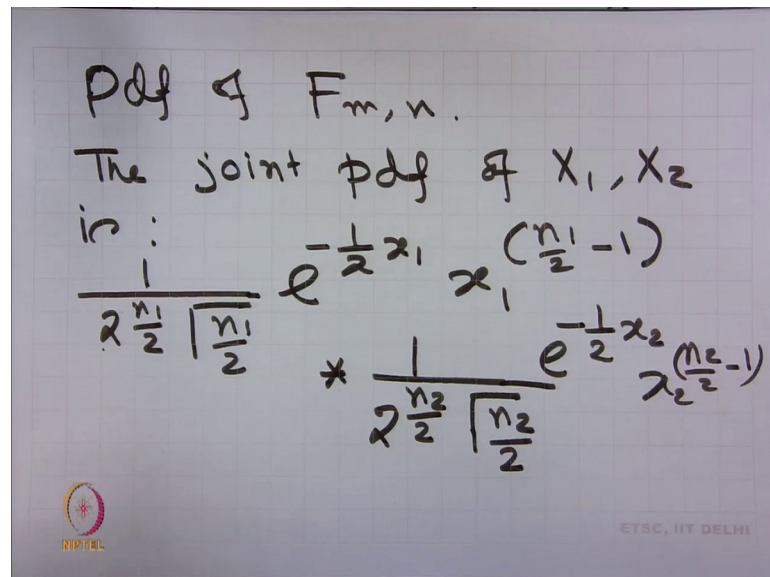

$$\therefore t^2_{(n)} = \frac{\chi^2_{(1)}}{\chi^2_{(n)}/n}$$
$$= \frac{\chi^2_{(1)}/1}{\chi^2_{(n)}/n}$$

$\hookrightarrow F_{1,n}$

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Therefore, t^2 is equal to chi square with one degrees of freedom divided by chi square n by n is equal to chi square 1 by 1 divided by chi square n by n . And this is precisely F of 1 and n degrees of freedom. Thus we can see that the square of t distribution also follows an F distribution.

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Handwritten text on a grid background:

pdf of $F_{m,n}$.

The joint pdf of X_1, X_2 is:

$$\frac{1}{2^{\frac{n_1}{2}} \Gamma(\frac{n_1}{2})} e^{-\frac{1}{2}x_1} x_1^{\frac{(n_1-1)}{2}} \times \frac{1}{2^{\frac{n_2}{2}} \Gamma(\frac{n_2}{2})} e^{-\frac{1}{2}x_2} x_2^{\frac{(n_2-1)}{2}}$$

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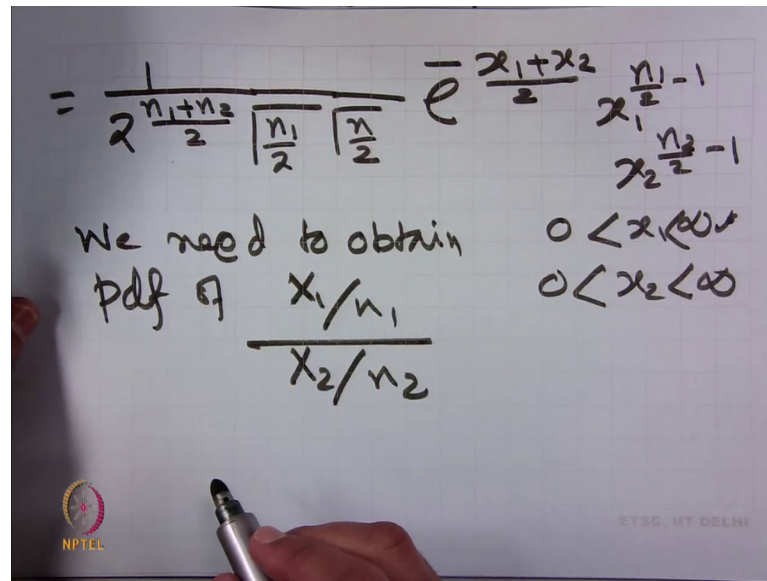
So, what is the pdf? As before, we appeal to the previous theorem. X_1 and X_2 are independent chi square with n_1 and n_2 degrees of freedom. Therefore, their joint pdf is the product of their individual pdf, and we can write it as $2^{-\frac{n_1}{2}} \Gamma(\frac{n_1}{2})^{-1} e^{-\frac{1}{2}x_1} x_1^{\frac{(n_1-1)}{2}}$ multiplied by $2^{-\frac{n_2}{2}} \Gamma(\frac{n_2}{2})^{-1} e^{-\frac{1}{2}x_2} x_2^{\frac{(n_2-1)}{2}}$; by now you are familiar with the gamma distribution. And chi square with n degrees of freedom is equal to gamma with half and n by 2. So, I am simply writing from there, it is $2^{-\frac{n_2}{2}} \Gamma(\frac{n_2}{2})^{-1} e^{-\frac{1}{2}x_2} x_2^{\frac{(n_2-1)}{2}}$.

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$$= \frac{1}{2^{\frac{n_1+n_2}{2}} \left(\frac{n_1}{2}\right)^{\frac{n_1}{2}} \left(\frac{n_2}{2}\right)^{\frac{n_2}{2}}} e^{-\frac{x_1+x_2}{2}} x_1^{\frac{n_1}{2}-1} x_2^{\frac{n_2}{2}-1}$$

We need to obtain pdf of $\frac{X_1/n_1}{X_2/n_2}$

$0 < x_1 < \infty$
 $0 < x_2 < \infty$



So, that is the joint pdf of x_1 and x_2 . So, let me write it as 2 to the power n_1 plus n_2 divided by 2 , $\Gamma(n_1/2) \Gamma(n_2/2)$ e to the power minus x_1 plus x_2 by 2 x_1 to the power $n_1/2 - 1$ x_2 to the power $n_2/2 - 1$; where $0 < x_1 < \infty$ and $0 < x_2 < \infty$. So, this is the joint distribution of X_1 and X_2 . We need to obtain pdf of X_1/n_1 divided by X_2/n_2 .

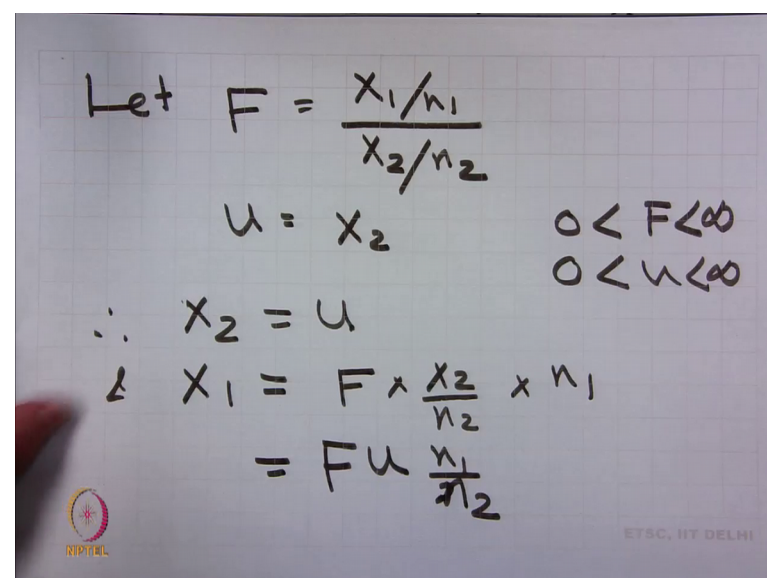
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Let $F = \frac{X_1/n_1}{X_2/n_2}$

$U = X_2$ $0 < F < \infty$
 $0 < U < \infty$

$\therefore X_2 = U$

$X_1 = F \times \frac{X_2}{n_2} \times n_1$
 $= F U \frac{n_1}{n_2}$



So, let us make the transformation as f is the ratio of 2 chi square both of them are going from 0 to infinity therefore, f is also going from 0 to infinity, and obviously, u is also

going from 0 to infinity. Therefore, now we make the inverse transformation. What we get? X_2 is equal to u and X_1 is equal to $F u^{n_1+1}$.

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$$\therefore \text{Let us calculate the Jacobian}$$

$$|J| = \begin{vmatrix} \frac{\partial x_1}{\partial F} & \frac{\partial x_1}{\partial u} \\ \frac{\partial x_2}{\partial F} & \frac{\partial x_2}{\partial u} \end{vmatrix}$$

$$= \begin{vmatrix} \frac{\partial F u^{n_1+1}}{\partial F} & \frac{\partial F u^{n_1+1}}{\partial u} \\ \frac{\partial u}{\partial F} & \frac{\partial u}{\partial u} \end{vmatrix}$$

Therefore, let us calculate the Jacobian, modulus of J is equal to $\frac{\partial x_1}{\partial F} \frac{\partial x_2}{\partial u} - \frac{\partial x_1}{\partial u} \frac{\partial x_2}{\partial F}$. $\frac{\partial x_1}{\partial F} = u^{n_1+1}$, $\frac{\partial x_1}{\partial u} = F u^{n_1}$, $\frac{\partial x_2}{\partial F} = 0$, $\frac{\partial x_2}{\partial u} = 1$. This determinant is u^{n_1+1} .

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$$\therefore |J| = u^{n_1+1}$$

$$\therefore \text{Joint pdf of } (F, u)$$

$$= \frac{1}{2^{\frac{n_1+n_2}{2}} \Gamma(\frac{n_1}{2}) \Gamma(\frac{n_2}{2})} \left(\frac{n_1}{n_2} F u \right)^{\frac{n_1}{2}-1} u^{\frac{n_2}{2}-1}$$

$$\times e^{-\frac{n_1}{2} F u} \times e^{-\frac{1}{2} u}$$

$$= \frac{1}{2^{\frac{n_1+n_2}{2}} \Gamma(\frac{n_1}{2}) \Gamma(\frac{n_2}{2})} \left(\frac{n_1}{n_2} F \right)^{\frac{n_1}{2}-1} u^{\frac{n_1+n_2}{2}-2} e^{-\frac{1}{2} (1 + \frac{n_1}{n_2} F) u}$$

Now, we can see that this is going to be 0, the Jacobian is u^{n_1+1} , therefore, joint pdf of F, u is equal to $\frac{1}{2^{\frac{n_1+n_2}{2}} \Gamma(\frac{n_1}{2}) \Gamma(\frac{n_2}{2})} \left(\frac{n_1}{n_2} F \right)^{\frac{n_1}{2}-1} u^{\frac{n_1+n_2}{2}-2} e^{-\frac{1}{2} (1 + \frac{n_1}{n_2} F) u}$.

2 by 2 into n_1 upon n_2 F u hold to the power n_1 by 2 minus 1 , because we are replacing x with n_1 upon n_2 into F u , multiplied by u to the power n_2 by 2 minus 1 , multiplied by e to the power minus n_1 upon n_2 fu . Because e to the power minus λx . So, e to the power minus half x x is X 1 is n_1 upon n_2 F u into e to the power minus half u .

So, this becomes 1 upon 2 to the power n_1 plus n_2 by 2 gamma n_1 by 2 gamma n_2 by 2 n_1 upon n_2 F to the power n_1 by 2 minus 1 , u to the power n_1 plus n_2 by 2 minus 2 . E to the power minus half u into 1 plus n_1 upon n_2 f e to the power minus f 1 plus n_1 by n_2 f into u . Therefore, this part is independent of u . And if we look at this part, again it comes e to the power minus some positive constant times u into u to the power n_1 plus n_2 by 2 minus 2 which we can write something minus 1 form.

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By integrating the variable u , the pdf of F_{n_1, n_2}

$$= \frac{\left(\frac{n_1}{n_2}\right)^{\frac{n_1}{2}} F^{\frac{(n_1-2)}{2}}}{B\left(\frac{n_1}{2}, \frac{n_2}{2}\right) \left(1 + \frac{n_1}{n_2} F\right)^{\frac{n_1+n_2}{2}}}$$

i.e. $F_{m,n} \neq F_{n,m}$ $0 < F < \infty$

Therefore, this again gives rise to a gamma integral, therefore, by integrating it, I am not doing the entire integration, I like you to do it. So, the result is going to be n_1 upon n_2 to the power n_1 by 2 , when beta n_1 by 2 n_2 by 2 F F to the power n_1 minus 2 by 2 divided by 1 plus n_1 by n_2 , F whole to the power none plus 1 2 by 2 .

So, this is a fairly complicated expression which gives the pdf of, and if F variate with parameters n_1 and n_2 ; Note that the order of the 2 constants n_1 and n_2 is very important; that is, F of m n is not equal to F of n comma m . Because F is the ratio of 2

chi square so, depending upon the chi square in the numerator, and the chi square in the denominator the pdf of these will change.

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$$\chi^2_{(n)}, t_{(n)}, F_{m,n}$$

$$\downarrow$$

$$\sum x_i^2 \sim \chi^2$$

$$\frac{\frac{\chi^2_{(n)}}{n}}{\frac{\chi^2_{(m)}}{m}}$$

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Now, you may ask me, why do we need these failures namely chi square t and F. Let us first look at chi square. Sigma xi square gives rise to chi square. Now suppose x is with mean 0, then variance of x is actually expected value of x square. So, if I consider a sequence of samples from a normal population with mean 0, and we want to find out the sum of it is variants, then we know that the variance of the sum is equal to sum of it is variants because they are independent, and therefore, we do not need their covariance. And therefore, we get to know the distribution of that variance and as you can understand that that will give rise to a chi square distribution.

Now, why do we need F? Suppose we want to compare the variances of two different populations. So, chi square m by n which is a sum of square divided by the divided by the degrees of freedom; so, that gives an idea of the variance of the numerator. Or chi square n by n gives you the idea of the variance of sum of square of normal distribution, or the variance of the population.

Similarly, chi square m by m also gives the variance of another population. So, when we want to compare the variances of 2 population. We know that variance depends upon the unit so; as such the difference between them does not really make sense. The best way to compare them; is by taking their ratio and see what is the relationship between these 2

variances. To compare the variances of two different populations with underlying distribution is normal we need F distribution.

Similarly, we will see later that t can be expressed as a mean upon standard deviation. So, from there we can look at the interesting property of the underlying population when we use t distribution. So, all three of them have come from normal distribution; n actually means the sample size. So, how many samples you are taking from a normal population? And then when we want to compare when we want to infer about one particular population or want to compare between 2 populations we will be using these random variables in an effective way. We shall discuss that in my subsequent lectures.

Thank you.