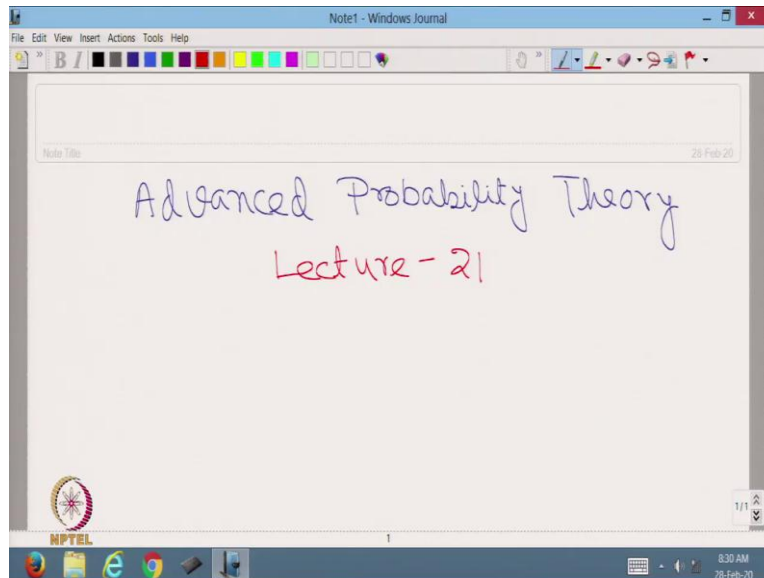


Advanced Probability Theory
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Lecture 21

(Refer Slide Time: 0:27)



Welcome students, the MOOCS series of lectures on Advance Probability Theory. This is lecture number 21. Hope you remember that in the last class we started with functions of two random variables. In this class, I shall continue with that and in particular I will give you several examples and also I will try to derive the distribution of two very important statistical distributions namely T and F.

Those who were working in statistics, they will know that these two are very important for different tests, but here in this course, we shall look at it mathematically and we shall try to see how to derive their pdf from their basic definitions. So, let me start with a simple example.

(Refer Slide Time: 1:17)

Ex Suppose $X \sim e^{-x} \quad 0 < x < \infty$
 $Y \sim 2e^{-2y} \quad 0 < y < \infty$
These are $\text{Exp}(1)$ & $\text{Exp}(2)$, respectively
Let X & Y be independent.
What is the distribution of $\frac{X}{Y}$?

Suppose, X is a random variable which is distributed as e to the power minus x , 0 less than x less than infinity and Y is another random variable which is distributed with this pdf. Again 0 less than y less than infinity. So, you understand that these are exponential with parameter 1 and exponential with parameter 2 respectively. Let X and Y be independent. So, what is the distribution of X by Y ? So, that is the question that we want to solve.

(Refer Slide Time: 2:36)

Solⁿ So let $U = \frac{X}{Y}$
We need to define a dummy variable, say V , and to obtain the joint pdf of U & V .
The V we like to keep simple, so that subsequent mathematics becomes easier.
Two cases ① $V = X$
② $V = Y$
And we shall see that we get the same answer

So, solution. So, let U is equal to X by Y . We need to define a dummy variable, say V , and to obtain the joint pdf of U and V . As I said, the V we like to keep simple so that subsequent mathematics becomes easier. So, I will take two cases. One is V is equal to X and second is I will take V is equal to Y and we will see that we get the same answer.

(Refer Slide Time: 4:21)

Case 1 $V = \frac{X}{Y} \therefore Y = \frac{X}{V} = \frac{V}{U}$
 $V = X \quad X = V$

$$\therefore |J| = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} 0 & 1 \\ -\frac{v}{u^2} & \frac{1}{u} \end{vmatrix} = \frac{v}{u^2}$$

$$\therefore f(u, v) = \frac{e^{-x} 2 e^{-2y} |J|}{\text{expressed in } (u, v)} = \frac{e^{-u} 2 e^{-\frac{2v}{u}} \cdot \frac{v}{u^2}}{}$$

\therefore To obtain the pdf of u we need to integrate out v .

So, case 1. U is equal to X by Y , V is equal to X . Therefore, Y is equal to X by U is equal to V by U . And X is equal to V . Therefore, Jacobian is equal to $\frac{\partial x}{\partial u} \frac{\partial x}{\partial v} \frac{\partial y}{\partial u} \frac{\partial y}{\partial v}$ and $\frac{\partial x}{\partial u}$ is equal to 0, $\frac{\partial x}{\partial v}$ is equal to 1, $\frac{\partial y}{\partial u}$ is equal to $-\frac{v}{u^2}$ and $\frac{\partial y}{\partial v}$ is equal to $\frac{1}{u}$. Therefore, the Jacobian is coming out to be $\frac{v}{u^2}$, which is the determinant to this matrix.

Therefore, joint pdf $f(u, v)$ is equal to $e^{-x} 2 e^{-2y}$ into determinant of J which is expressed in u, v is equal to $e^{-u} 2 e^{-\frac{2v}{u}} \frac{v}{u^2}$. So, that is the pdf of $f(u, v)$. Therefore, to obtain the pdf of u , we need to integrate out v .

(Refer Slide Time: 6:52)

$$\therefore f(u) = \frac{2}{u^2} \int_0^{\infty} v \cdot e^{-v(1+\frac{2}{u})} dv$$

$$= \frac{2}{u^2} \cdot \frac{1}{1+\frac{2}{u}} \int_0^{\infty} v \cdot e^{-v(1+\frac{2}{u})} dv$$

$\therefore f(u) = \frac{2}{u^2} \cdot \frac{1}{1+\frac{2}{u}} \cdot \frac{1}{1+\frac{2}{u}}$ Expectation of an Exp(λ) variable where $\lambda = 1 + \frac{2}{u}$

$$= \frac{2}{u^2} \cdot \frac{1}{(1+\frac{2}{u})^2}$$

$$= \frac{2}{u^2} \cdot \frac{u^2}{(2+u)^2} = \frac{2}{(2+u)^2}$$

Case 1 $V = \frac{X}{Y} \therefore Y = \frac{X}{V} = \frac{V}{u}$
 $V = X \quad X = V$

$$|J| = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} 0 & 1 \\ -\frac{v}{u^2} & \frac{1}{u} \end{vmatrix} = \frac{v}{u^2}$$

$$\therefore f(u,v) = \frac{e^{-x} 2e^{-2y} |J|}{\text{expressed in } (u,v)} = \frac{e^{-v} 2e^{-\frac{2v}{u}} \cdot \frac{v}{u^2}}{v}$$

\therefore To obtain the pdf of u we need to integrate out v .

Therefore, f of u is equal to 2 by u square integration 0 to infinity v e to the power minus v into 1 plus 2 by u dv . Is equal to 2 by u square into 1 upon 1 plus 2 by u multiplied by 0 to infinity 1 plus 2 by u into v e to the power minus v into 1 plus 2 by u dv .

Now, this is the expectation of an exponential lambda variable where lambda is equal to 1 plus 2 by u . Therefore, expected value will come out to be 1 upon lambda is equal to 1 upon 1 plus 2 by u . Therefore, f u is equal to 2 upon u square into 1 plus 2 by u into 1 upon 1 plus 2 by u is equal to 2 by u square into 1 upon 1 plus 2 by u whole square which is is equal to 2 upon u square multiplied by u square upon 2 plus u whole square is equal to 2 upon 2 plus u whole square. So, that is the distribution of u . By considering if you remember, V is equal to X . Now, I go to the second case.

(Refer Slide Time: 9:23)

Case 2 $U = \frac{X}{Y} \quad X = UY = UV$
 $V = Y \quad Y = V$

$$|J| = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} v & u \\ 0 & 1 \end{vmatrix} = v$$

$$\therefore f(u,v) = \frac{e^{-x} 2e^{-2y} |J|}{v} = \frac{e^{-uv} 2e^{-2v} \cdot v}{v}$$

$$= 2e^{-v(u+2)} v$$

$$\therefore f(u) = \int_0^\infty 2v e^{-v(u+2)} dv = \frac{2}{u+2} \int_0^\infty (u+2)v e^{-v(u+2)} dv$$

$$= \frac{2}{u+2} \cdot \frac{1}{u+2} = \frac{2}{(u+2)^2}$$

Therefore, as before, U is equal to X by Y , but let us take V is equal to Y . In that case what is going to happen? We can see that X is equal to UY is equal to UV . And Y is another V . Therefore, Jacobian is equal to determinant of $\frac{\partial x}{\partial u} \frac{\partial x}{\partial v} \frac{\partial y}{\partial u} \frac{\partial y}{\partial v}$ is equal to $\frac{\partial x}{\partial u}$ is equal to v , $\frac{\partial x}{\partial v}$ is equal to u , $\frac{\partial y}{\partial u}$ is equal to 0 and this is 1 therefore, the Jacobian is equal to v .

Therefore, f of u, v is equal to e to the power minus x 2 e to the power minus $2 y$ into the Jacobian which we can write now as e to the power minus $u v$ 2 e to the power minus $2 v$ into v is equal to $2 e$ to the power minus v into u plus 2 into v . Therefore, f of u is equal to integration 0 to infinity $2 v e$ to the power minus $v u$ plus $2 dv$ is equal to 2 upon u plus 2 integration 0 to infinity u plus $2 v e$ to the power minus $v u$ plus $2 dv$ is equal to as before, we can see is equal to 2 upon u plus 2 into 1 upon u plus 2 is equal to 2 upon u plus 2 whole square. Thus, we see that we get the same result by taking two different choices of V .

(Refer Slide Time: 12:09)

Ex Suppose X & Y are independent Gamma variables
 s.t. $X \sim (\lambda, \alpha)$ what is the pdf of
 $Y \sim (\lambda, \beta)$ $U = \frac{X}{Y}$?

$U = \frac{X}{Y} \therefore Y = \frac{X}{U} \therefore |J| = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} v & u \\ 0 & 1 \end{vmatrix} = v$
 $V = Y \quad X = UV$

$\therefore f(u, v) = f(x, y) \cdot |J|$
 expressed in u, v .

Let us now consider another example. Suppose, X and Y are independent gamma variables such that X is distributed as gamma lambda alpha and Y is distributed as gamma lambda beta. What is the pdf of U is equal to X by Y ? So, that is the question. Therefore, as before, we go U is equal to X by Y , and let us consider V is equal to Y . Therefore, as before, Y is equal to V and X is equal to UV .

Therefore, the Jacobian we have just seen will come out to be v u 0 1 determinant of this matrix is equal to v . Since, we have just worked it out in the previous example, I am not going into detail. Therefore, f of u, v is equal to $f x, y$ into the Jacobian expressed in u, v .

(Refer Slide Time: 14:05)

The image shows a handwritten derivation in a Windows Journal window titled 'Note1 - Windows Journal'. The derivation starts with the joint PDF of two independent Gamma random variables, X and Y , with parameters α and β respectively, and a common rate parameter λ . The joint PDF is given as $f(x,y) = \frac{\lambda^\alpha}{\Gamma(\alpha)} e^{-\lambda x} x^{\alpha-1} \cdot \frac{\lambda^\beta}{\Gamma(\beta)} e^{-\lambda y} y^{\beta-1}$. An arrow points to this expression with the text 'expressed in u, v'. The next step shows the transformation to $u = x$ and $v = x+y$, resulting in $f(u,v) = \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} e^{-\lambda uv} (uv)^{\alpha-1} e^{-\lambda u} v^{\beta-1} v$. This is then simplified to $f(u,v) = \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} e^{-\lambda v(1+u)} u^{\alpha-1} v^{\alpha+\beta-1}$. The final result is underlined and labeled 'joint pdf of u, v'.

$$f(x,y) = \frac{\lambda^\alpha}{\Gamma(\alpha)} e^{-\lambda x} x^{\alpha-1} \cdot \frac{\lambda^\beta}{\Gamma(\beta)} e^{-\lambda y} y^{\beta-1}$$

↑ expressed in u, v

$$f(u,v) = \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} e^{-\lambda uv} (uv)^{\alpha-1} e^{-\lambda u} v^{\beta-1} v$$

$$= \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} e^{-\lambda v(1+u)} u^{\alpha-1} v^{\alpha+\beta-1}$$

joint pdf of u, v.

Therefore, joint pdf $f(u, v)$ is equal to $\lambda^{\alpha+\beta}$ upon $\Gamma(\alpha)\Gamma(\beta)$ $e^{-\lambda v(1+u)}$ $u^{\alpha-1}$ $v^{\alpha+\beta-1}$. This is from the Jacobian. Is equal to $\lambda^{\alpha+\beta}$ upon $\Gamma(\alpha)\Gamma(\beta)$ $e^{-\lambda v}$ $u^{\alpha-1}$ $v^{\alpha+\beta-1}$ v . Therefore, $\alpha + \beta - 1$ and therefore that is the joint pdf of u, v .

Therefore, $f(u, v)$ is equal to $\lambda^{\alpha+\beta}$ upon $\Gamma(\alpha)\Gamma(\beta)$ $e^{-\lambda v}$ $u^{\alpha-1}$ $v^{\alpha+\beta-1}$ v . This is from the Jacobian. Is equal to $\lambda^{\alpha+\beta}$ upon $\Gamma(\alpha)\Gamma(\beta)$ $e^{-\lambda v}$ $u^{\alpha-1}$ $v^{\alpha+\beta-1}$ v . Therefore, $\alpha + \beta - 1$ and therefore that is the joint pdf of u, v .

(Refer Slide Time: 15:58)

The image shows a handwritten derivation of the Beta distribution probability density function (PDF) in a Windows Journal window. The derivation is as follows:

$$\begin{aligned}
 f(u) &= \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} \int_0^\infty u^{\alpha-1} e^{-\lambda(u+1)v} v^{\alpha+\beta-1} dv \\
 &= \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} u^{\alpha-1} \int_0^\infty e^{-\lambda(u+1)v} v^{\alpha+\beta-1} dv \\
 &= \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} u^{\alpha-1} \frac{\Gamma(\alpha+\beta)}{(\lambda(u+1))^{\alpha+\beta}} \quad \text{Gamma integration} \\
 &= \frac{1}{\Gamma(\alpha)\Gamma(\beta)} \frac{u^{\alpha-1}}{(1+u)^{\alpha+\beta}} \quad \text{Beta dist'n with parameters } \alpha \text{ \& } \beta
 \end{aligned}$$

Therefore, $f(u)$ is equal to $\lambda^{\alpha+\beta}$ upon $\Gamma(\alpha)\Gamma(\beta)$ integration of 0 to infinity u to the power $\alpha-1$, e to the power minus $\lambda(u+1)v$, v to the power $\alpha+\beta-1$ dv . Is equal to $\lambda^{\alpha+\beta}$ upon $\Gamma(\alpha)\Gamma(\beta)$ u to the power $\alpha-1$ integration 0 to infinity e to the power minus $\lambda(u+1)v$, v to the power $\alpha+\beta-1$ dv .

Is equal to $\lambda^{\alpha+\beta}$ upon $\Gamma(\alpha)\Gamma(\beta)$ u to the power $\alpha-1$ into $\Gamma(\alpha+\beta)$ divided by $(\lambda(u+1))^{\alpha+\beta}$. This is because this is our gamma integration and this result we have seen many times.

This is is equal to 1 upon $\Gamma(\alpha)\Gamma(\beta)$ upon $\Gamma(\alpha+\beta)$, $\lambda^{\alpha+\beta}$ cancels therefore what is remaining is $u^{\alpha-1}$ upon $(1+u)^{\alpha+\beta}$. So, we get this is our beta 2 distribution with parameters α and β .

(Refer Slide Time: 18:23)

Ex $X \sim (\lambda, \alpha)$ are independent. Find the distribution of $\frac{X}{X+Y}$
 $Y \sim (\lambda, \beta)$

$U = \frac{X}{X+Y}$
 $V = X+Y$
 $\therefore X+Y = V$
 $\therefore X = UV$
 $Y = V - UV = V(1-U)$

Note that U takes values only in the interval $(0, 1)$
 \therefore Since X, Y are both positive
 $X \leq X+Y$
 $\therefore 0 \leq \frac{X}{X+Y} \leq 1$

Let us consider a very similar example under the same of that is, X is gamma lambda, comma alpha, Y is gamma lambda, comma beta are independent. Find the distribution of X upon X plus Y . Slightly tricky. So, let us call U is equal to X upon X plus Y . Note that U takes value only in the interval 0 to 1 because since X and Y are both positive, X is always less than equal to X plus Y . Hence, this ratio X upon X plus Y is between 0 to 1.

Let us consider V is equal to X plus Y . Therefore, what we get. X plus Y is equal to V . Therefore, X is equal to $U V$. Therefore, Y is equal to V minus uv is equal to V into 1 minus u . So, this is important because this is the inverse transformation from $u v$ to $x y$.

(Refer Slide Time: 20:40)

$\therefore X = UV$
 $Y = V(1-U)$

$\therefore |J| = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} v & u \\ -v & 1-u \end{vmatrix}$
 $= v - uv + uv = v \geq 0$

$\therefore f(u, v) = f(x, y) \cdot |J|$ \rightarrow expressed in (u, v)
 $= \frac{\lambda^\alpha}{\Gamma(\alpha)} e^{-\lambda x} x^{\alpha-1} \cdot \frac{\lambda^\beta}{\Gamma(\beta)} e^{-\lambda y} y^{\beta-1} \cdot |J|$
 $= \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} e^{-\lambda uv} (uv)^{\alpha-1} e^{-\lambda(1-u)v} (v(1-u))^{\beta-1} \cdot v$ \rightarrow expressed in u, v
 $= \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} e^{-\lambda(uv - uv + v)} u^{\alpha-1} v^{\alpha-1} v^{\beta-1} (1-u)^{\beta-1} \cdot v$

Therefore, X is equal to uv , Y is equal to v into 1 minus u . Therefore, Jacobian is equal to $\frac{\partial x}{\partial u} \frac{\partial x}{\partial v} \frac{\partial y}{\partial u} \frac{\partial y}{\partial v}$ is equal to v u minus v 1 minus u is equal to v minus uv plus uv is equal to v , which is greater than equal to 0 . Therefore, we need not take any modulus here. Therefore, joint distribution of u and v is equal to $f(x, y)$ into Jacobian expressed in u, v .

Is equal to $\lambda^\alpha \lambda^\beta$ upon $\Gamma(\alpha) \Gamma(\beta)$ $e^{-\lambda x}$ $x^{\alpha-1}$ $x^{\beta-1}$ $e^{-\lambda y}$ $y^{\alpha-1}$ $y^{\beta-1}$ multiplied by the Jacobian expressed in u, v , is equal to $\lambda^{\alpha+\beta}$ upon $\Gamma(\alpha) \Gamma(\beta)$ $e^{-\lambda uv}$ $(uv)^{\alpha-1}$ $(v(1-u))^{\beta-1}$ v into v into 1 minus u whole to the power $\beta-1$ into v .

Is equal to $\lambda^{\alpha+\beta}$ upon $\Gamma(\alpha) \Gamma(\beta)$ $e^{-\lambda uv}$ $u^{\alpha-1}$ $v^{\alpha+\beta-1}$ $(1-u)^{\beta-1}$ v . By combining these two into u to the power $\alpha-1$, v to the power $\alpha+\beta-1$, v to the power $\beta-1$ $1-u$ to the power $\beta-1$ into v .

(Refer Slide Time: 24:07)

The image shows a handwritten derivation in a Windows Journal window. The derivation starts with the joint probability density function of X and Y , which are independent Gamma random variables with parameters α and β respectively. The joint PDF is given by:

$$f(x, y) = \frac{\lambda^\alpha}{\Gamma(\alpha)} e^{-\lambda x} x^{\alpha-1} \frac{\lambda^\beta}{\Gamma(\beta)} e^{-\lambda y} y^{\beta-1}$$

Then, the transformation $u = \frac{x}{x+y}$ and $v = x+y$ is used. The Jacobian of this transformation is v . The joint PDF in terms of u and v is:

$$f(u, v) = \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha) \Gamma(\beta)} e^{-\lambda uv} (uv)^{\alpha-1} (v(1-u))^{\beta-1} v$$

Simplifying this, we get:

$$f(u, v) = \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha) \Gamma(\beta)} e^{-\lambda uv} u^{\alpha-1} v^{\alpha+\beta-1} (1-u)^{\beta-1} v$$

Integrating with respect to v from 0 to ∞ , we get the marginal PDF of u :

$$f(u) = \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha) \Gamma(\beta)} u^{\alpha-1} (1-u)^{\beta-1} \int_0^\infty e^{-\lambda uv} v^{\alpha+\beta-1} dv$$

The integral is a Gamma function, and the result is:

$$f(u) = \frac{1}{\Gamma(\alpha) \Gamma(\beta)} u^{\alpha-1} (1-u)^{\beta-1} \Gamma(\alpha+\beta)$$

Therefore, the ratio $\frac{X}{X+Y}$ follows a Beta distribution with parameters α and β :

$$\frac{X}{X+Y} \sim \text{Beta}(\alpha, \beta)$$

Handwritten derivation in a Windows Journal window:

$$\begin{aligned} \therefore X &= uv \\ Y &= v(1-u) \end{aligned} \quad \therefore |J| = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} v & u \\ -v & 1-u \end{vmatrix}$$

$$= v - uv + uv = v \geq 0$$

$$\therefore f(u, v) = f(x, y) \cdot |J| \quad \text{expressed in } (u, v)$$

$$= \frac{\lambda^\alpha}{\Gamma(\alpha)} e^{-\lambda x} x^{\alpha-1} \cdot \frac{\lambda^\beta}{\Gamma(\beta)} e^{-\lambda y} y^{\beta-1} \cdot |J|$$

$$= \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} e^{-\lambda uv} (uv)^{\alpha-1} e^{-\lambda(1-u)v} (v(1-u))^{\beta-1} \cdot v$$

$$= \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} e^{-\lambda(uv - uv + uv)} u^{\alpha-1} v^{\alpha-1} v^{\beta-1} (1-u)^{\beta-1} \cdot v$$

Is equal to lambda to the power alpha plus beta upon gamma alpha gamma beta e to the power minus lambda v. This I am getting from here. u to the power alpha minus 1, 1 minus u to the power beta minus 1 and v to the power alpha plus beta minus 1. U to the power alpha minus 1, 1 minus u to the power beta minus 1, v to the power alpha plus beta minus 1.

Therefore, f of u is equal to, let me take out the terms independent of v to be out of the integration. Therefore, lambda to the power alpha plus beta gamma alpha gamma beta u to the power alpha minus 1, 1 minus u to the power beta minus 1, integration 0 to infinity e to the power minus lambda v, v to the power alpha plus beta minus 1 dv.

Is equal to lambda to the power alpha plus beta gamma alpha gamma beta u to the power alpha minus 1, 1 minus u to the power beta minus 1, and this again using gamma integration, we are getting gamma alpha plus beta upon lambda to the power alpha plus beta. Is equal to, because this gets cancelled, we have 1 upon gamma alpha gamma beta upon gamma alpha plus beta, u to the power alpha minus 1, 1 minus u to the power beta minus 1, when 0 less than u less than 1.

Therefore, we get X upon X plus Y is distributed as beta 1 with parameter alpha, beta. So, we have seen these distributions before, but now we can see from how, from known distributions particularly gamma distribution with same parameters lambda, we can get both beta 1 and beta 2 distributions.

(Refer Slide Time: 26:54)

EX Let X, Y be iid Cauchy $(1, 0)$.
 Find the distribution of XY .
 Let $U = XY$ $\therefore X = \frac{U}{V}$ $\therefore |J| = \begin{vmatrix} 0 & 1 \\ \frac{1}{V} & -\frac{U}{V^2} \end{vmatrix} = \frac{1}{V}$
 $V = X$ $Y = \frac{U}{V}$
 $\therefore g(u, v) = \frac{1}{\pi^2} \cdot \frac{1}{1+u^2} \cdot \frac{1}{1+\frac{u^2}{v^2}} \cdot \frac{1}{|v|}$ Post $\therefore -\infty < v < \infty$
 $- \infty < v < \infty$ \therefore We shall take $|v|$ when $v < 0$.
 \therefore We integrate out v to get the pdf of U .

So, let us take another example which is slightly difficult but still let us do it. Let X, Y be iid Cauchy with 1, 0 that is standard Cauchy distribution. Find the distribution of XY . So, let us take U is equal to XY and V is equal to X . Therefore, X is equal to v , Y is equal to u by v . Therefore, Jacobian is going to be $\frac{\partial x}{\partial u} \frac{\partial x}{\partial v} \frac{\partial y}{\partial u} \frac{\partial y}{\partial v}$ is equal to 1 upon v . But since minus infinity less than v less than infinity, therefore we shall take modulus of v when v is less than 0.

Therefore, $g(u, v)$ is equal to $\frac{1}{\pi^2} \cdot \frac{1}{1+u^2} \cdot \frac{1}{1+\frac{u^2}{v^2}} \cdot \frac{1}{|v|}$ when minus infinity less than v less than infinity. Therefore, we integrate out v to get the pdf of u .

(Refer Slide Time: 29:25)

$\therefore g(u) = \int_{-\infty}^{\infty} \frac{1}{\pi^2} \cdot \frac{1}{1+u^2} \cdot \frac{v^2}{v^2+u^2} \cdot \frac{1}{|v|} dv$
 Since this is an even function we write as:
 $g(u) = 2 \int_0^{\infty} \frac{1}{\pi^2} \cdot \frac{1}{1+u^2} \cdot \frac{v}{v^2+u^2} dv$
 $= \frac{1}{\pi^2} \int_0^{\infty} \frac{1}{(u^2-1)} \cdot \frac{u^2-1}{(1+u^2)(v^2+u^2)} 2v dv$
 $= \frac{1}{\pi^2} \int_0^{\infty} \frac{1}{(u^2-1)} \left(\frac{1}{1+u^2} - \frac{1}{v^2+u^2} \right) 2v dv$
 Now consider
 $\frac{1}{1+u^2} - \frac{1}{v^2+u^2} = \frac{v^2+u^2 - 1 - u^2}{(1+u^2)(v^2+u^2)} = \frac{v^2-1}{(1+u^2)(v^2+u^2)}$

Therefore, g of u is equal to integration minus infinity to infinity $\frac{1}{1 + v^2}$ into $\frac{1}{1 + v^2 + u^2}$ dv . And v is going from minus infinity to infinity. Since, this is an even function, we write as g of u is equal to 2 times 0 to infinity $\frac{1}{1 + v^2}$ $\frac{1}{1 + v^2 + u^2}$ dv .

Now, consider $\frac{1}{1 + v^2} - \frac{1}{v^2 + u^2}$. So, this is equal to $\frac{1 + v^2 - (v^2 + u^2)}{(1 + v^2)(v^2 + u^2)}$ in the denominator and in the numerator we have $1 + v^2 - v^2 - u^2$ is equal to $1 - u^2$ over $(1 + v^2)(v^2 + u^2)$.

Therefore, this we write as $\frac{1 - u^2}{\pi^2(u^2 - 1)}$, we take out of the integration, 0 to infinity $\frac{1 - u^2}{u^2 - 1}$ into $\frac{1}{1 + v^2 + u^2}$ $2v dv$. Is equal to $\frac{1 - u^2}{\pi^2(u^2 - 1)}$ 0 to infinity $\frac{1}{1 + v^2 + u^2}$ $2v dv$.

Note that in both of them, v^2 is there in the denominator so by replacing $1 + v^2$ say as z , we shall get $2v dv$ is equal to dz and in a similar way for $v^2 + u^2$ we shall get $2v dv$ to be say, d of w .

(Refer Slide Time: 32:40)

The image shows a handwritten derivation in a Windows Journal window. The derivation is as follows:

$$\begin{aligned}
 &= \frac{1}{\pi^2(u^2-1)} \int_0^\infty \left(\frac{1}{1+v^2} - \frac{1}{v^2+u^2} \right) 2v dv \\
 &= \frac{1}{\pi^2(u^2-1)} \left[\log(1+v^2) - \log(v^2+u^2) \right]_0^\infty \\
 &= \frac{1}{\pi^2(u^2-1)} \left[\log \frac{1+u^2}{u^2+u^2} \right]_0^\infty \\
 &= \frac{1}{\pi^2(u^2-1)} \left(\lim_{v \rightarrow \infty} \left(\log \frac{1+u^2}{v^2+u^2} \right) - \log \frac{1}{u^2} \right) \\
 &\therefore \frac{1}{\pi^2(u^2-1)} \cdot (-2 \log |u|) = \boxed{\frac{2 \log |u|}{\pi^2(u^2-1)}} \quad -\infty < u < \infty
 \end{aligned}$$

On the right side, there is a note:

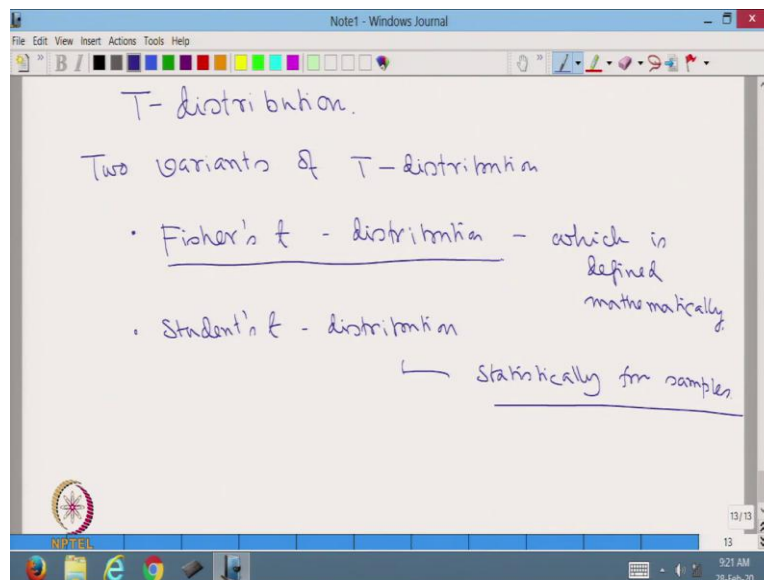
Note
 $\log \frac{1+u^2}{u^2+u^2}$
 $= \log \frac{1+u^2}{1+u^2}$
 \therefore Taking $\lim_{v \rightarrow \infty}$
 $= \log \frac{1}{1}$
 $= \log 1$
 $= 0$

So, this we write as, $\frac{1}{\pi^2(u^2 - 1)}$ into $u^2 - 1$ integration 0 to infinity $\frac{1}{1 + v^2 + u^2}$ $2v dv$. Is equal to $\frac{1}{\pi^2(u^2 - 1)}$ 0 to infinity $\frac{1}{1 + v^2 + u^2}$ $2v dv$. Is equal to $\frac{1}{\pi^2(u^2 - 1)}$ 0 to infinity $\frac{1}{1 + v^2 + u^2}$ $2v dv$.

$\int_0^\infty \frac{1}{1+u^2} du$ is equal to $\frac{1}{\pi} \int_0^\infty \frac{1}{1+u^2} du$ minus $\frac{1}{\pi} \log(1+u^2)$ evaluated from 0 to ∞ . By putting the value $u=0$ we have $\log(1+0) = 0$.

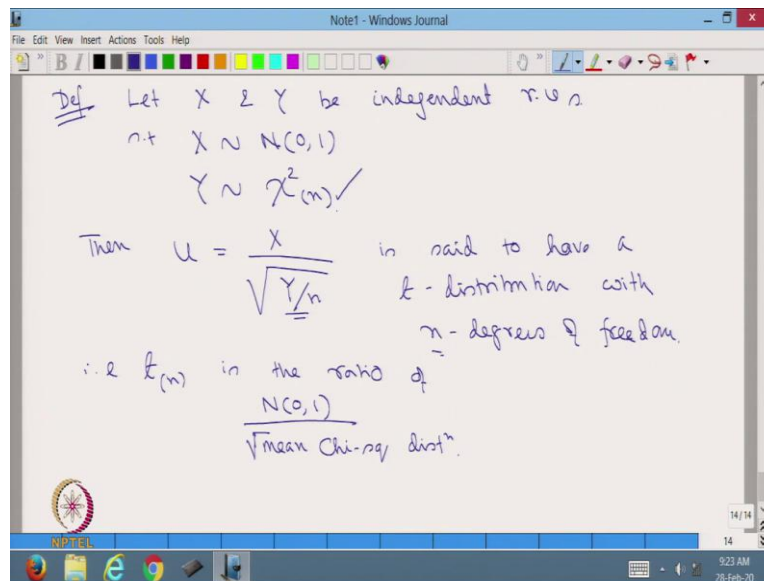
Now, $\log(1+u^2)$ upon $1+u^2$ is equal to $\log(1+u^2)$ upon $1+u^2$. Therefore, taking limit u going to infinity, we get $\frac{\log(1+u^2)}{1+u^2} \rightarrow 0$. Therefore, this term goes to 0 and we get $\frac{1}{\pi} \int_0^\infty \frac{1}{1+u^2} du = \frac{1}{\pi} \left[\tan^{-1} u \right]_0^\infty = \frac{1}{\pi} \left(\frac{\pi}{2} - 0 \right) = \frac{1}{2}$. So, we get another new density function although this is not very commonly used function.

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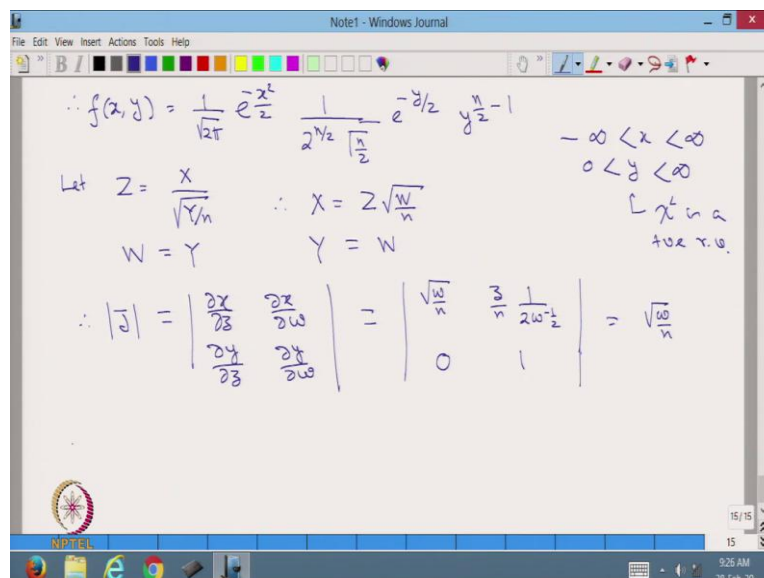
Let me now define T - distribution two variants of it. One is called Fisher's t - distribution which is defined mathematically and the second one is called Student's t - distribution which is defined statistically from samples. This is important to know if some of you are going to use it in testing statistical hypothesis but for this class we are sticking to Fisher's t - distribution.

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So, definition, let X and Y be independent random variables such that X is distributed as normal $0, 1$ and Y is distributed as chi square with n degrees freedom then u which is defined as X upon square root of Y by n is said to have a t - distribution with n degrees of freedom. This n is coming from the degrees of freedom of the chi square distribution. That is, t_n is the ratio of standard normal $0, 1$ and square root of mean chi square distribution. Mean is coming because we are dividing by n the degrees of freedom. So, what is the pdf?

(Refer Slide Time: 39:04)



Therefore, f of x, y we can write it as $\frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$ upon $\frac{1}{2^{n/2} \Gamma(\frac{n}{2})} e^{-\frac{y}{2}}$, y to the power $\frac{n}{2}$

minus 1, when minus infinity less than x less than infinity and 0 less than y less than infinity. This is because chi square is a positive random variable.

Let Z is equal to X upon root over Y by n and let W is equal to Y. Therefore, X is equal to Z into root over W by n and Y is equal to W. Therefore, the Jacobian is equal to del x del z del x del w del y del z del y del w is equal to root of w by n z by and n half w to the power minus half 0 and 1 is equal to root over w by n.

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Handwritten derivation of the marginal probability density function $f(w, z)$ for a chi-square distribution. The derivation starts with the joint density function $f(w, z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2 w}{2}} \cdot \frac{1}{2^{n/2} \sqrt{\frac{n}{2}}} e^{-\frac{w}{2}} w^{\frac{n}{2}-1} \cdot \frac{\sqrt{w}}{n}$. This is simplified to $\frac{1}{\sqrt{2\pi} 2^{n/2} \sqrt{\frac{n}{2}} \sqrt{n}} e^{-\frac{w}{2}(1 + \frac{z^2}{n})} w^{\frac{n}{2}-1}$. Then, the marginal density $f(z)$ is found by integrating over w from 0 to infinity: $f(z) = \int_0^\infty \frac{1}{\sqrt{2\pi} 2^{n/2} \sqrt{\frac{n}{2}} \sqrt{n}} e^{-\frac{w}{2}(1 + \frac{z^2}{n})} w^{\frac{n}{2}-1} dw$. This integral is evaluated using the gamma function, resulting in $f(z) = \frac{1}{\sqrt{2\pi} 2^{n/2} \sqrt{\frac{n}{2}} \sqrt{n}} \frac{\sqrt{\frac{n}{2}}}{(\frac{1}{2}(1 + \frac{z^2}{n}))^{\frac{n+1}{2}}} = \frac{1}{\sqrt{2\pi} \sqrt{n}} \frac{1}{(1 + \frac{z^2}{n})^{\frac{n+1}{2}}}$.

Handwritten derivation of the joint probability density function $f(x, y)$ and the Jacobian for the transformation from (X, Y) to (Z, W) . The joint density is given as $f(x, y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \cdot \frac{1}{2^{n/2} \sqrt{\frac{n}{2}}} e^{-\frac{y}{2}} y^{\frac{n}{2}-1}$, with the domain $-\infty < x < \infty$ and $0 < y < \infty$. The transformation is defined by $Z = \frac{X}{\sqrt{Y/n}}$ and $W = Y$, which implies $X = Z\sqrt{\frac{W}{n}}$ and $Y = W$. The Jacobian determinant is calculated as $|J| = \begin{vmatrix} \frac{\partial x}{\partial z} & \frac{\partial x}{\partial w} \\ \frac{\partial y}{\partial z} & \frac{\partial y}{\partial w} \end{vmatrix} = \begin{vmatrix} \frac{\sqrt{w}}{n} & \frac{3}{2} \frac{1}{2w^{1/2}} \\ 0 & 1 \end{vmatrix} = \frac{\sqrt{w}}{n}$.

Therefore, as before f of w and z is equal to 1 over root 2 pi e to the power minus z square w by n by 2. This is because X is equal to $Z w$ by n . Therefore, X square is equal to z square w by n . So, I am using that multiplied by 1 upon 2 to the power n by 2 gamma n by 2 e to the power minus w by 2 w to the power n by 2 minus 1 multiplied by root over w by n .

This is from the Jacobian is equal to, let us take out all the constants, 1 over root over 2π to the power n by 2 gamma n by 2 and root over n multiplied by e to the power minus w by 2 into 1 plus z square by n into w to the power n by 2 minus half. Because we get w power half from there. Therefore, f of z is equal to we are integrating out w therefore, taking out the constant, 1 over root over 2π to the power n by 2 gamma n by 2 root over n e to the power minus w by 2 1 plus z square by n w to the power n minus 1 by 2 .

And I am integrating it from 0 to infinity with respect to dw is equal to all the constant terms come out. 1 over root over 2π to the power n by 2 gamma n by 2 root over n integration 0 to infinity e to the power minus w by 2 1 plus z square by n w to the power n plus 1 by 2 minus 1 . We are writing it in this form dw is equal to 1 over root over 2π to the power n by 2 gamma n by 2 root over n .

Now, this is again our familiar gamma integral. Therefore, we can write it as gamma n plus 1 by 2 upon half 1 plus z square by n whole to the power n plus 1 by 2 . Fairly complicated but we can make it slightly simpler is equal to now here it is root 2 to the power n by 2 so together it is 2 to the power n plus 1 by 2 . And here it is half to the power n plus 1 by 2 . So, these cancels.

Therefore, we can see that it is coming out to be gamma n plus 1 by 2 upon gamma n by 2 and root over π into root over n into 1 upon 1 plus z square by n whole to the power n plus 1 by 2 . So, let me write it again.

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The image shows a digital whiteboard with handwritten mathematical derivations and notes. The derivations are as follows:

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

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

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

The final expression is boxed and labeled $k(z)$.

Notes on the right side:

- Note that:
 - i) It is symmetric around 0 .
 - ii) Its expected value is 0 .
- Note that:
 - $-\infty < z < \infty$
 - $\therefore N(0,1)$ takes values in $(-\infty, \infty)$
 - $\sqrt{2n}/n$ is $+ve$

The whiteboard interface includes a menu bar (File, Edit, View, Insert, Actions, Tools, Help), a toolbar with various drawing tools, and a taskbar at the bottom showing the Windows logo, taskbar icons, and system clock (9:35 AM, 28-Feb-20).

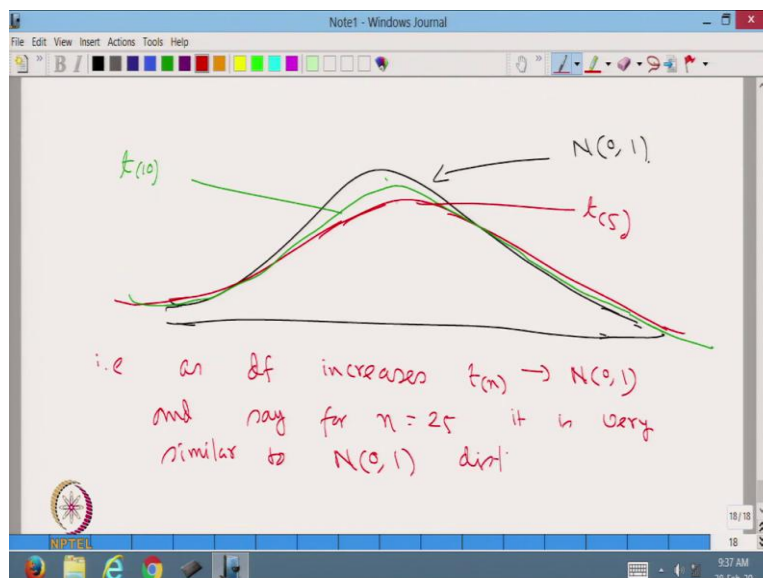
Handwritten derivation of the characteristic function $f(\omega, \beta)$ for a t-distribution. The derivation starts with the definition of the characteristic function and uses the Gamma function to simplify the integral. The final result is:

$$f(\omega, \beta) = \frac{1}{\sqrt{2\pi}} \frac{\Gamma\left(\frac{n+1}{2}\right)}{\Gamma\left(\frac{n}{2}\right)} \left(1 + \frac{\omega^2 \beta^2}{n}\right)^{-\frac{n+1}{2}}$$

So, $\frac{\Gamma\left(\frac{n+1}{2}\right)}{\Gamma\left(\frac{n}{2}\right)} \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{n}}$ Now, we know that $\frac{1}{\sqrt{2\pi}}$ is equal to $\frac{1}{\sqrt{2\pi}}$ multiplied by $\frac{1}{\sqrt{n}}$ to the power $n+1$ by 2. Is equal to $\frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{n}}$ into $\frac{1}{\sqrt{2\pi}}$ multiplied by $\frac{1}{\sqrt{n}}$ to the power $n+1$ by 2. Is equal to $\frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{n}}$ multiplied by $\frac{1}{\sqrt{n}}$ to the power $n+1$ by 2.

Note that minus infinity less than z less than infinity. Because normal 0, 1 takes values in minus infinity to plus infinity. And root over chi square n by n is positive. So, that is the density function for t with n degrees of freedom. Note that one, it is symmetric around 0 and two is therefore, its expected values is 0. One can compute the other moments from the first definition, but let me explain one diagram.

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Suppose this is a normal 0, 1 diagram. Normal 0, 1 density. Then, t will look slightly flatter than that and as the degrees of freedom increases, it will go like this. Therefore, this is say, t with say, 10 degrees of freedom. But suppose, this is say, t with 5 degrees of freedom, that is, as df increases t converges toward normal 0, 1 and say, for n is equal to 25, it is very similar to standard normal distribution.

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F-distribution (Snedecor's F)
with two parameters m, n .

Def: X, Y are independent χ^2 distribution with m & n degrees of freedom, respectively
then $U = \frac{X/m}{Y/n}$ is said to have F-distribution with parameters m, n .

Note that $z(m) = \frac{N(0,1)}{\sqrt{\chi^2_m/n}} \therefore z^2(m) = \frac{\chi^2_1}{\chi^2_m/n} = \frac{\chi^2_1/1}{\chi^2_m/n}$
 $\therefore z^2(m) \equiv F(1, n)$

So, let us conclude the talk with one more distribution namely F - distribution which is called Snedecor's F with two parameters m , comma n . So, definition, if X and Y are independent, chi square distribution with m and n degrees of freedom respectively, then U is equal to X by m upon Y by n is said to have F - distribution with parameters m and n . Note that t is equal to normal 0, 1 upon square root of chi square n by n .

Therefore, t^2 of n is equal to chi square 1 because we know normal 0, 1 square is equal to chi square 1 divided by chi square n upon n is equal to chi square 1 by 1 divided by chi square n by n . Therefore, t^2 of n is same as F with 1, comma n . So, that is the relationship between t and f .

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What is the pdf?

We do it in a simpler way:

$$F_{m,n} = \frac{\chi^2_m / m}{\chi^2_n / n} = \frac{n}{m} \frac{\chi^2_m}{\chi^2_n}$$

$$= \frac{n}{m} \frac{\Gamma(\frac{n}{2})}{\Gamma(\frac{m}{2})}$$

we know $\frac{\Gamma(\lambda)}{\Gamma(\beta)}$ when independent = $\text{Beta}_2(\alpha, \beta)$

$$\therefore F_{m,n} = \frac{n}{m} \text{Beta}_2\left(\frac{m}{2}, \frac{n}{2}\right)$$

So, what is the pdf? We do it as follows in a simpler way. So, $F_{m,n}$ is equal to chi square m by m upon chi square n by n is equal to n by m chi square m divided by chi square n is equal to n by m gamma with half, comma m by 2 upon gamma with half n by 2 . Now, we know that gamma lambda comma alpha upon gamma lambda, comma beta when independent becomes beta 2 with alpha, comma beta. Therefore, $F_{m,n}$ is equal to n by m times beta 2 distribution with parameter m by 2 and n by 2 . Thus, from 2 variables, we convert it into 1 variable.

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\therefore Let $X \sim \text{Beta}_2\left(\frac{m}{2}, \frac{n}{2}\right)$

to find pdf of $\frac{n}{m} X$

\therefore Let $Z = \frac{n}{m} X \quad \therefore X = \frac{m}{n} Z \quad \therefore \frac{dx}{dz} = \frac{m}{n}$

$$\therefore f(z) = \frac{1}{\text{Beta}\left(\frac{m}{2}, \frac{n}{2}\right)} \cdot \frac{\left(\frac{m}{n} z\right)^{\frac{m}{2}-1}}{\left(1 + \frac{m}{n} z\right)^{\frac{m+n}{2}}} \cdot \frac{m}{n} \left|\frac{dx}{dz}\right|$$

$$= \frac{\left(\frac{m}{n}\right)^{\frac{m}{2}}}{\text{Beta}\left(\frac{m}{2}, \frac{n}{2}\right)} \frac{z^{\frac{m}{2}-1}}{\left(1 + \frac{m}{n} z\right)^{\frac{m+n}{2}}} \quad \left| 0 < z < \infty \right.$$

$\text{Beta}_2\left(\frac{m}{2}, \frac{n}{2}\right)$
Replacing x with $\frac{m}{n} z$

Therefore, let X is distributed as beta 2 with m by 2 , comma n by 2 to find pdf of n by m X . Therefore, let Z is equal to n by m X . Therefore, X is equal to m by n Z , therefore dx/dz is

equal to $m \times n$. Therefore, $f(z)$ from the theory of single variable function is $\frac{1}{\Gamma(m) \Gamma(n)} z^{m-1} (1-z)^{n-1}$ to the power $m+n-2$ multiplied by $m \times n$.

So, this is coming from beta 2 with m by 2, n by 2 replacing x with z , and this is coming from $dx dz$ is equal to as you can understand it is going to be $m \times n$ to the power $m+n-2$ because I am taking this term and this term upon beta m by 2, n by 2 z to the power $m+n-2$, when $0 < z < 1$. So, that is the pdf of F - $m \times n$ distribution.

Again one can think of computing its expectation variance etc the way we have done in earlier cases. Okay friends, I stop here today. I hope you have understood how to compute the distribution of a function of a random variable when the distribution of the original random variable is known and over the last few classes, we have seen such development of pdf's from single variable and two variables. So, with that I stop on functions of random variable. From the next class, I shall start with a very interesting topic which is called ordered statistics. Okay then. Thank you.