

Unit IV	Non-Central distributions
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## 4.1 Non-central t-distribution

### t-distribution (Central t-distribution)

Let  $x_i, i=1, 2, \dots, n$  be a random sample size 'n' drawn from normal population with  $N(\mu, \sigma^2)$  then the student 't' is defined by

$$t = \frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}}$$

This statistic follows a student 't' distribution with  $(n-1)$  df the pdf  $g(t)$  is given by

$$f(t) = \frac{1}{\sqrt{\gamma}} \cdot \frac{1}{B(1/2, \gamma/2)} \cdot \frac{1}{(1 + \frac{t^2}{\gamma})^{\frac{\gamma+1}{2}}} \quad ; -\infty < t < \infty$$

and  $\gamma = n-1$

If  $\gamma = 1$ , the pdf  $g(t)$  reduced to

$$f(t) = \frac{1}{B(1/2, 1/2)} \cdot \frac{1}{1+t^2} \quad ; -\infty < t < \infty$$

$$= \frac{1}{\pi} \cdot \frac{1}{1+t^2}, \quad -\infty < t < \infty$$

### Non-central t-distribution:

The non-central 't' distribution is the distribution of the ratio of the normal variate with non-zero mean and unit variance to the root of an independent  $\chi^2$  variate defined by its density function.

i.e.,  $x \sim N(\mu, 1)$  and  $y \sim \chi_n^2$ , then

$t = \frac{x}{\sqrt{y/n}}$  is said to have a non-central 't' distribution with 'n' d.f and the non-centrality parameter  $\mu$ .

As  $x \sim N(\mu, 1)$  we have

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2}}$$

Also we have

$$f(y) = \frac{1}{2^{n/2} \Gamma(n/2)} \cdot e^{-y/2} \cdot y^{n/2 - 1}, \quad 0 \leq y \leq \infty$$

Since  $x$  and  $y$  are independent, the joint p.d.f of  $x$  and  $y$  is

$$f(x, y) = f(x) \cdot f(y) \\ = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2}} \cdot \frac{1}{2^{n/2} \Gamma(n/2)} \cdot e^{-y/2} \cdot y^{n/2 - 1} \quad \text{--- (1)}$$

Now

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2}} \\ = \frac{1}{\sqrt{2\pi}} e^{-1/2(x^2 + \mu^2 - 2x\mu)}$$

$$\begin{aligned}
 &= \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\bar{x}^2 + \mu^2)} e^{x\mu} \\
 &= \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\bar{x}^2 + \mu^2)} \left[ 1 + \bar{x}\mu + \frac{(\bar{x}\mu)^2}{2!} + \dots \right] \\
 &= \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\bar{x}^2 + \mu^2)} \sum_{r=0}^{\infty} \frac{(\bar{x}\mu)^r}{r!}
 \end{aligned}$$

put this in ①, we get

$$f(x, y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\bar{x}^2 + \mu^2)} \sum_{r=0}^{\infty} \frac{(\bar{x}\mu)^r}{r!} \cdot \frac{1}{2^{r/2} r!} e^{-y/2} y^{r/2-1} \quad \text{--- (2)}$$

Let us introduce the variables 't' and z

$$t' = \frac{x}{\sqrt{y/n}} \text{ and } z^2 = y$$

$$\Rightarrow x = \frac{\sqrt{y} t'}{\sqrt{n}} \text{ and } y = z^2$$

$$\Rightarrow x = \frac{z t'}{\sqrt{n}} \text{ and } y = z^2$$

The Jacobian transformation is

$$\begin{aligned}
 |J| &= \begin{vmatrix} \frac{\partial x}{\partial t'} & \frac{\partial x}{\partial z} \\ \frac{\partial y}{\partial t'} & \frac{\partial y}{\partial z} \end{vmatrix} = \begin{vmatrix} z/\sqrt{n} & t'/\sqrt{n} \\ 0 & 2z \end{vmatrix} \\
 &= \frac{2z^2}{\sqrt{n}}
 \end{aligned}$$

∴ The joint pdf of t' and z from ② is

$$f(t', z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} \left[ \frac{t'^2 z^2}{n} + \mu^2 \right]} \sum_{r=0}^{\infty} \frac{\left( \frac{z t' \mu}{\sqrt{n}} \right)^r}{r!} \frac{e^{-z^2/2}}{2^{r/2} r!} (z^2)^{r/2-1}$$

$$= \frac{1}{\sqrt{2\pi} z^{r/2} r!} e^{-\frac{\mu^2}{2}} e^{-\frac{1}{2} \left[ \frac{t'^2 z^2}{n} + z^2 \right]} [z^2]^{\frac{n}{2}} \sum_{r=0}^{\infty} \frac{\mu^r (e^z)}{n(r/2 + 1)r!}$$

$$\begin{aligned}
 &= \frac{1}{\sqrt{\pi} \frac{\gamma_1}{2} \frac{\gamma_2}{\Gamma(\gamma_2)}} e^{-\mu^2/2} \cdot e^{-z^2/2} \sum_{r=0}^{\infty} \frac{\mu^r (t^r z)^r}{r! (\gamma_1 + \gamma_2 - r)!} \\
 &= \frac{1}{\sqrt{\pi}} \cdot \frac{1}{\frac{\gamma_1+1}{2}-1} \cdot \frac{1}{\Gamma(\gamma_2)} \cdot e^{-\mu^2/2} \cdot e^{-z^2/2} \sum_{r=0}^{\infty} \frac{\mu^r (t^r z)^r}{[z^2]^{r/2} \sum_{r=0}^{\infty} \frac{\mu^r (t^r z)^r}{r! (\gamma_1 + \gamma_2 - r)!}} \\
 &= \frac{1}{\sqrt{\pi}} \cdot \frac{1}{\frac{\gamma_1+1}{2}-1} \cdot \frac{1}{\Gamma(\gamma_2)} \cdot e^{-\mu^2/2} \cdot e^{-z^2/2} \sum_{r=0}^{\infty} \frac{\mu^r t^r z^r}{\sum_{r=0}^{\infty} \frac{\mu^r t^r z^r}{r! (\frac{\gamma_1+1}{2}-1)^r}}
 \end{aligned}$$

Integrate out  $z$  in the interval 0 to  $\infty$ :

The pdf  $g(t)$  is

$$df(t) = \frac{e^{-\mu^2/2}}{\sqrt{\pi} \frac{\gamma_1+1}{2} \frac{\gamma_2}{\Gamma(\gamma_2)}} \sum_{r=0}^{\infty} \frac{\mu^r t^r}{n^{\gamma_1+\gamma_2-r} r!} \int_0^{\infty} e^{-\frac{z^2}{2}} \left[ \frac{t^r}{n} + 1 \right] z^{r+n-1} dz$$

$$= \int_0^{\infty} e^{-\frac{z^2}{2}} \left( \frac{t^r}{n} + 1 \right) z^{r+n-1} dz$$

$$\text{Put } z^2 = u \Rightarrow 2z dz = du \Rightarrow dz = \frac{du}{2z} = \frac{du}{2\sqrt{u}}$$

$$= \frac{1}{2} \int_0^{\infty} e^{-\frac{u}{2}} \left( \frac{t^r}{n} + 1 \right) u^{\frac{r+n-1}{2}} du$$

$$\text{Let } \lambda = \frac{1}{2} \left( \frac{t^r}{n} + 1 \right)$$

$$df(t) = \frac{e^{-\mu^2/2}}{\sqrt{\pi} \frac{\gamma_1+1}{2} \frac{\gamma_2}{\Gamma(\gamma_2)}} \sum_{r=0}^{\infty} \frac{\mu^r t^r}{n^{\gamma_1+\gamma_2-r} r!} \int_0^{\infty} e^{-\lambda u} u^{\frac{r+n-1}{2}} du$$

$$= \frac{e^{-\mu^2/2}}{\sqrt{\pi} \frac{\gamma_1+1}{2} \frac{\gamma_2}{\Gamma(\gamma_2)}} \sum_{r=0}^{\infty} \frac{\mu^r t^r}{n^{\gamma_1+\gamma_2-r} r!} \times \frac{\sqrt{\frac{n}{r+n+1}}}{\lambda^{\frac{r+n+1}{2}}}$$

$$= \frac{e^{-\mu^2/2}}{\sqrt{\pi} \frac{\gamma_1+1}{2} \frac{\gamma_2}{\Gamma(\gamma_2)}} \sum_{r=0}^{\infty} \frac{\mu^r (t^r)^r}{n^{\gamma_1+\gamma_2-r} r!} \left[ \frac{1}{2} \left( \frac{t^r}{n} + 1 \right) \right]^{\frac{r+n+1}{2}}$$

which is the pdf of non-central 't' distribution  
 which 'n' df and non-centrality parameter  $\mu$ .

## 4.2 Non-central F-distribution

The ratio of two independent  $\chi^2$  variates divided by the corresponding df has a non-central F distribution if the numerator has a non-central  $\chi^2$  distribution.

Thus if  $x$  has a non-central  $\chi^2$  distribution with  $n_1$  df

i.e.,  $X \sim \chi_{n_1}^{n_1}$  and  $y$  is an independent  $\chi^2$  variate with  $n_2$  df i.e.,  $y \sim \chi_{n_2}^{n_2}$  then the non-central F statistic is defined as

$$F' = \frac{X/n_1}{Y/n_2} = \frac{n_2 X}{n_1 Y}$$

Probability distribution function of  $F'$

Since  $x$  and  $y$  are independent their j-pmf is given by  $f(x, y) = f(x) \cdot f(y)$

$$f(x) = \frac{1}{\left(\frac{n_1+2r}{2}\right) \int_{\frac{n_1}{2}}^{\infty}} e^{-\frac{x}{2}} x^{\frac{n_1+2r-1}{2}} \sum_{r=0}^{\infty} \frac{e^{-\lambda} \lambda^r}{r!} x^r$$

$$f(y) = \frac{1}{\left(\frac{n_2+2r}{2}\right) \int_{\frac{n_2}{2}}^{\infty}} e^{-\frac{y}{2}} y^{\frac{n_2+2r-1}{2}}$$

$$f(x, y) = \frac{1}{\left(\frac{n_1+2r}{2}\right) \int_{\frac{n_1}{2}}^{\infty}} e^{-\frac{x}{2}} x^{\frac{n_1+2r-1}{2}} \sum_{r=0}^{\infty} \frac{e^{-\lambda} \lambda^r}{r!} x \\ \frac{1}{\left(\frac{n_2+2r}{2}\right) \int_{\frac{n_2}{2}}^{\infty}} e^{-\frac{y}{2}} y^{\frac{n_2+2r-1}{2}}$$

$$= \sum_{r=0}^{\infty} \frac{e^{-\lambda} \lambda^r}{r!} \frac{e^{-x/2} x^{(n_1/2+r)-1}}{\left(\frac{n_1+2r}{2}\right) \int_{\frac{n_1}{2}}^{\infty}} \cdot \frac{e^{-y/2} y^{(n_2/2+r)-1}}{\left(\frac{n_2+2r}{2}\right) \int_{\frac{n_2}{2}}^{\infty}}$$

Let us define the variate  $F'$  and  $V$  as

$$F' = \frac{n_2 X}{n_1 Y} \quad X \sim V$$

$$\Rightarrow x = \frac{n_1 F' y}{n_2} \quad \text{&} \quad y = v$$

$$\Rightarrow x = \frac{n_1 F' v}{n_2} \quad \text{&} \quad y = v$$

$$|J| = \begin{vmatrix} \frac{\partial x}{\partial F'} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial F'} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} \frac{n_1 v}{n_2} & \frac{n_1 F'}{n_2} \\ 0 & 1 \end{vmatrix} = \frac{n_1}{n_2} v$$

The joint density is

$$f(F'v) = \sum_{r=0}^{\infty} \frac{e^{-\lambda} \lambda^r}{r!} \frac{e^{-\left(\frac{n_1}{2} F' v\right)}}{\frac{(n_1+2v)}{2}} \frac{\Gamma\left(\frac{n_1}{2} F' v\right)}{\Gamma\left(\frac{n_1+2v}{2}\right)} \\ \frac{e^{-v/2} v^{n_2/2-1}}{2^{n_2/2} \Gamma(n_2/2)} \cdot \frac{n_1}{n_2} v \\ = \sum_{r=0}^{\infty} \frac{e^{-\lambda} \lambda^r}{r!} \cdot e^{-\frac{v}{2}} \left[ \frac{n_1}{n_2} F' + 1 \right] \left( \frac{n_1}{n_2} \right)^{n_1/2+r} \frac{e^{\frac{n_1}{2} F' v}}{v^{n_1/2+r-1}} \frac{\Gamma\left(\frac{n_1+n_2}{2}\right)}{\Gamma\left(\frac{n_1+2r}{2}\right)}$$

Integrating "x" in the range 0 to  $\infty$  we get

$$= \sum_{r=0}^{\infty} \frac{e^{-\lambda} \lambda^r}{r!} \frac{\left(\frac{n_1}{n_2}\right)^{n_1/2+r} (F')^{n_1/2+r-1}}{\frac{n_1+n_2+2r}{2} \Gamma\left(\frac{n_1+2r}{2}\right) \Gamma\left(\frac{n_1}{2}\right)} \int_0^\infty e^{-\frac{v}{2}(1+\frac{n_1}{n_2} F')} \frac{\frac{n_1+n_2}{2}}{v^{n_1/2+r-1}} dv \\ = \sum_{r=0}^{\infty} \frac{e^{-\lambda} \lambda^r}{r!} \frac{\left(\frac{n_1}{n_2}\right)^{\frac{n_1}{2}+r} (F')^{\frac{n_1}{2}+r-1}}{\frac{n_1+n_2+2r}{2} \Gamma\left(\frac{n_1+2r}{2}\right) \Gamma\left(\frac{n_1}{2}\right)} \frac{\frac{n_1+n_2}{2}}{\Gamma\left(\frac{n_1+n_2}{2}\right)} \\ = \sum_{r=0}^{\infty} \frac{e^{-\lambda} \lambda^r}{r!} \frac{\left(\frac{n_1}{n_2}\right)^{\frac{n_1}{2}+r} \left(\frac{n_1}{n_2}\right)^{\frac{n_1}{2}+r-1}}{\left(1+\frac{n_1}{n_2} F'\right)^{\frac{n_1+n_2}{2}+r} \Gamma\left(\frac{n_1+n_2}{2}\right)}$$

which is the pdf of non-central  $F$ -distribution with non-centrality parameter  $\lambda$ .

#### 4.3 Non-central $\chi^2$ -distribution

The  $\chi^2$  distribution is defined as the sum of squares of independent standard normal variates and this often referred to as central  $\chi^2$  distribution.

The distribution of sum of squares of independent normal variates having unit variance but with non-zero means is known as non-central  $\chi^2$  distribution.

Thus if  $x_i$ 's are independent normal  $N(\mu_i, 1)$  random variable's and  $\chi^2 = \sum_{i=1}^n x_i^2$  as the non-central  $\chi^2$  distribution

with  $n$  degrees of freedom. This distribution would seem to depend upon the  $n$  parameters  $\mu_1, \mu_2, \dots, \mu_n$  but it will be seen that it depends on these parameters only through the non-centrality parameter

$$\lambda = \frac{1}{2} (\mu_1^2 + \mu_2^2 + \dots + \mu_n^2) \text{ and we write } X^2 \sim X^2(n, \lambda)$$

Non-Central  $X^2$  distribution with non-centrality parameter  $\lambda$

pdf is given by

$$f(X_n^2, \lambda) = \sum_{j=0}^{\infty} \frac{e^{-\lambda} \lambda^j}{j!} (P[X_n^2 \geq j])$$

where  $P(X_n^2, \lambda)$  is a mixture of  $n$   $\chi^2$  distributions with degrees of freedom  $n, n-1, \dots, n-j$

The corresponding weights being the terms of the Poisson distribution with parameter  $\lambda$ .

Derivation of pdf of Non-Central  $\chi^2(X^2)$

We obtain the pdf of non-central  $\chi^2$  distribution through mgf by using uniqueness theorem of mgf.

$$\text{If } X \sim N(\mu, 1), \text{ then } \mu_X(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{tx^2} e^{-\frac{(x-\mu)^2}{2}} dx = e^{\mu t + \frac{\mu^2}{2}}$$

$$\exp\left\{t\left(x^2 - \frac{1}{2}(\mu - \mu^2)\right)\right\} = \exp\left\{t\left(\frac{1-\mu}{2}\right)x^2 - \mu x + \frac{\mu^2}{2}\right\}$$

Add and subtract  $\frac{\mu^2}{(1-\mu)^2}$  we get

$$\exp\left\{-\left(\frac{1-\mu}{2}\right)\left(x^2 - \frac{2\mu x}{1-\mu} + \frac{\mu^2}{1-\mu}\right)\right\}$$

$$= \exp\left\{-\left(\frac{1-\mu}{2}\right)\left(x^2 - \frac{2\mu x}{1-\mu} + \frac{\mu^2}{1-\mu}\right) + \frac{\mu^2}{(1-\mu)^2} \frac{\mu^2}{(1-\mu)^2}\right\}$$

$$\begin{aligned}
 &= \exp \left\{ -\left(\frac{1-2t}{2}\right) \left[ x^2 - \frac{2\mu x}{1-2t} + \frac{\mu^2}{1-2t} + \frac{\mu^2}{(1-2t)^2} - \frac{\mu^2}{(1-2t)^2} \right] \right\} \\
 &= \exp \left\{ -\left(\frac{1-2t}{2}\right) \left[ \left(x - \frac{\mu}{1-2t}\right)^2 + \frac{\mu^2}{1-2t} - \frac{\mu^2}{(1-2t)^2} \right] \right\} \\
 &= \exp \left\{ -\left(\frac{1-2t}{2}\right) \left[ \left(x - \frac{\mu}{1-2t}\right)^2 + \left(\frac{-2\mu t}{(1-2t)^2}\right) \right] \right\} \\
 &= \exp \left[ -\left(\frac{1-2t}{2}\right) \left( x - \frac{\mu}{1-2t} \right)^2 + \frac{t\mu^2}{1-2t} \right] \\
 &= \exp \left( \frac{t\mu^2}{1-2t} \right) \exp \left[ -\left(\frac{1-2t}{2}\right) \left( x - \frac{\mu}{1-2t} \right)^2 \right]
 \end{aligned}$$

$$M_{X^2}(t) = \exp \left( \frac{t\mu^2}{1-2t} \right) \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \exp \left\{ -\left(\frac{1-2t}{2}\right) \left( x - \frac{\mu}{1-2t} \right)^2 \right\} dx \quad \text{--- (1)}$$

$$\text{If } u = (1-2t)^{1/2} \left( x - \frac{\mu}{1-2t} \right)$$

$$\frac{du}{dx} = (1-2t)^{1/2}$$

$$du = (1-2t)^{1/2} dx$$

$$= \exp \left( \frac{t\mu^2}{1-2t} \right) \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-u^2/2} \frac{du}{(1-2t)^{1/2}}$$

$$M_{X^2}(t) = \exp \left( \frac{t\mu^2}{1-2t} \right) \cdot \frac{1}{\sqrt{2\pi}} \cdot \frac{\sqrt{2\pi}}{(1-2t)^{1/2}}$$

$$= \frac{1}{(1-2t)^{1/2}} \exp \left( \frac{t\mu^2}{1-2t} \right)$$

$$= (1-2t)^{-1/2} \exp \left( \frac{t\mu^2}{1-2t} \right)$$

If  $X_i$  ( $i=1, 2, \dots, n$ ) are independent normal  $(\mu_i, 1)$  then m.g.f of non-central  $\chi^2$  variate  $\chi'^2 = \sum_{i=1}^n X_i^2$  is given by

$$M_{\chi'^2}(t) = M_{\sum X_i^2}(t)$$

$$= \prod_{i=1}^n M_{X_i^2}(t)$$

$$= \prod_{i=1}^n (1-2t)^{-1/2} e^{(t\mu_i^2)/(1-2t)}$$

$$\begin{aligned}
 &= (1-2t)^{-n/2} e^{(t/(1-2t) - \sum_{i=1}^n \mu_i^2)} \\
 &= (1-2t)^{-n/2} e^{(\lambda t/(1-2t))} ; \quad t < 1/2 \text{ where } \lambda = \frac{1}{2} \sum_{i=1}^n \mu_i^2 \\
 &\quad \text{is the non-centrality parameter} \\
 &= (1-2t)^{-n/2} e^{\{\lambda(-1 + \frac{t}{1-2t})\}} \\
 &= (1-2t)^{-n/2} e^{-\lambda} e^{\frac{\lambda}{1-2t}} \\
 &= (1-2t)^{-n/2} e^{-\lambda} \sum_{r=0}^{\infty} \left(\frac{\lambda}{1-2t}\right)^r \frac{1}{r!} ; \quad t < 1/2 \\
 &= \sum_{r=0}^{\infty} \frac{e^{-\lambda} \lambda^r}{r!} (1-2t)^{-n/2+r}
 \end{aligned}$$

$$= (1-2t)^{-(n/2+r)} \sum_{r=0}^{\infty} \frac{e^{-\lambda} \lambda^r}{r!} ; \quad t < 1/2$$

Thus the m.g.f of non-central chi-square distribution is seen to be the complex combination of the  $\chi^2$  m.g.f with  $n, n+2, n+4, \dots$  degrees of freedom. The coefficients appearing in the complex combination of the Poisson probability

Hence by uniqueness theorem of m.g.f the p.d.f of non-central  $\chi^2$  distribution with  $n$ -degrees of freedom and with non-centrality parameter  $\lambda$  is given by

$$f(\chi^2, \lambda) = \sum_{r=0}^{\infty} \frac{e^{-\lambda} \lambda^r}{r!} p(\chi^2_{n+2r})$$

$$\text{where } p(\chi^2_{n+2r}) = \frac{1}{2^{(n+2r)/2} \sqrt{\frac{n+2r}{2}}} e^{-\frac{1}{2} \frac{\chi^2}{(n+2r)}} \frac{\chi^{\frac{n}{2}+r-1}}{1052 \pi^2}$$

Is the p.d.f of central Chi-Square distribution with  $n+2r$  degrees of freedom.

Additive property (or) Reproductive property of non-central  $\chi^2$  distribution:

If  $Y_i$  ( $i=1, 2, \dots, k$ ) are independent non-central  $\chi^2$  variate with  $n_i$  d.f and non-centrality element  $\lambda_i$ ,  $\sum_{i=1}^k Y_i$  is also a non-central  $\chi^2$  variate with,  $n = \sum_{i=1}^k n_i$

$$\lambda = \sum_{i=1}^k \lambda_i$$

Proof:

Let  $y_i \sim \chi^2$  with  $n_i$  d.f and non-centrality parameter  $\lambda_i$ , then the mgf of  $y_i$  is

$$\begin{aligned} M_{\sum_{i=1}^k Y_i}(t) &= M_{Y_1}(t) + M_{Y_2}(t) + \dots + M_{Y_k}(t) \\ &= \prod_{i=1}^k M_{Y_i}(t) \\ &= \prod_{i=1}^k (1-2t)^{-n_i/2} e^{(\lambda_i+2t)/1-2t} \\ &= (1-2t)^{-\frac{n}{2}} \sum_{i=1}^k n_i \exp \left[ \frac{2t}{1-2t} \cdot \sum_{i=1}^k \lambda_i \right] \end{aligned}$$

which is the mgf of non-central  $\chi^2$  variate with  $\sum_i n_i$  d.f and non-centrality parameter  $\lambda$ .

Hence by uniqueness theorem of mgf

$\sum_{i=1}^k Y_i \sim \chi^2$  with  $\sum n_i$  d.f and non-centrality parameter

$$M_{\chi^2}(t) = (1-2t)^{-n/2} \exp \left[ \frac{2t+\lambda}{1-2t} \right]$$

$$\text{where } n = \sum_{i=1}^k n_i \text{ and } \lambda = \sum_{i=1}^k \lambda_i$$

Cumulant generating function:

$$M_{\chi^2}(t) = \log M_{\chi^2}(t)$$

$$= \log (1-2t)^{-n/2} \exp \left[ \frac{2t+\lambda}{1-2t} \right]$$

$$= -\frac{n}{2} \log (1-2t) + 2\lambda t (1-2t)^{-1}$$

$$\begin{aligned}
 &= -\frac{n}{2} \left[ -2t - \frac{(2t)^2}{2} - \frac{(2t)^3}{3} + \dots \right] + 2t + 2 \left[ 1 + 2t + (2t)^2 + \dots \right] \\
 &= \left[ nt + nt^2 + \frac{2nt^3}{3} + \frac{8nt^4}{4} + \dots \right] + \left[ 2t + 2 + 4t^2 + 8t^3 + \dots \right] \\
 &= t(n+2) + t^2(n+4) + t^3\left(\frac{2n}{3} + 8\lambda\right) + \dots + t^r\left(\frac{2^{r-1}}{r} + 2\lambda\right) + \dots
 \end{aligned}$$

$$\text{The coefficient of } t^r = \frac{n2^{r-1}}{r} + 2^r\lambda$$

$$= 2^{r-1} \left( \frac{n}{r} + 2\lambda \right)$$

$$\begin{aligned}
 \text{The coefficient of } \frac{t^r}{r!} &= 2^{r-1} \left( \frac{n+r-1}{r} + 2\lambda r! \right) \\
 &= 2^{r-1} (r-1)! [n+2\lambda r]
 \end{aligned}$$

The  $r$ th cumulant

$$k_r = \text{coeff of } \frac{t^r}{r!} \text{ is } k_{x^2}(+) = 2^{r-1} (r-1)! (n+2\lambda r)$$

$$\text{Put } r=1 \Rightarrow k_1 = n+2\lambda$$

$$\text{Put } r=2 \Rightarrow k_2 = 2(n+4\lambda) = 2n+8\lambda$$

$$\text{Put } r=3 \Rightarrow k_3 = 48(n+6\lambda) = 8n+48\lambda$$

## 4.4 Relationships

**Relation between F and  $\chi^2$ .** In  $F(n_1, n_2)$  distribution if we let  $n_2 \rightarrow \infty$ , then  $\chi^2 = n_1 F$  follows  $\chi^2$ -distribution with  $n_1$  d.f.

**Proof.** We have

$$P(F) = \frac{(n_1/n_2)^{n_1/2} F^{(n_1/2)-1}}{\Gamma(n_1/2) \Gamma(n_2/2)} \cdot \frac{\Gamma(n_1+n_2)/2}{\left[1 + \frac{n_1}{n_2} F\right]^{(n_1+n_2)/2}}, \quad 0 < F < \infty$$

In the limit as  $n_2 \rightarrow \infty$ , we have

$$\frac{\Gamma(n_1+n_2)/2}{n_2^{n_1/2} \Gamma(n_2/2)} \rightarrow \frac{(n_2/2)^{n_1/2}}{n_2^{n_1/2}} = \frac{1}{2^{n_1/2}}$$

$$\left[ \because \frac{\Gamma(n+k)}{\Gamma(n)} \rightarrow n^k \text{ as } n \rightarrow \infty. \text{ (c.f. Remark below.)} \right]$$

$$\begin{aligned}
 \text{Also } \lim_{n_2 \rightarrow \infty} \left[ 1 + \frac{n_1}{n_2} F \right]^{(n_1+n_2)/2} &= \lim_{n_2 \rightarrow \infty} \left[ \left( 1 + \frac{n_1}{n_2} F \right)^{n_2} \right]^{1/2} \\
 &\times \lim_{n_2 \rightarrow \infty} \left( 1 + \frac{n_1}{n_2} F \right)^{n_1/2} \\
 &= \exp(n_1 F/2) = \exp(\chi^2/2) \quad (\because n_1 F = \chi^2)
 \end{aligned}$$

Hence in the limit, the p.d.f. of  $\chi^2 = n_1 F$  becomes

$$\begin{aligned}
 dP(\chi^2) &= \frac{(n_1/2)^{n_1/2} e^{-\chi^2/2}}{\Gamma(n_1/2)} \cdot \left( \frac{\chi^2}{n_1} \right)^{(n_1/2)-1} d\left( \frac{\chi^2}{n_1} \right) \\
 &= \frac{1}{2^{n_1/2} \Gamma(n_1/2)} \cdot e^{-\chi^2/2} (\chi^2)^{(n_1/2)-1} d\chi^2, \quad 0 < \chi^2 < \infty
 \end{aligned}$$

which is the p.d.f. of chi-square distribution with  $n_1$  d.f.

**Relation between t and F distributions.** In F-distribution with  $(v_1, v_2)$  d.f. [c.f. 14.5 (a)], take  $v_1 = 1$ ,  $v_2 = v$  and  $t^2 = F$ , i.e.,  $dF = 2t dt$ . Thus the probability differential of F transforms to

$$\begin{aligned} dG(t) &= \frac{(1/v)^{1/2}}{B\left(\frac{1}{2}, \frac{v}{2}\right)} \cdot \frac{(t^2)^{\frac{1}{2}-1}}{\left[1 + \frac{t^2}{v}\right]^{(v+1)/2}} 2t dt, \quad 0 \leq t^2 < \infty \\ &= \frac{1}{\sqrt{v} B\left(\frac{1}{2}, \frac{v}{2}\right)} \cdot \frac{1}{\left[1 + \frac{t^2}{v}\right]^{(v+1)/2}} dt, \quad -\infty < t < \infty \end{aligned}$$

the factor 2 disappearing since the total probability in the range  $(-\infty, \infty)$  is unity. This is the probability function of Student's t-distribution with  $v$  d.f. Hence we have the following relation between t and F distributions.

'If a statistic  $t$  follows Student's t-distribution with  $n$  d.f., then  $t^2$  follows Snedecor's F-distribution with  $(1, n)$  d.f. Symbolically,

$$\left. \begin{array}{l} \text{if } t \sim t_{(n)} \\ \text{then } t^2 \sim F_{(1, n)} \end{array} \right\} \dots (1)$$

**Aliter Proof of (1)** If  $\xi \sim N(0, 1)$  and  $X \sim \chi^2_{(n)}$  are independent r.v.'s then :

$$U = \xi^2 \sim \chi^2_{(1)} \quad [\text{Square of a S.N.V.}]$$

$$\text{and } t = \frac{\xi}{\sqrt{X/n}} \sim t_{(n)}$$

$$\Rightarrow t^2 = \frac{\xi^2}{(X/n)} = \frac{(\xi^2/1)}{(X/n)},$$

being the ratio of two independent chi-square variates divided by their respective degrees of freedom is  $F(1, n)$  variate.

$$\text{Hence } t^2 \sim F(1, n)$$

With the help of relation (14.19), all the uses of t-distribution can be regarded as the applications of F-distribution also, e.g., for test for a single mean, instead of computing

$$t = \frac{\bar{x} - \mu}{S/\sqrt{n}},$$

we may compute

$$F = t^2 = \frac{n(\bar{x} - \mu)^2}{S^2}$$

and then apply F-test with  $(1, n)$  d.f. and so on.

#### 4.5 Sampling Distribution of Simple correlation co-efficient for null case

Sampling distribution of correlation coefficient ( $r$ ):  
 Let  $x$  and  $y$  follows Bivariate normal distribution with parameters  $\mu_x = \mu_y = 0$ ,  $\sigma_x^2$ ,  $\sigma_y^2$  and  $\rho = 0$ .

Let us select a random sample of size ' $n$ ' from the above population. Let  $\bar{x}$  and  $\bar{y}$  be the mean,  $s_x^2$  and  $s_y^2$  be the variance of  $x$  and  $y$  respectively in the sample.

Let  $r$  be the correlation coefficient between  $x$  and  $y$  given by,

$$r = \frac{1}{n} \frac{\sum (x - \bar{x})(y - \bar{y})}{s_x s_y} \quad \text{--- (1)}$$

Let us introduce a new variable  $\eta_i$  using the orthogonal transformation  $\eta_i = ay$

where  $\eta = \begin{pmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_n \end{pmatrix}$ ,  $y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}$  and  $a = (a_{ij})_{n \times n}$

$$\text{such that } \sum_{i=1}^n y_i^2 = \sum_{i=1}^n \eta_i^2 \quad \text{--- (2)}$$

$$\text{Let us assume that } a_{11} = a_{12} = \dots = a_{1n} = \frac{1}{\sqrt{n}}$$

$$\begin{aligned} \text{so that } \eta_1 &= \frac{1}{\sqrt{n}} y_1 + \frac{1}{\sqrt{n}} y_2 + \dots + \frac{1}{\sqrt{n}} y_n \\ &= \frac{1}{\sqrt{n}} (y_1 + y_2 + \dots + y_n) = \frac{n\bar{y}}{\sqrt{n}} = \sqrt{n}\bar{y} \end{aligned}$$

$$\text{or } \eta_1^2 = n\bar{y}^2 \quad \text{--- (3)}$$

$$\text{consider } ns_y^2 = \sum_{i=1}^n (y_i - \bar{y})^2$$

$$\therefore \sum y_i^2 - n\bar{y}^2 = \sum_{i=1}^n \eta_i^2 - \eta_1^2 = \sum_{i=1}^n \eta_i^2 \quad \because \sum a_{ij}^2 = 1$$

We know that

$$= \sum \left( \frac{1}{\sqrt{n}} \right)^2$$

$$\frac{ns_y^2}{\sigma_y^2} \sim \chi_{(n-1)}^2 \quad \text{i.e., } \sum_{i=1}^n \frac{\eta_i^2}{\sigma_y^2} \sim \chi_{(n-1)}^2$$

$$\text{From (1) } \sqrt{n} r s_y = \frac{1}{\sqrt{n}} \sum \frac{(x - \bar{x})(y - \bar{y})}{s_x}$$

$$= \frac{\sum (x_i - \bar{x}) y_i}{\sqrt{n} s_x} \therefore \sum (x_i - \bar{x}) \bar{y} = 0$$

$$\Rightarrow \sqrt{n} r s_y = n t_2 \text{ (say)}$$

$$\Rightarrow t_2^2 = n r^2 s_y^2$$

We know that,  $\frac{t_2^2}{s_y^2} = \frac{r^2 s_y^2}{s_y^2} = \chi_{(1)}^2$  as  $t_2$  is also normal

Consider,  $n s_y^2 = (r^2 + 1 - r^2) n s_y^2 = r^2 n s_y^2 + (1 - r^2) n s_y^2 \quad \text{--- (5)}$

$$\frac{n s_y^2}{s_y^2} = \frac{r^2 s_y^2}{s_y^2} + \frac{(1 - r^2) n s_y^2}{s_y^2}$$

$$\chi_{(n-1)}^2 = \chi_r^2 + \chi_{n-2}^2 \quad \text{--- (6)}$$

By the converse : if the additive property of  $\chi^2$  consider

$$\chi_r^2 = \frac{r^2 n s_y^2}{n s_y^2} = \frac{r^2 n s_y^2}{r^2 n s_y^2 + (1 - r^2) n s_y^2} \text{ from (5)}$$

$$= \frac{\chi_r^2}{\chi_r^2 + \chi_{n-2}^2} \text{ from (6)}$$

We know that

$$\frac{\chi_r^2}{\chi_r^2 + \chi_{n-2}^2} \sim \beta_1 \left( \frac{1}{2}, \frac{n-2}{2} \right)$$

Sampling distribution of  $r^2 = f(r^2) dr^2$

$$= (r^2)^{1/2-1} \frac{(n-2)^{1/2-1}}{\beta_1 \left( \frac{1}{2}, \frac{n-2}{2} \right)} dr^2 \quad ; \quad 0 \leq r^2 \leq 1$$

$$= \frac{(1-r^2)^{n-2}}{\beta_1 \left( \frac{1}{2}, \frac{n-2}{2} \right)} \quad ; \quad -1 \leq r \leq 1 \text{ of which the pdf } g(r)$$

$$\therefore \text{note } t = \frac{r \sqrt{n-2}}{\sqrt{1-r^2}}$$

$$\sim t(n-1)$$

#### 4.6 Sampling Distribution of Simple Regression co-efficient.

Let  $x$  and  $y$  have bivariate normal distribution with S.D  $\sigma_x$   $\sigma_y$  respectively.

Let us select a random sample of size ' $n$ ' from the above population. we know that

$b = r \cdot \frac{s_y}{s_x}$  is the regression coefficient of  $y$  on  $x$  in the sample.

$$\begin{aligned} b^2 &= r^2 \frac{s_y^2}{s_x^2} = \frac{n r^2 s_y^2}{n s_x^2} = \frac{n r^2 s_y^2 / \sigma_y^2}{n r^2 s_x^2 / \sigma_x^2} \\ &= \frac{\chi^2}{\chi^2_{n-1}} \sim \beta_2 \left( \frac{1}{2}, \frac{n-1}{2} \right) \end{aligned}$$

The distribution of  $b^2 \frac{s_y^2}{s_x^2}$  as

$$f \left( b^2 \frac{\sigma_y^2}{\sigma_x^2} \right) db^2 \frac{\sigma_y^2}{\sigma_x^2} = \frac{1}{\beta \left( \frac{1}{2}, \frac{n-1}{2} \right)} \frac{b^2 \frac{\sigma_y^2}{\sigma_x^2}}{\left( 1 + b^2 \frac{\sigma_y^2}{\sigma_x^2} \right)^{\frac{1}{2} + \frac{n-1}{2}}} \left( \frac{1}{2}, \frac{n-1}{2} \right).$$

pdf of  $b$  as

$$f(b) db = \frac{1}{\beta \left( \frac{1}{2}, \frac{n-1}{2} \right)} \frac{\left( b^2 \frac{\sigma_y^2}{\sigma_x^2} \right)^{1/2 - 1}}{\left( 1 + b^2 \frac{\sigma_y^2}{\sigma_x^2} \right)^{-\frac{1}{2} + \frac{n-1}{2}}} \cdot \frac{b^2 \frac{\sigma_y^2}{\sigma_x^2}}{\sigma_x^2} 2b db ; 0 \leq b \leq \infty,$$

$$= \frac{1}{\beta \left( \frac{1}{2}, \frac{n-1}{2} \right)} \frac{\left( \sigma_x^2 / \sigma_y^2 \right)^{1/2}}{\left( 1 + b^2 \frac{\sigma_y^2}{\sigma_x^2} \right)^{n/2}} db ; 0 \leq b \leq \infty$$

$$= \frac{1}{\beta \left( \frac{1}{2}, \frac{n-1}{2} \right)} \frac{\left( \sigma_x \cdot \sigma_y \right) \sigma_x^n}{\left( \sigma_x^2 + b^2 \sigma_y^2 \right)^{n/2}} db = \frac{1}{\beta} \frac{\sigma_x^{n+1} / \sigma_y}{\sigma_x^2 + b^2 \sigma_y^2} db.$$

$$f(b_{xy}) db_{xy} = \frac{1}{\beta \left( \frac{1}{2}, \frac{n-1}{2} \right)} \cdot \frac{\sigma_x \sigma_y^{n-1}}{\left( \sigma_y^2 + b^2 \sigma_x^2 \right)^{n/2}}$$

$$\text{Mean of } b = \int_{-\infty}^{\infty} b f(b) db = \int \frac{b}{\beta \left( \frac{1}{2}, \frac{n-1}{2} \right)} \frac{\sigma_x \sigma_y^{n-1}}{\left( \sigma_y^2 + b^2 \sigma_x^2 \right)^{n/2}} db$$

$$= \frac{\sigma_x \sigma_y^{n-1}}{\beta\left(\frac{1}{2}, \frac{n-1}{2}\right)} \int \frac{b}{(\sigma_y^2 + \sigma_x^2)^{n/2}} db$$

$$= 0 = \beta$$

[∴ The integrand is odd]

Mean of  $f(r)$ ,

$$E(r) = \int r f(r) dr = \int r (1-r^2)^{\frac{n-4}{2}} dr = 0 = \beta$$

∴ integrand is an odd = 0

Variance:

$$V(r) = E(r^2) - E(r)^2 = E(r^2) - \beta = 0$$

$$= \int r^2 f(r) dr = \int r^2 (1-r^2)^{\frac{n-4}{2}} dr$$

$$= \frac{2}{\beta\left(\frac{1}{2}, \frac{n-2}{2}\right)} \int_0^1 r^2 (1-r^2)^{\frac{n-4}{2}} dr$$

$$= \frac{2}{\beta\left(\frac{1}{2}, \frac{n-2}{2}\right)} \int_0^1 \theta^{\frac{n}{2}-1} (1-\theta)^{\frac{n-4}{2}} \frac{d\theta}{2\sqrt{\theta}}$$

$$= \frac{1}{\beta\left(\frac{1}{2}, \frac{n-2}{2}\right)} \int_0^1 \theta^{\frac{n}{2}-1} (1-\theta)^{\frac{n-4}{2}} d\theta$$

∴ put  $r^2 = \theta$

$$2rdr = d\theta \Rightarrow dr = \frac{d\theta}{2\sqrt{\theta}} = \frac{d\theta}{2\theta^{1/2}}$$

$$= \frac{1}{\beta\left(\frac{1}{2}, \frac{n-2}{2}\right)} \int_0^1 \theta^{\frac{n}{2}-1} (1-\theta)^{\frac{n-4}{2}-1} d\theta$$

$$= \frac{\beta\left(\frac{3}{2}, \frac{n-2}{2}\right)}{\beta\left(\frac{1}{2}, \frac{n-2}{2}\right)}$$

$$= \frac{\sqrt{\beta_{12}} \sqrt{\frac{n-2}{2}} / \sqrt{\frac{\beta_{11}}{2} + \frac{n-2}{2}}}{\sqrt{\frac{1}{2} \sqrt{\frac{n+2}{2}}} / \sqrt{\frac{1}{2} + \frac{n-2}{2}}}$$

$$\begin{aligned}
 &= \frac{\sqrt{3/2} / \sqrt{\frac{n+1}{2}}}{\sqrt{1/2} \sqrt{\frac{n-1}{2}}} = \frac{\frac{1}{2} \sqrt{\frac{1}{2}} \sqrt{\frac{n-1}{2}}}{\sqrt{\frac{1}{2}} \sqrt{\frac{n+1}{2}}} \\
 &= \frac{\frac{1}{2} \sqrt{\frac{n-1}{2}}}{\frac{n-1}{2} \sqrt{\frac{n-1}{2}}} = \frac{\frac{1}{2} \cdot 2}{n-1} = \frac{1}{n-1}
 \end{aligned}$$

Mode (b)

$$f(b) = \frac{\sigma_x \sigma_y^{n-1}}{\beta(\frac{1}{2}, \frac{n-1}{2})} = \frac{\sigma_x \sigma_y^{n-1}}{\beta(\frac{1}{2}, \frac{n-1}{2})} \left(-\frac{n}{2}\right) \left(\sigma_y^2 + b^2 \sigma_x^2\right)^{-\frac{n-1}{2}}$$

$$2b \sigma_x^2 = 0 \quad (\text{say})$$

$b = 0$ , which is the mode

$\therefore \text{mean} = \text{mode} = 0$ . The curve of  $b$  is symmetric