

**Statistics**  
**Bivariate Normal Distribution**  
**(Part-2)**  
**Conditional Distributions and Results**

**1. Introduction**

Welcome to the series of E-learning modules on Bivariate Normal Distribution- conditional distributions and results.

By the end of this session, you will be able to:

- Explain the conditional distribution
- Explain the coefficient of correlation
- Explain the recurrence relation of central moments

In the previous module, we have discussed about the bivariate normal distribution, its probability density function and marginal distributions. Hence, we know that the probability density function of bivariate normal distribution is given by,  $f_{XY}$  of  $x, y$  is equal to  $\frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left[\frac{(x-\mu_1)^2}{\sigma_1^2} - 2\rho\frac{(x-\mu_1)(y-\mu_2)}{\sigma_1\sigma_2} + \frac{(y-\mu_2)^2}{\sigma_2^2}\right]}$ .

Its marginal probability density functions are given by,  $f_X$  of  $x$  is equal to  $\frac{1}{\sigma_1\sqrt{2\pi}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}}$  and  $f_Y$  of  $y$  is equal to  $\frac{1}{\sigma_2\sqrt{2\pi}} e^{-\frac{(y-\mu_2)^2}{2\sigma_2^2}}$ .

**2. Conditional Distribution**

Now, let us obtain conditional distribution of  $X$ . Conditional distribution of  $X$  for fixed  $Y$  is given by,  $f_{X|Y}$  of  $x$  given  $y$  is equal to  $\frac{f_{XY}}{f_Y}$  of  $x, y$  is equal to  $\frac{1}{\sigma_1\sigma_2\sqrt{2\pi(1-\rho^2)}} e^{-\frac{1}{2(1-\rho^2)}\left[\frac{(x-\mu_1)^2}{\sigma_1^2} - 2\rho\frac{(x-\mu_1)(y-\mu_2)}{\sigma_1\sigma_2} + \frac{(y-\mu_2)^2}{\sigma_2^2}\right]}$  divided by  $\frac{1}{\sigma_2\sqrt{2\pi}} e^{-\frac{(y-\mu_2)^2}{2\sigma_2^2}}$ . Is equal to  $\frac{1}{\sigma_1\sqrt{2\pi(1-\rho^2)}} e^{-\frac{1}{2(1-\rho^2)}\left[\frac{(x-\mu_1)^2}{\sigma_1^2} - 2\rho\frac{(x-\mu_1)(y-\mu_2)}{\sigma_1\sigma_2} + \frac{(y-\mu_2)^2}{\sigma_2^2}\right]}$ .

Is equal to  $1$  divided by square root of  $2$  into  $\phi$  into  $\sigma_1$  into square root of  $1 - \rho$  square into,  $e$  power minus  $1$  divided by  $2$  into  $1 - \rho$  square into  $\sigma_1$  square, into  $x - \mu_1$ , minus  $\rho$  into  $\sigma_1$  divided by  $\sigma_2$  into  $y - \mu_2$  the whole square. Is equal to  $1$  divided by square root of  $2$  into  $\phi$  into  $\sigma_1$  into square root of  $1 - \rho$  square into,  $e$  power minus  $1$  divided by  $2$  into  $1 - \rho$  square into  $\sigma_1$  square, into  $x - \mu_1$  plus  $\rho$  into  $\sigma_1$  divided by  $\sigma_2$  into  $y - \mu_2$  the whole square. which is the probability function of a univariate normal distribution with mean and variance, which is given by, Expectation of  $X$  given  $Y$  is equal to  $\mu_1 + \rho$  into  $\sigma_1$  divided by  $\sigma_2$  into  $y - \mu_2$  and variance of  $X$  given  $Y$  is equal to  $1 - \rho$  square into  $\sigma_1$  square. Hence, conditional distribution of  $X$  for fixed  $Y$  is also normal given by,  $X$  given  $Y$  is equal to  $y$  follows Normal distribution with parameters  $(\mu_1 + \rho$  into  $\sigma_1$  divided by  $\sigma_2$  into  $y - \mu_2$  and  $1 - \rho$  square into  $\sigma_1$  square).

Similarly, the conditional distribution of Y for fixed X is given by,  $f_{Y|X}$  given X of y given x is equal to  $f_{X,Y}$  of x, y divided by  $f_X$  of x. Is equal to  $1/\sqrt{2\pi(1-\rho^2)} \exp\left[-\frac{1}{2(1-\rho^2)}\left(y - \mu_2 + \rho\frac{\sigma_2}{\sigma_1}(x - \mu_1)\right)^2\right]$ . Thus, conditional distribution of Y for fixed X is also normal and given by, Y given X is equal to x follows Normal distribution with parameters  $(\mu_2 + \rho\frac{\sigma_2}{\sigma_1}(x - \mu_1), 1 - \rho^2\frac{\sigma_2^2}{\sigma_1^2})$ .

It is apparent from the above results that the array mean are collinear. That is the regression equations are linear (involving linear functions of the independent variables) and the array variance are constant (that is free from independent variable). We express this by saying that the regression equations of Y on X and X on Y are linear and homoscedastic.

For  $\rho$  is equal to zero, the conditional variance  $V$  of  $(Y \text{ given } X)$  is equal to the marginal variance  $\sigma^2$  and the conditional mean of Expectation of  $Y$  given  $X$  is equal to the marginal mean  $\mu$  and the two variables become independent, which is also apparent from joint distribution function. In between the two extremes when  $\rho$  is equal to plus or minus 1, the coefficient  $\rho$  provides a measure of degree of association or interdependence between the two variables.

### 3. Coefficient of Correlation

Now, consider the following results. Show that if  $X$  and  $Y$  are standard normal variates with correlation coefficient  $\rho$  between them, then the correlation coefficient between  $X^2$  and  $Y^2$  is given by  $\rho^2$ .

We prove this result as follows.

Given X and Y are two standard normal variates. Hence, we have, Expectation of X is equal to Expectation of Y is equal to zero. Variance of X is equal to Expectation of X square is equal to 1, which is equal to Variance of Y is equal to Expectation of Y square. Therefore,  $M_{X,Y}(t_1, t_2)$  is equal to  $e^{\frac{1}{2}(t_1^2 + 2\rho t_1 t_2 + t_2^2)}$ .

Now, consider the coefficient of correlation,  $\rho$  of  $X^2$  and  $Y^2$  is equal to expectation of  $X^2$  into  $X^2$  square minus expectation of  $X^2$  square into expectation of  $X^2$  square whole divided by square root of expectation of  $X^2$  power 4 minus expectation of  $X^2$  square the whole square into expectation of  $X^2$  power 4 minus expectation of  $X^2$  square the whole square, where expectation of  $X^2$  into  $X^2$  square is equal to coefficient of  $t_1^2$  divided by  $2!$  into  $t_2^2$  divided by  $2!$  in  $M$  of  $t_1, t_2$  is equal to  $2\rho^2 + 1$ . Expectation of  $X^2$  power 4 is equal to coefficient of  $t_1^4$  divided by  $4!$  in  $M$  of  $t_1, t_2$  is equal to 3. Expectation of  $X^2$  power 4 is equal to coefficient of  $t_2^4$  divided by  $4!$  in  $M$  of  $t_1, t_2$  is equal to 3. By substituting the different values, in  $\rho$  of  $X^2$  and  $Y^2$ , we get,  $\rho$  of  $X^2$  and  $Y^2$  is equal to  $2\rho^2 + 1 - 1$  divided by square root of  $3 - 1$  into  $3 - 1$  is equal to  $\rho$ . Therefore, the correlation coefficient between  $X^2$  and  $Y^2$  is given by  $\rho$ .

Consider the 2<sup>nd</sup> result. If  $X$  and  $Y$  are standard normal variates with coefficient of correlation  $\rho$ , then show that,  $Q$  is equal to  $(X^2 + 2\rho XY + Y^2)$  divided by  $(1 - \rho^2)$  is distributed like a chi-square, that is as that of the sum of the squares of standard normal variates.

To prove this result, let us consider the moment generating function of  $Q$ . The MGF of  $t$  is equal to the expectation of  $e^{tQ}$ . This is equal to the double integral from minus infinity to infinity of  $e^{tQ} f(x, y) dx dy$ .

Is equal to  $\frac{1}{2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{tQ} e^{-\frac{1}{2}(1-\rho^2)(x^2+y^2)} dx dy$  Is equal to  $\frac{1}{2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(1-\rho^2)(x^2+y^2)} dx dy$  Is equal to  $\frac{1}{2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(1-\rho^2)(x^2+y^2)} dx dy$  Put  $x$  into  $\frac{1}{\sqrt{1-\rho^2}} u$  and  $y$  into  $\frac{1}{\sqrt{1-\rho^2}} v$  Implies  $dx$  is equal to  $\frac{du}{\sqrt{1-\rho^2}}$  and  $dy$  is equal to  $\frac{dv}{\sqrt{1-\rho^2}}$  Also,  $Q$  is equal to  $-\frac{1}{2}(1-\rho^2)(x^2+y^2)$  Is equal to  $-\frac{1}{2}(1-\rho^2)(\frac{u^2}{1-\rho^2} + \frac{v^2}{1-\rho^2})$  Is equal to  $-\frac{1}{2}(u^2+v^2)$  divided by  $1-\rho^2$ .

Therefore,  $M_Q(t)$  is equal to  $1$  divided by  $2$  into  $\phi$  into  $1 - 2$  into  $t$  into square root of  $1 - \rho$  square, double integral from minus infinity to infinity  $e$  power minus  $1$  divided by  $2$  into  $1 - \rho$  square into  $u$  square minus  $2$  into  $\rho$  into  $u$  into  $v$  plus  $v$  square  $du, dv$ . Is equal to  $1$  divided by  $1 - 2$  into  $t$  into  $1$ , is equal to  $1 - 2$  into  $t$  whole power minus  $1$ , Which is the moment generating function of Chi-square variate with  $n$  (equal to  $2$ ) degrees of freedom. (We study about chi-square distribution in the later modules.)

#### **4. Recurrence Relation of Central Moments**

Show that for a bivariate normal distribution with probability function  $f$  of  $x, y$  is equal to  $1$  divided by  $2\pi\sqrt{1-\rho^2}$  into  $e^{-\frac{1}{2(1-\rho^2)}[x^2 - 2\rho xy + y^2]}$ , the moments obey the recurrence relation  $\mu_{r,s}$  is equal to  $\rho$  into  $\mu_{r-1,s-1}$  plus  $r-1$  into  $s-1$  into  $1-\rho^2$  into  $\mu_{r-2,s-2}$ .

Let us prove this result using moment generating function.

We know that moment generating function of above distribution is given by,

$M$  is equal to  $M(t_1, t_2)$  is equal to  $e^{\frac{1}{2}(t_1^2 + 2\rho t_1 t_2 + t_2^2)}$

Now, finding partial differentiation, we get,  $\frac{\partial M}{\partial t_1}$  is equal to  $M(t_1, t_2)$  plus  $\rho t_2$

$\frac{\partial M}{\partial t_2}$  is equal to  $M(t_1, t_2)$  plus  $\rho t_1$   $\frac{\partial^2 M}{\partial t_1 \partial t_2}$  is equal to  $\rho$  by  $\frac{\partial M}{\partial t_1}$ ,  $\frac{\partial^2 M}{\partial t_1^2}$  is equal to  $M(t_1, t_2)$  plus  $\rho t_2$  plus  $\rho t_1$  into  $\frac{\partial M}{\partial t_2}$

Therefore,  $\frac{\partial^2 M}{\partial t_1 \partial t_2}$  minus  $\rho$  into  $\frac{\partial M}{\partial t_1}$  minus  $\rho$  into  $\frac{\partial M}{\partial t_2}$  is equal to  $M(t_1, t_2)$  plus  $\rho t_2$  plus  $\rho t_1$  into  $\frac{\partial M}{\partial t_2}$  minus  $\rho$  into  $\frac{\partial M}{\partial t_1}$  minus  $\rho$  into  $\frac{\partial M}{\partial t_2}$  plus  $\rho t_1$  into  $\frac{\partial M}{\partial t_2}$  On simplification, we get,  $M(t_1, t_2)$  plus  $\rho t_2$  plus  $\rho t_1$  into  $\frac{\partial M}{\partial t_2}$  minus  $\rho$  into  $\frac{\partial M}{\partial t_1}$  is equal to  $M(t_1, t_2)$  plus  $\rho t_2$  plus  $\rho t_1$  into  $\frac{\partial M}{\partial t_2}$ .

Therefore,  $\frac{\partial^2 M}{\partial t_1 \partial t_2}$  is equal to  $\rho$  into  $\frac{\partial M}{\partial t_1}$  plus  $\rho$  into  $\frac{\partial M}{\partial t_2}$  plus  $M(t_1, t_2)$  plus  $\rho t_2$  plus  $\rho t_1$  into  $\frac{\partial M}{\partial t_2}$ . Name it as star. But  $M$  is equal to  $e^{\frac{1}{2}(t_1^2 + 2\rho t_1 t_2 + t_2^2)}$  is equal to summation from  $r$  is equal to zero to infinity, summation from  $s$  is equal to zero to infinity  $\mu_{r,s}$  into  $t_1^r t_2^s$  divided by  $r!$  into  $s!$

Therefore, star equation gives

Summation over  $r$  is equal to 1 to infinity, summation over  $s$  is equal to 1 to infinity  $\mu_{r,s}$  into  $t_1^{r-1} t_2^{s-1}$  divided by  $(r-1)!$  into  $(s-1)!$  is equal to  $\rho$  into summation over  $r$  is equal to 1 to infinity,  $s$  is equal to zero to infinity  $r$  into  $\mu_{r,s}$   $t_1^{r-1} t_2^s$  divided by  $r!$  into  $s!$  plus  $\rho$  into summation over  $r$  is equal to zero to infinity, summation over  $s$  is equal to 1 to infinity  $s$  into  $\mu_{r,s}$   $t_1^r t_2^{s-1}$  divided by  $r!$  into  $s!$  plus  $\rho$  into summation over  $r$  is equal to zero to infinity,  $s$  is equal to zero to infinity  $\mu_{r,s}$   $t_1^r t_2^{s-1}$  divided by  $r!$  into  $s!$  plus  $1-\rho^2$  into summation over  $r$  is equal to zero to infinity,  $s$  is equal to zero to infinity  $\mu_{r,s}$   $t_1^{r-1} t_2^{s-1}$  divided by  $(r-1)!$  into  $(s-1)!$  Equating the coefficients of  $t_1^{r-1} t_2^{s-1}$  divided by  $(r-1)!$  into  $(s-1)!$  on both sides and

simplifying we get,  $\mu_{r,s}$  is equal to  $r + s - 1$  into  $\rho$  into  $\mu_{r-1, s-1}$  plus  $r - 1$  into  $s - 1$  into  $1 - \rho^2$  into  $\mu_{r-2, s-2}$ .

## **5. Illustration**

If  $X$  and  $Y$  are independent standard normal variates, obtain the moment generating function of  $X$  into  $Y$ . Let us find the moment generating function as follows

By definition, we have,  $M_{X \text{ into } Y} \text{ of } t$  is equal to expectation of  $e^{\text{power } t \text{ into } X \text{ into } Y}$  Is equal to double integral from minus infinity to infinity  $e^{\text{power } t \text{ into } x \text{ into } y}$  into  $f \text{ of } x, y \text{ dx dy}$  Since  $X$  and  $Y$  are independent standard normal variates, their joint pdf  $f(x,y)$  is given by,  $f \text{ of } x, y$  is equal to  $1$  divided by  $2$  into  $\phi$  into  $e^{\text{power minus } x^2 \text{ divided by } 2 \text{ into } e^{\text{power minus } y^2 \text{ divided by } 2}}$ ; where  $(x, y)$  lies between minus infinity to infinity.

Therefore,  $M_{X \text{ into } Y} \text{ of } t$  is equal to  $1$  divided by  $2$  into  $\phi$  into double integral from minus infinity to infinity  $e^{\text{power minus half into } x^2 \text{ minus } 2 \text{ into } t \text{ into } x \text{ into } y \text{ plus } y^2 \text{ dx dy}}$  is equal to  $1$  divided by  $2$  into  $\phi$ , double integral from minus infinity to infinity  $e^{\text{power minus } 1 \text{ divided by } 2 \text{ into } 1 \text{ minus } t \text{ square, into } x^2 \text{ divided by } 1 \text{ by } 1 \text{ minus } t \text{ square minus } 2 \text{ into } t \text{ into } x \text{ into } y \text{ divided by } 1 \text{ by square root of } 1 \text{ minus } t \text{ square into } 1 \text{ by square root of } 1 \text{ minus } t \text{ square plus } y^2 \text{ divided by } 1 \text{ by } 1 \text{ minus } t \text{ square dx dy}}$ . If  $U$  and  $Y$  follows bivariate normal distribution with parameters zero, zero  $\sigma_1^2$ ,  $\sigma_2^2$  and  $\rho$ , then we have, Double integral from minus infinity to infinity,  $1$  divided by  $2$  into  $\phi$  into  $\sigma_1$  into  $\sigma_2$  into square root of  $1 - \rho^2$  into  $e^{\text{power minus } 1 \text{ divided by } 2 \text{ into } 1 \text{ minus } \rho \text{ square, into } x^2 \text{ divided by } \sigma_1^2 \text{ minus } 2 \text{ into } \rho \text{ into } x \text{ into } y \text{ divided by } \sigma_1 \text{ into } \sigma_2, \text{ plus } y^2 \text{ divided by } \sigma_2^2, \text{ dx dy}}$  is equal to  $1$ . Implies, double integral from minus infinity to infinity  $e^{\text{power minus } 1 \text{ divided by } 2 \text{ into } 1 \text{ minus } \rho \text{ square, into } x^2 \text{ divided by } \sigma_1^2 \text{ minus } 2 \text{ into } \rho \text{ into } x \text{ into } y \text{ divided by } \sigma_1 \text{ into } \sigma_2 \text{ plus } y^2 \text{ divided by } \sigma_2^2 \text{ dx dy}}$  is equal to  $2$  into  $\phi$  into  $\sigma_1$  into  $\sigma_2$  into square root of  $1 - \rho^2$ . On comparison, we get,  $M_{X \text{ into } Y} \text{ of } t$  is equal  $1$  divided by  $2$  into  $\phi$ , into  $2$  into  $\phi$  into  $1$  divided by square root of  $1 - t \text{ square}$  into  $1$  divided by square root of  $1 - t \text{ square}$  into square root of  $1 - t \text{ square}$  Implies,  $M_{X \text{ into } Y} \text{ of } t$  is equal to  $1 - t$  square whole power minus half.

Our learning in this session, where we have understood:

- The conditional distribution
- The coefficient of correlation
- The recurrence relation of central moments