

Note :-

When $n \rightarrow \infty$ $\beta_1 \rightarrow 0$

$$\beta_2 = \lim_{n \rightarrow \infty} 3 \left[\frac{n-2}{n-4} \right]$$

$$= 3 \lim_{n \rightarrow \infty} \left[\left\{ \frac{1-2/n}{1-4/n} \right\}_1 \right] \rightarrow 1$$

$$= 3$$

\therefore Hence for large degrees of freedom 't' distribution tends to normal distribution.

Applications of t Distribution :-

1. To test if the sample mean (\bar{x}) differs significantly from the hypothetical value μ of the population mean.
2. To test the [significance of difference] between two sample means.
3. To test the significance of an observed sample correlation Co-efficient and sample regression Co-efficient.
4. To test the [significance of] observed Partial Correlation Co-efficient.

(119)

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

$$= \frac{n^r \sqrt{\frac{1}{2} + n/2}}{\sqrt{\frac{1}{2}} \sqrt{n/2}} \frac{\sqrt{n/2 - r} \sqrt{r + 1/2}}{\sqrt{n/2 - r} \sqrt{r + 1/2}} \quad \text{In}$$

$$= \frac{n^r \sqrt{\frac{n+1}{2}}}{\sqrt{\frac{1}{2}} \sqrt{n/2}} \times \frac{\sqrt{n/2 - r} \sqrt{r + 1/2}}{\sqrt{n/2 - r} \sqrt{r + 1/2}} \quad \text{①}$$

$$= \frac{n^r \sqrt{n/2} / r (r - 1/2) (r - 3/2) \dots 3/2 \cdot 1/2 \cdot 1/2}{\sqrt{1/2} (n/2 - 1) (n/2 - 2) \dots (n/2 - 1) \cdot 1/2}$$

$$= \frac{n^r (2r - 1) (2r - 3) \dots 3 \cdot 1}{(n - 2) (n - 4) \dots (n - 2r)}$$

Let:

$$\mu_{2r} = n \cdot \frac{1}{n-2} = \frac{n}{n-2}$$

$$\mu_4 = \frac{n^2(3)(1)}{(n-2)(n-4)} = \frac{3n^2}{(n-2)(n-4)}$$

$$\beta_1 = \frac{\mu_3^2}{\mu_2^3} = 0$$

$$\beta_2 = \frac{\mu_4}{\mu_2^2} = \frac{3n^2 / ((n-2)(n-4))}{(n/n-2)^2}$$

$$= \frac{3n^2 (n-2)^2}{n^2 (n-2)(n-4)}$$

$$= 3 \left(\frac{n-2}{n-4} \right)$$

$n^2 (2(2)-1)$
 $(2(2)-3)$
 $n^2 (3)(1)$
 $= 3n^2$
 $\frac{3n^2}{n^2(n-2)}$
 $\frac{3n^2}{(n-2)(n-4)}$
 $\left(\frac{n-2}{n-4}\right)$

$$= \int_{-\infty}^{\infty} t^{2r} f(t) dt = 2 \int_0^{\infty} t^{2r} f(t) dt$$

$$= 2 \frac{1}{\Gamma(\frac{1}{2}, \frac{n}{2}) \sqrt{n}} \int_0^{\infty} \frac{t^{2r}}{(1+t^2/n)^{n+1/2}} dt$$

Let $1 + t^2/n = 1/y$
 $t^2/n = 1/y - 1 = (1-y)/y$
 $t^2 = \frac{n(1-y)}{y}$

when $t=0$ $y=1$
 $t=\infty$ $y=0$

$$2t dt = \frac{-n}{y^2} dy$$

$$dt = -\frac{n}{y^2} dy$$

$$\therefore \text{Mom} = \frac{2}{\sqrt{n} \Gamma(\frac{1}{2}, \frac{n}{2})} \int_0^1 \frac{t^{2r}}{(1/y)^{n+1/2}} \cdot \frac{-n}{2ty^2} dy$$

$$= \frac{-2/n}{2\sqrt{n} \Gamma(\frac{1}{2}, \frac{n}{2})} \int_0^1 t^{2r} (t^2)^{-1/2} y^{n+1/2} y^{-2} dy$$

$$= \frac{\sqrt{n}}{\Gamma(\frac{1}{2}, \frac{n}{2})} \int_0^1 t^{2r-1/2} (1-y)^{n+1/2-2} dy$$

$$= \frac{\sqrt{n}}{\Gamma(\frac{1}{2}, \frac{n}{2})} \int_0^1 \left[\frac{n(1-y)}{y} \right]^{r-1/2} y^{\frac{n+1}{2}-2} dy$$

$$= \frac{\sqrt{n}}{\Gamma(\frac{1}{2}, \frac{n}{2})} \int_0^1 n^{r-1/2} (1-y)^{r-1/2} y^{-r+1/2} y^{\frac{n+1}{2}-2} dy$$

$$= \frac{\sqrt{n} n^{r-1/2}}{\Gamma(\frac{1}{2}, \frac{n}{2})} \int_0^1 y^{-r+1/2+r/2+1/2-2} (1-y)^{r-1/2} dy$$

$$= \frac{n^r}{\Gamma(\frac{1}{2}, \frac{n}{2})} \int_0^1 y^{n/2-r-1} (1-y)^{r+1/2-1} dy$$

$$Y = \frac{\bar{x} - \mu}{\sigma/\sqrt{n}} \sim N(0,1) \quad \text{--- (1)}$$

$$\text{and } \chi^2 = \frac{ns^2}{\sigma^2} = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{\sigma^2} \quad \text{--- (2)}$$

is independently distributed as Chi-Square Variate with $(n-1)$ d. of f. Hence Fisher's 't' is given by

$$t = \frac{\left\{ \frac{\bar{x} - \mu}{\sigma/\sqrt{n}} \right\}}{\sqrt{\frac{s^2}{n-1}}} = \frac{\sqrt{n}(\bar{x} - \mu)}{\sigma} \cdot \frac{\sigma}{\sqrt{\frac{1}{n-1} \sum (x_i - \bar{x})^2}} \quad \text{--- (3)}$$

and it follows student's 't' distribution with $(n-1)$ degrees of freedom. It is same as Student's 't' defined as before. Hence Student's 't' is a particular case of Fisher's 't'.

Ex. 20 more

Constants of 't' distribution:

Since $f(t)$ is symmetrical about the line $t=0$, all the moments of odd order about origin vanishes,

i.e. $\mu_{2r+1}(\text{about origin}) = 0$

In particular,

$\mu_1(\text{about origin}) = 0 = \text{Mean}$

Hence central moments coincide with moments about origin.

$\therefore \mu_{2r+1} = 0$

The moments of even order are given by $\mu_{2r} = \mu'_{2r}(\text{about origin})$

$$dG(t) = \frac{1}{\sqrt{2\pi} 2^{n/2} \sqrt{n/2} \sqrt{n}} \int_0^{\infty} e^{-ax} x^{\lambda-1} dx = \frac{\sqrt{\lambda}}{a^{\lambda}}$$

using the result $\int_0^{\infty} e^{-ax} x^{\lambda-1} dx = \frac{\sqrt{\lambda}}{a^{\lambda}}$

$$dG(t) = \frac{1}{\sqrt{2\pi} 2^{n/2} \sqrt{n/2} \sqrt{n}} \frac{\sqrt{\frac{n+1}{2}}}{\left[\frac{1}{2}\left(1+\frac{t^2}{n}\right)\right]^{\frac{n+1}{2}}} dt$$

$$= \frac{\sqrt{\frac{n+1}{2}}}{\sqrt{2} \sqrt{\pi} 2^{n/2} \sqrt{n/2} \sqrt{n} \left(\frac{1}{2}\right)^{\frac{n+1}{2}} \left(1+\frac{t^2}{n}\right)^{\frac{n+1}{2}}} dt$$

$$= \frac{\sqrt{\frac{n+1}{2}}}{2^{1/2} \sqrt{\frac{1}{2}} 2^{n/2} \sqrt{n/2} \sqrt{n} \cdot 2^{-\frac{(n+1)}{2}} \left(1+\frac{t^2}{n}\right)^{\frac{n+1}{2}}} dt$$

Om muruga

$$= \frac{\sqrt{\frac{n+1}{2}}}{\sqrt{n} \cdot \sqrt{1/2} \sqrt{n/2}} \cdot \frac{1}{\left(1+\frac{t^2}{n}\right)^{\frac{n+1}{2}}} dt \quad -\infty \leq t \leq \infty$$

$$= \frac{1}{\sqrt{n} \beta(1/2, n/2)} \cdot \frac{1}{\left(1+\frac{t^2}{n}\right)^{\frac{n+1}{2}}} dt$$

which is same as the probability function of standard 't' distribution with n degrees of freedom.

Remarks:

(1) In Fisher's 't' the degrees of freedom is same as the degrees of freedom of chi-square variate.

Students 't' may be regarded as a particular case of Fisher's 't'

Since $\bar{x} \sim N(\mu, \sigma^2/n)$

Let $t = \frac{\bar{X}}{\sqrt{S^2/n}}$ and $U = X^2$

$$\bar{X} = t \sqrt{S^2/n}$$

$$S = t \sqrt{u/n}$$

$$d\bar{X} = t \sqrt{u/n}$$

$$\frac{d\bar{X}}{dt} = t \frac{u^{1/2}}{n^{1/2}} \quad \text{u diff}$$

$$\frac{d\bar{X}}{du} = \frac{t}{\sqrt{n}} \cdot \frac{1}{2} u^{-1/2} = \frac{t}{2\sqrt{nu}}$$

Jacobian Transformation J is

$$J = \frac{\partial(\bar{X}, X^2)}{\partial(t, u)} = \begin{vmatrix} \frac{\partial \bar{X}}{\partial t} & \frac{\partial \bar{X}}{\partial u} \\ \frac{\partial X^2}{\partial t} & \frac{\partial X^2}{\partial u} \end{vmatrix}$$

$$= \begin{vmatrix} \sqrt{u/n} & t/2\sqrt{un} \\ 0 & 1 \end{vmatrix} = \sqrt{u/n}$$

Now the joint distribution of t and u becomes,

$$dG(t, u) = \frac{1}{\sqrt{2\pi} 2^{n/2} \sqrt{n/2}} e^{-\frac{t^2 u}{2n}} e^{-\frac{u}{2}} \sqrt{u/n} dt du$$

$$= \frac{1}{\sqrt{2\pi} 2^{n/2} \sqrt{n/2} \sqrt{n}} e^{-\frac{u}{2}(1+t^2/n)} u^{n/2-1/2} dt du$$

Integrating out u over the range 0 to ∞ marginal distribution of t becomes

2) \rightarrow $\frac{2 \cdot t \cdot dt}{\sqrt{\nu} \cdot \beta(1/2, \nu/2) (1+t^2/\nu)^{\nu/2+1/2}}$

$$f_T(t) = \frac{1}{\sqrt{\nu} \beta(1/2, \nu/2) (1+t^2/\nu)^{\nu/2+1/2}} dt$$

The factor 2 disappearing since the integral from $-\infty$ to ∞ must be unity. This is the required probability function of student's 't' distribution with $\nu = (n-1)$ degrees of freedom.

Fisher's 't' definition:

It is the ratio of standard normal variate to the square root of an independent chi-square variate divided by its degrees of freedom. If z is a $N(0,1)$ and χ^2 is an independent chi-square variate with n degrees of freedom, then Fisher's 't' distribution is given by

$$t = \frac{z}{\sqrt{\chi^2/n}}$$

Denominator

and it follows that 't' distribution is with 'n' degrees of freedom.

Distribution of Fisher's 't'

Since z and χ^2 are independent, their joint probability differential is given by

$$dF(z, \chi^2) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2} \frac{e^{-\chi^2/2} (\chi^2)^{\nu/2-1}}{d^{\nu/2} \sqrt{\nu/2}}$$

$\frac{1}{\sqrt{n}}$ z z

$$d \cdot \int \int dx^2$$

$-\infty \leq z \leq \infty$
 $0 \leq \chi^2 < \infty$

(163)

Since x_i ($i=1, 2, \dots, n$) is a random sample from the normal population with mean μ and variance σ^2 ,

$\bar{x} \sim N(\mu, \sigma^2/n)$
 $\frac{\bar{x} - \mu}{\sigma/\sqrt{n}} \sim N(0, 1)$

Standard normal variate is a chi square variate with one degree of freedom.

Also $\frac{ns^2}{\sigma^2}$ is a variate with $(n-1)$ degrees of freedom.

Since \bar{x} and s^2 are independently distributed, $\frac{t^2}{n-1}$ being the ratio of two independent χ^2 variate with 1 and $(n-1)$ degrees of freedom respectively, it is $B(\frac{1}{2}, \frac{n-1}{2})$ variate & its distribution is given by

$$f(t) = \frac{1}{B(\frac{1}{2}, \frac{\nu}{2})} \frac{(t^2/\nu)^{\frac{\nu}{2}-1} \cdot d(t^2/\nu)}{(1+t^2/\nu)^{\frac{\nu}{2}+1/2}}$$
$$= \frac{(t^2/\nu)^{-1/2}}{B(\frac{1}{2}, \frac{\nu}{2}) \cdot (1+t^2/\nu)^{\frac{\nu}{2}+1/2}} \cdot d(t^2/\nu)$$
$$= \frac{1/\nu \cdot 2t \, dt}{(t^2/\nu)^{1/2} B(\frac{1}{2}, \frac{\nu}{2}) (1+t^2/\nu)^{\frac{\nu}{2}+1/2}}$$
$$= \frac{2t \, dt}{\nu (t/\sqrt{\nu}) B(\frac{1}{2}, \frac{\nu}{2}) (1+t^2/\nu)^{\frac{\nu}{2}+1/2}}$$

(112)

is the sample mean and $s^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2$ is an (unbiased estimate) of the population variance σ^2 and it follows Student's 't' distribution with $\nu = (n-1)$ degrees of freedom with probability distribution.

$$f(t) = \frac{1}{\sqrt{\nu} \beta (\frac{1}{2})^{\nu/2}} \cdot \frac{1}{(1+t^2/\nu)^{\nu+1/2}}$$

Derivation of Student's 't' distribution

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

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

Square on both sides

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

Since,

$$s^2 = \frac{ns^2}{n-1}$$

$$t^2 = \frac{(\bar{x} - \mu)^2 \cdot n}{ns^2/n-1}$$

$$t^2 = \frac{n(\bar{x} - \mu)^2 (n-1)}{ns^2}$$

$$s^2 = \frac{1}{n} \sum (x_i - \bar{x})^2$$

$$ns^2 = \sum (x_i - \bar{x})^2$$

$$s^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2$$

$$(n-1)s^2 = \sum (x_i - \bar{x})^2$$

$$(n-1)s^2 = ns^2$$

$$s^2 = \frac{n}{n-1} s^2$$

Multiplying and dividing by σ^2 ,

$$\frac{t^2}{n-1} = \frac{n(\bar{x} - \mu)^2 \cdot \sigma^2}{ns^2 \cdot \sigma^2}$$

$$(\bar{x} - \mu)^2 / \sigma^2 / n$$

Sampling Distribution

The Number of possible samples of size n that can be drawn from a finite population of size N is $N C n$. For each of these samples we can compute a statistic say 't' ... eg:- mean, variance etc (...) which will obviously vary from sample to sample. The aggregate of the various values of the statistic under consideration so obtained may be grouped into a frequency distribution which is known as the sampling distribution of the statistic.

Standard Error:-

The standard deviation of the sampling distribution of a statistic is known as standard error. For eg:

$$\text{eg:- } \bar{x} = \sigma / \sqrt{n}$$

$$\left. \begin{array}{l} \text{observed sample} \\ \text{proportion} \end{array} \right\} 'p' = \sqrt{pq/n}$$

Students 't' distribution:

Let x_i ($i = 1, 2, \dots, n$) be a random sample of size 'n' from a normal population with mean μ and variance σ^2 . Then student's 't' is defined by the statistic, $t = \frac{\bar{x} - \mu}{s/\sqrt{n}}$ where $\bar{x} = \frac{1}{n} \sum x_i$

Important day

January - 9

$$= e^{\mu_1 t_1 + \mu_2 t_2 + \frac{1}{2}(t_1^2 \sigma_1^2 + t_2^2 \sigma_2^2 + 2\rho t_1 t_2 \sigma_1 \sigma_2)} \int_{-\infty}^{\infty} e^{-w^2/2} dw \cdot \int_{-\infty}^{\infty} e^{-z^2/2} dz$$

$$= e^{\frac{2\pi}{\sqrt{2\pi} \sqrt{2\pi}} (\mu_1 t_1 + \mu_2 t_2 + \frac{1}{2}(t_1^2 \sigma_1^2 + t_2^2 \sigma_2^2 + 2\rho t_1 t_2 \sigma_1 \sigma_2))}$$

$$= e^{\mu_1 t_1 + \mu_2 t_2 + \frac{1}{2}(t_1^2 \sigma_1^2 + t_2^2 \sigma_2^2 + 2\rho t_1 t_2 \sigma_1 \sigma_2)}$$

In particular if $(X, Y) \sim \text{BVN}(0, 0, 1, 1, \rho)$

$$M_{XY}(t) = e^{\frac{1}{2}(t_1^2 + t_2^2 + 2\rho t_1 t_2)}$$

(110) $M_{XY}(t_1, t_2) = e^{\frac{1}{2}(t_1^2 + t_2^2 + 2\rho t_1 t_2)}$

$M_{XY} = E[e^{t_1 X + t_2 Y}]$

$(t_1, t_2) = (0, 0)$ (Gaussian)

$(t_1, t_2) = (0, 0)$ (Gaussian)

$(t_1, t_2) = (0, 0)$ (Gaussian)

Double Samples

Sample Partition

$$\frac{1}{2} e^{-1/2} t_1^2 + \dots$$

$$u \cdot \sigma_1 = \mu$$

$$\mu_1 + u \cdot \sigma_1 = \mu$$

$$\Rightarrow v \cdot \sigma_2 = \nu$$

$$\mu_2 + v \cdot \sigma_2 = \nu$$

$$\frac{\partial x}{\partial u} = \sigma_1$$

$$\frac{\partial x}{\partial v} = 0$$

$$J = \frac{\partial(x, y)}{\partial(u, v)} = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{vmatrix}$$

131
 Jacobian of transformation

$$\frac{\partial y}{\partial u} = 0$$

$$= |\sigma_1 \sigma_2| = \sigma_1 \sigma_2$$

$$= \frac{1}{2(1-\rho^2)} [u^2 - 2\rho uv + v^2]$$

Now $M_{xy}(t_1, t_2) = \iint_{u, v} e^{t_1(\mu_1 + \sigma_1 u) + t_2(\mu_2 + v \sigma_2)} \frac{1}{2\pi \sigma_1 \sigma_2 \sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)} [u^2 - 2\rho uv + v^2]} du dv$ (10)

$$= \frac{1}{2\pi \sigma_1 \sigma_2 \sqrt{1-\rho^2}} \iint_{u, v} e^{u(t_1 \sigma_1 + t_2 \rho v) + v(t_2 \sigma_2 + t_1 \rho u)} - \frac{1}{2(1-\rho^2)} [u^2 - 2\rho uv + v^2] du dv$$

$$= \frac{e^{(t_1 \mu_1 + t_2 \mu_2)}}{2\pi \sqrt{1-\rho^2}} \iint_{u, v} e^{-\frac{1}{2(1-\rho^2)} [u^2 - 2\rho uv + v^2 - 2(t_1 \sigma_1 u + t_2 \sigma_2 v) y]} du dv$$

$\hookrightarrow: \int (u - \rho v) - (1 - \rho^2) + \dots$

$(v - \rho t_1 \sigma_1 - t_2 \sigma_2) y^2 - t_1^2 \sigma_1^2 - t_2^2 \sigma_2^2 - \dots$

$u - \rho v - (1 - \rho^2) t_1 \sigma_1 = \omega \sqrt{1 - \rho^2}$

$v - \rho t_1 \sigma_1 - t_2 \sigma_2 = z$

Calculation of

$$= \frac{1}{\sqrt{2\pi} \sigma_2 \sqrt{1-\rho^2}} \cdot e^{-\frac{1}{2(1-\rho^2)} \left[\frac{(y-\mu_2) - \rho \frac{\sigma_2}{\sigma_1} (x-\mu_1)}{\sigma_2} \right]^2}$$

Thus the conditional distribution of Y for a fixed x is

$$(Y/x=x) \sim N \left[\mu_2 + \rho \frac{\sigma_2}{\sigma_1} (x-\mu_1), \sigma_2^2 (1-\rho^2) \right]$$

M.G.F of Bivariate Normal Distribution

Let $(X, Y) \sim \text{BVN}(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \rho)$

By definition $M_{XY}(t_1, t_2) = E \left[e^{t_1 X + t_2 Y} \right]$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{(t_1 x + t_2 y)} \frac{1}{2\pi \sigma_1 \sigma_2 \sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)} \left[\frac{(x-\mu_1) + \rho \frac{\sigma_1}{\sigma_2} (y-\mu_2)}{\sigma_1} \right]^2} dx dy$$

put $u = \frac{x-\mu_1}{\sigma_1}$

and $v = \frac{y-\mu_2}{\sigma_2}$

$u \cdot \sigma_1 = x - \mu_1$

$\Rightarrow v \cdot \sigma_2 = y - \mu_2$

$\mu_1 + u \cdot \sigma_1 = x$

$\mu_2 + v \cdot \sigma_2 = y$

$\mu_1 + \rho \frac{\sigma_1}{\sigma_2} (\mu_2 - \mu_1) + \rho \frac{\sigma_1}{\sigma_2} (v \cdot \sigma_2) = \mu_1 + \rho v$

3

$$= \frac{1}{\sqrt{2\pi} \sigma_1 \sqrt{1-\rho^2}} \cdot e^{-\frac{1}{2(1-\rho^2)} \frac{\sigma_1^2}{\sigma_2^2} \left[x - (\mu_1 + \rho \frac{\sigma_1}{\sigma_2} (y - \mu_2)) y^2 \right]}$$

$$= \frac{1}{\sqrt{2\pi} \sigma_1 \sqrt{1-\rho^2}} \cdot e^{-\frac{1}{2(1-\rho^2)} \frac{\sigma_1^2}{\sigma_2^2} \left[x - (\mu_1 + \rho \frac{\sigma_1}{\sigma_2} (y - \mu_2)) y^2 \right]}$$

Which is the probability function of a univariate normal distribution with mean and variance given by

$$E \left[X/Y=y \right] = \underbrace{\mu_1 + \rho \frac{\sigma_1}{\sigma_2} (y - \mu_2)}_{\text{Mean}} \text{ and } \text{var} \left[X/Y=y \right] = \underbrace{\sigma_1^2 (1-\rho^2)}_{\text{Variance}}$$

Hence the conditional distribution X for a fixed Y is

$$\left[X/Y=y \right] \sim N \left[\mu_1 + \rho \frac{\sigma_1}{\sigma_2} (y - \mu_2), \sigma_1^2 (1-\rho^2) \right]$$

Similarly the conditional distribution of Y for a fixed X is

$$f(Y/x) = \frac{f(x,y)}{f(x)}$$

Prubly

Conditional Distribution of x for a fixed y is

$$f(x/y) = \frac{f(x,y)}{f(y)}$$

$$f(x/y) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \cdot e^{-\frac{1}{2}(1-\rho^2)} \left\{ \left(\frac{x-\mu_1}{\sigma_1}\right)^2 - 2\rho \frac{(x-\mu_1)(y-\mu_2)}{\sigma_1\sigma_2} + \left(\frac{y-\mu_2}{\sigma_2}\right)^2 \right\}$$

$$\cdot \frac{1}{\sigma_2\sqrt{2\pi}} \left[e^{-\frac{1}{2}\left(\frac{y-\mu_2}{\sigma_2}\right)^2} \right]$$

$$= \frac{\sqrt{\pi}}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}}$$

$$e^{-\frac{1}{2}(1-\rho^2)} \left[\left(\frac{x-\mu_1}{\sigma_1}\right)^2 - 2\rho \left(\frac{x-\mu_1}{\sigma_1}\right)\left(\frac{y-\mu_2}{\sigma_2}\right) + e^{-\frac{1}{2}\left(\frac{y-\mu_2}{\sigma_2}\right)^2} \right]$$

$$= \frac{1}{\sqrt{2\pi}\sigma_1\sqrt{1-\rho^2}}$$

$$e^{-\frac{1}{2}(1-\rho^2)} \left[\left(\frac{x-\mu_1}{\sigma_1}\right)^2 - 2\rho \left(\frac{x-\mu_1}{\sigma_1}\right)\left(\frac{y-\mu_2}{\sigma_2}\right) \right]$$

$$= \frac{1}{\sqrt{2\pi}\sigma_1\sqrt{1-\rho^2}} \cdot e^{-\frac{1}{2}(1-\rho^2)} \left[\left(\frac{x-\mu_1}{\sigma_1}\right)^2 - 2\rho \left(\frac{x-\mu_1}{\sigma_1}\right)\left(\frac{y-\mu_2}{\sigma_2}\right) + \left(\frac{y-\mu_2}{\sigma_2}\right)^2 \right]$$

$$\left[1 - (1-\rho^2) \right]$$

$$= \frac{1}{\sqrt{2\pi}\sigma_1\sqrt{1-\rho^2}}$$

$$e^{-\frac{1}{2}(1-\rho^2)} \sigma_1^2 \left\{ (x-\mu_1)^2 - 2\rho \frac{\sigma_1}{\sigma_2} (x-\mu_1)(y-\mu_2) + \frac{\sigma_1^2}{\sigma_2^2} e^{\frac{1}{2}(y-\mu_2)^2} \right\}$$

$$= \frac{1}{\sqrt{2\pi}\sigma_1\sqrt{1-\rho^2}}$$

$$e^{-\frac{1}{2}(1-\rho^2)} \sigma_1^2 \left[\left\{ (x-\mu_1) - \rho \frac{\sigma_1}{\sigma_2} (y-\mu_2) \right\}^2 \right]$$

$$= \frac{1}{\sqrt{2\pi}\sigma_1\sqrt{1-\rho^2}}$$

★

$$= \frac{1}{2\pi\sigma_1\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)} \left\{ \left(\frac{x-\mu_1}{\sigma_1} \right)^2 (1-\rho^2) \right.}$$

$$\left. - \frac{1}{2(1-\rho^2)} \left[u - \rho \left(\frac{x-\mu_1}{\sigma_1} \right) \right]^2 \right\}}$$

$$= \frac{1}{2\pi\sigma_1} e^{-\frac{1}{2} \left(\frac{x-\mu_1}{\sigma_1} \right)^2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{1-\rho^2}} e^{-\frac{1}{2} \left[u - \rho \left(\frac{x-\mu_1}{\sigma_1} \right) \right]^2} dt$$

Put $\frac{1}{\sqrt{1-\rho^2}} \left[u - \rho \left(\frac{x-\mu_1}{\sigma_1} \right) \right] = t$

$$\Rightarrow u - \rho \left(\frac{x-\mu_1}{\sigma_1} \right) = t \sqrt{1-\rho^2}$$

$$\therefore f(x) = \frac{1}{2\pi\sigma_1} e^{-\frac{1}{2} \left(\frac{x-\mu_1}{\sigma_1} \right)^2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{1-\rho^2}} e^{-\frac{t^2}{2}} dt$$

$$\int_{-\infty}^{\infty} e^{-t^2/2} dt = \sqrt{2\pi}$$

$$\therefore f(x) = \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{1}{2} \left(\frac{x-\mu_1}{\sigma_1} \right)^2} \cdot \sqrt{2\pi}$$

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{1}{2} \left(\frac{x-\mu_1}{\sigma_1} \right)^2} \rightarrow N, \mu$$

Similarly, Marginal Distribution of Y

$$f(y) = \int_{-\infty}^{\infty} f(x,y) dx$$

$$\therefore f(y) = \frac{1}{\sqrt{2\pi}\sigma_2} e^{-\frac{1}{2} \left(\frac{y-\mu_2}{\sigma_2} \right)^2}$$

Similarly, Marginal distribution

Bivariate Normal Distributions

2M Let X and Y be two normally correlated variables with correlation coefficient ρ and $E(X) = \mu_1, \text{Var}(X) = \sigma_1^2;$

$E(Y) = \mu_2, \text{Var}(Y) = \sigma_2^2$

Assumptions for deriving Bivariate

(i) The Regression of Y on X is linear

(ii) The arrays are homoscedastic

i.e., variance in each array is same. The (common variance) of estimate of Y in each array is then given by $\sigma_2^2(1-\rho^2)$.

ρ is the correlation coefficient of X and Y and it is independent of X .

(iii) The distribution of Y in different array is normal.

The density function of bivariate

$$f(x, y) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \cdot e^{-\frac{1}{2(1-\rho^2)} \left[\frac{(x-\mu_1)^2}{\sigma_1^2} - \right]}$$

$$f(x, y) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \cdot e^{-\frac{1}{2(1-\rho^2)} \left[\frac{(x-\mu_1)^2}{\sigma_1^2} - \frac{2\rho(x-\mu_1)(y-\mu_2)}{\sigma_1\sigma_2} + \frac{(y-\mu_2)^2}{\sigma_2^2} \right]}$$

Hence $\mu_1, \mu_2, \sigma_1 (>0),$

$\sigma_2 (>0)$ and $\rho (-1 < \rho < 1)$ are the

five parameters of the distributions.

Com 13 June, July

(10)

Marginal Distributions of Bivariate N.D

The Marginal distribution of X is

$$f(x) = \int_{-\infty}^{\infty} f(x, y) dy$$

$$\therefore f(x) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \int_{-\infty}^{\infty} e^{-\frac{1}{2(1-\rho^2)} \left[\frac{(x-\mu_1)^2}{\sigma_1^2} - \frac{2\rho(x-\mu_1)(y-\mu_2)}{\sigma_1\sigma_2} + \frac{(y-\mu_2)^2}{\sigma_2^2} \right]}$$

Put $u = \frac{y-\mu_2}{\sigma_2} \Rightarrow u \cdot \sigma_2 = y - \mu_2$

$\therefore \sigma_2 du = dy$

$$\therefore f(x) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \int_{-\infty}^{\infty} e^{-\frac{1}{2(1-\rho^2)} \left[\frac{(x-\mu_1)^2}{\sigma_1^2} - 2\rho u \left(\frac{x-\mu_1}{\sigma_1} \right) + u^2 \right]} \cdot \sigma_2 du$$

$$= \frac{1}{2\pi\sigma_1\sqrt{1-\rho^2}} \int_{-\infty}^{\infty} e^{-\frac{1}{2(1-\rho^2)} \left(\frac{x-\mu_1}{\sigma_1} \right)^2} e^{-\frac{1}{2(1-\rho^2)} \left[u^2 - 2\rho u \left(\frac{x-\mu_1}{\sigma_1} \right) \right]} du$$

Add & Subtract $\rho^2 \left(\frac{x-\mu_1}{\sigma_1} \right)^2$

$$= \frac{1}{2\pi\sigma_1\sqrt{1-\rho^2}} \int_{-\infty}^{\infty} e^{-\frac{1}{2(1-\rho^2)} \left(\frac{x-\mu_1}{\sigma_1} \right)^2} e^{-\frac{1}{2(1-\rho^2)} \left[u^2 - 2\rho u \left(\frac{x-\mu_1}{\sigma_1} \right) + \rho^2 \left(\frac{x-\mu_1}{\sigma_1} \right)^2 - \rho^2 \left(\frac{x-\mu_1}{\sigma_1} \right)^2 \right]} du$$

$$= \frac{1}{2\pi\sigma_1\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)} \left(\frac{x-\mu_1}{\sigma_1} \right)^2} \int_{-\infty}^{\infty} e^{-\frac{1}{2(1-\rho^2)} \left[u - \rho \left(\frac{x-\mu_1}{\sigma_1} \right) \right]^2} du$$