

## Section Two

# "Marginal and Conditional Distribution" And Stochastic Independent

### Notation

For two r.v's  $X_1$  and  $X_2$ , we shall call

$f(x_1, x_2)$  a joint p.d.f of  $X_1$  and  $X_2$

$F(x_1, x_2) = P_r(X_1 \leq x_1, X_2 \leq x_2)$  a joint c.d.f of  $X_1$  and  $X_2$

$M(t_1, t_2) = E(e^{t_1 X_1 + t_2 X_2})$  a joint m.g.f of  $X_1$  and  $X_2$

In general, when we have  $n$  r.v's  $X_1, X_2, \dots, X_n$ , we shall call

$f(x_1, x_2, \dots, x_n)$  a joint p.d.f of  $X_1, X_2, \dots, X_n$

$F(x_1, x_2, \dots, x_n) = P_r(X_1 \leq x_1, X_2 \leq x_2, \dots, X_n \leq x_n)$  a joint c.d.f of  $X_1, X_2, \dots, X_n$

$M(t_1, t_2, \dots, t_n) = E(e^{t_1 X_1 + t_2 X_2 + \dots + t_n X_n})$  a joint m.g.f of  $X_1, X_2, \dots, X_n$ .

### Marginal Distributions

"In 2-D case"

Defn. Let  $f(x_1, x_2)$  be the joint p.d.f of r.v's  $X_1$  and  $X_2$ . We define the marginal p.d.f of  $X_1$  and the marginal p.d.f of  $X_2$  as

$$f_1(x_1) = \begin{cases} \sum_{x_2} f(x_1, x_2) & , \text{ for disc. case} \\ \int_{x_2} f(x_1, x_2) dx_2 & , \text{ for cont. case} \end{cases}$$

$$f_2(x_2) = \begin{cases} \sum_{x_1} f(x_1, x_2) & , \text{ disc} \\ \int_{x_1} f(x_1, x_2) dx_1 & , \text{ cont.} \end{cases}$$

### Note

suppose, we require to evaluate

$$1. P_r(a \leq X_1 \leq b) = \begin{cases} \sum_{x_1=a}^b f_1(x_1) = \sum_{x_1=a}^b \sum_{x_2} f(x_1, x_2) & , \text{ disc} \\ \int_a^b f_1(x_1) dx_1 = \int_a^b \int_{x_2} f(x_1, x_2) dx_2 dx_1 & , \text{ cont.} \end{cases}$$

$$2. P_r(c_1 \leq X_1 \leq d) = \begin{cases} \sum_{x_2=c}^d f_2(x_2) = \sum_{x_2=c}^d \sum_{x_1} f(x_1, x_2) & \text{disc} \\ \int_c^d f_2(x_2) dx_2 = \int_c^d \int_{x_1} f(x_1, x_2) dx_1 dx_2 & \text{cont.} \end{cases}$$

$$3. E[u(X_1)] = \begin{cases} \sum_{x_1} u(x_1) f_1(x_1) = \sum_{x_1} \sum_{x_2} u(x_1) f(x_1, x_2) & \text{disc} \\ \int_{x_1} u(x_1) f_1(x_1) dx_1 = \int_{x_1} \int_{x_2} u(x_1) f(x_1, x_2) dx_2 dx_1 & \text{cont.} \end{cases}$$

$$4. E[u(X_2)] = \begin{cases} \sum_{x_2} u(x_2) f_2(x_2) = \sum_{x_2} \sum_{x_1} u(x_2) f(x_1, x_2) & \text{disc} \\ \int_{x_2} u(x_2) f_2(x_2) dx_2 = \int_{x_2} \int_{x_1} u(x_2) f(x_1, x_2) dx_1 dx_2 & \text{cont.} \end{cases}$$

Example (1) Let the joint p.d.f of r.v's  $X$  and  $Y$  be

(i)  $f(x, y) = \frac{1}{21}(x+y), x=1, 2, 3; y=1, 2$   
 $= 0$  , e.w

(ii)  $f(x, y) = e^{-(x+y)}, 0 < x < \infty, 0 < y < \infty$   
 $= 0$  , e.w

(a) Find the marginal p.d.f of  $X$  and the marginal p.d.f of  $Y$

(b) Find  $E(X), \text{Var}(X), E(Y), \text{Var}(Y), E(XY)$

Solution (i)

(a) The marginal p.d.f of  $X$  is  $f_1(x) = \sum_y f(x, y)$

$$\Rightarrow f_1(x) = \sum_{y=1}^2 \frac{1}{21}(x+y) = \frac{1}{21}[(x+1) + (x+2)] = \frac{1}{21}(2x+3), x=1, 2, 3$$

$= 0$  , e.w

The marginal p.d.f of  $Y$  is  $f_2(y) = \sum_x f(x, y)$

$$\Rightarrow f_2(y) = \sum_{x=1}^3 \frac{1}{21}(x+y) = \frac{1}{21}[(1+y) + (2+y) + (3+y)] = \frac{1}{7}(y+2), y=1, 2$$

$= 0$  , e.w

(3)

$$\mu_1 = E(X) = \sum_x x f_1(x) = \frac{1}{21} \sum_{x=1}^3 x(2x+3) = \frac{46}{21}$$

$$E(X^2) = \sum_x x^2 f_1(x) = \frac{1}{21} \sum_{x=1}^3 x^2(2x+3) = \frac{114}{21}$$

$$\text{Var}(X) = \sigma_1^2 = E(X^2) - \mu_1^2 = \frac{114}{21} - \left(\frac{46}{21}\right)^2 = \frac{278}{441}$$

$$\mu_2 = E(Y) = \sum_y y f_2(y) = \frac{1}{7} \sum_{y=1}^2 y(y+2) = \frac{11}{7}$$

$$E(Y^2) = \sum_y y^2 f_2(y) = \frac{1}{7} \sum_{y=1}^2 y^2(y+2) = \frac{19}{7}$$

$$\text{Var}(Y) = \sigma_2^2 = E(Y^2) - \mu_2^2 = \frac{19}{7} - \left(\frac{11}{7}\right)^2 = \frac{12}{49}$$

$$E(XY) = \sum_x \sum_y xy f(x,y) = \frac{1}{21} \sum_{x=1}^3 \sum_{y=1}^2 xy(x+y) = \frac{1}{21} \sum_{x=1}^3 [x(x+1) + 2x(x+2)]$$

$$= \frac{1}{21} \sum_{x=1}^3 (3x^2 + 5x) = \frac{1}{21} (8 + 22 + 42) = \frac{24}{7}$$

Solution (ii)

$$(a) f_1(x) = \int_y f(x,y) dy = \int_0^{\infty} e^{-(x+y)} dy = e^{-x} \int_0^{\infty} e^{-y} dy = -e^{-x} (e^{-y}) \Big|_0^{\infty}$$

$$= -e^{-x} (0 - 1) = e^{-x}, \quad 0 < x < \infty$$

$$= 0, \quad \text{e.w}$$

Similarly

$$f_2(y) = e^{-y}, \quad 0 < y < \infty$$

$$= 0, \quad \text{e.w}$$

$$\mu_1 = E(X) = \int_x x f_1(x) dx = \int_0^{\infty} x e^{-x} dx = 1 = E(Y) = \mu_2$$

$$E(X^2) = \int_x x^2 f_1(x) dx = \int_0^{\infty} x^2 e^{-x} dx = 2 = E(Y^2)$$

$$\text{Var}(X) = \sigma_1^2 = E(X^2) - \mu_1^2 = 2 - (1)^2 = 1 = \text{Var}(Y) = \sigma_2^2$$

$$E(XY) = \int_x \int_y xy f(x,y) dx dy = \int_0^{\infty} \int_0^{\infty} xy e^{-(x+y)} dx dy$$



$$= \left( \int_0^{\infty} x e^{-x} dx \right) \left( \int_0^{\infty} y e^{-y} dy \right) = \left( \int_0^{\infty} x e^{-x} dx \right)^2 = (1)^2 = 1$$

The

Defn Let  $f(x_1, x_2)$  and  $F(x_1, x_2) = \Pr(X_1 \leq x_1, X_2 \leq x_2)$  be the joint p.d.f and the joint c.d.f of r.v.s  $X_1$  and  $X_2$ . Then the marginal c.d.f of  $X_1$  and the marginal c.d.f of  $X_2$  are respectively

$$F_1(x_1) = F(x_1, \infty) \text{ and } F_2(x_2) = F(\infty, x_2)$$

Note If  $f_1(x_1)$  and  $f_2(x_2)$  are the marginal p.d.f's, then the marginal c.d.f's  $F_1(x_1)$  and  $F_2(x_2)$  can be obtained

as :

$$F_1(x_1) = \begin{cases} \sum_{t_1=-\infty}^{x_1} f_1(t_1) & , \text{ disc} \\ \int_{-\infty}^{x_1} f_1(t_1) dt_1 & , \text{ cont.} \end{cases}$$

$$F_2(x_2) = \begin{cases} \sum_{t_2=-\infty}^{x_2} f_2(t_2) & , \text{ disc} \\ \int_{-\infty}^{x_2} f_2(t_2) dt_2 & , \text{ cont.} \end{cases}$$

Example (2) Back to Example (1) and find the joint c.d.f of  $X$  and  $Y$ . Also find the marginal c.d.f's.

(i) We have  $f(x, y) = \frac{1}{2!}(x+y)$  ,  $x=1, 2, 3$  ,  $y=1, 2$   
 $= 0$  i.e.w

$$F(x, y) = \sum_{t=-\infty}^x \sum_{s=-\infty}^y f(t, s) = \sum_{t=1}^x \sum_{s=1}^y \frac{1}{2!}(t+s) = \frac{1}{2!} \sum_{t=1}^x [(t+1) + (t+2) + \dots + (t+y)]$$

$$= \frac{1}{2!} \sum_{t=1}^x \left[ yt + \frac{y(y+1)}{2} \right] = \frac{1}{2!} \left[ \frac{yx(x+1)}{2} + \frac{xy(y+1)}{2} \right] = \frac{1}{4!} xy(x+y+2)$$



$$F(x, y) = \begin{cases} 0 & , x < 1, y < 1 \\ \frac{1}{42} xy(x+y+2) & , 1 \leq x < 3, 1 \leq y < 2 \\ 1 & , x \geq 3, y \geq 2 \end{cases}$$

The marginal c.d.f of  $X$  and the marginal c.d.f of  $Y$  are :-

$$F_1(x) = F(x, 2) = \begin{cases} 0 & , x < 1 \\ \frac{1}{21} x(x+4) & , 1 \leq x < 3 \\ 1 & , x \geq 3 \end{cases}$$

$$F_2(x) = F(3, y) = \begin{cases} 0 & , y < 1 \\ \frac{1}{14} y(y+5) & , 1 \leq y < 2 \\ 1 & , y \geq 2 \end{cases}$$

$$(ii) f(x, y) = \begin{cases} e^{-(x+y)} & , 0 < x < \infty, 0 < y < \infty \\ 0 & , \text{e.w} \end{cases}$$

$$F(x, y) = \int_{-\infty}^x \int_{-\infty}^y f(t, s) dt ds = \int_0^x \int_0^y e^{-(t+s)} ds dt = \left( \int_0^x e^{-t} dt \right) \left( \int_0^y e^{-s} ds \right)$$

$$= \left( -e^{-t} \Big|_0^x \right) \left( -e^{-s} \Big|_0^y \right) = \begin{cases} 0 & , x < 0, y < 0 \\ (1 - e^{-x})(1 - e^{-y}) & , 0 < x < \infty, 0 < y < \infty \\ 1 & , x = y = \infty \end{cases}$$

$$F_1(x) = F(x, \infty) = \begin{cases} 0 & , x < 0 \\ 1 - e^{-x} & , 0 < x < \infty \\ 1 & , x = \infty \end{cases}$$

$$F_2(y) = F(\infty, y) = \begin{cases} 0 & , y < 0 \\ 1 - e^{-y} & , 0 < y < \infty \\ 1 & , y = \infty \end{cases}$$

### The Covariance and The Correlation Coefficient

Let the r.v's  $X$  and  $Y$  have means  $\mu_1, \mu_2$  and variances  $\sigma_1^2, \sigma_2^2$  respectively. The mathematical expectation  $E[(X - \mu_1)(Y - \mu_2)]$  is called the covariance of  $X$  and  $Y$ , and denoted by  $\text{cov}(X, Y)$ .

Note:  $\text{cov}(X, Y) = E[(X - \mu_1)(Y - \mu_2)] = E[XY - \mu_1 Y - \mu_2 X + \mu_1 \mu_2]$   
 $= E(XY) - \mu_1 E(Y) - \mu_2 E(X) + \mu_1 \mu_2$   
 $= E(XY) - \mu_1 \mu_2 - \mu_2 \mu_1 + \mu_1 \mu_2 = E(XY) - \mu_1 \mu_2$

Defn The correlation coefficient between two r.v.'s  $X$  and  $Y$ , denoted by  $\rho = \rho(X, Y)$ , is defined to be

$$\rho = \frac{\text{cov}(X, Y)}{\sigma_1 \sigma_2} = \frac{E(XY) - \mu_1 \mu_2}{\sigma_1 \sigma_2}$$

Note:  $-1 \leq \rho \leq 1$

Example (3) Let the joint p.d.f of r.v.'s  $X$  and  $Y$  be

$$f(x, y) = x + y, \quad 0 < x < 1, \quad 0 < y < 1$$

$$= 0, \quad \text{e.w.}$$

Compute the correlation coefficient between  $X$  and  $Y$ .

Solution

the marginal p.d.f of  $X$  is

$$f_1(x) = \int_y f(x, y) dy = \int_{y=0}^1 (x+y) dy = xy + \frac{1}{2}y^2 \Big|_0^1 = x + \frac{1}{2}, \quad 0 < x < 1$$

$$= 0, \quad \text{e.w.}$$

Similarly, the marginal p.d.f of  $Y$  is

$$f_2(y) = y + \frac{1}{2}, \quad 0 < y < 1$$

$$= 0, \quad \text{e.w.}$$

$$\mu_1 = E(X) = \int_x x f_1(x) dx = \int_0^1 x(x + \frac{1}{2}) dx = \frac{x^3}{3} + \frac{x^2}{4} \Big|_0^1 = \frac{7}{12} = E(Y) = \mu_2$$

$$E(X^2) = \int_x x^2 f_1(x) dx = \int_0^1 x^2(x + \frac{1}{2}) dx = \frac{x^4}{4} + \frac{x^3}{6} \Big|_0^1 = \frac{5}{12}$$

$$\sigma_1^2 = \text{Var}(X) = E(X^2) - \mu_1^2 = \frac{5}{12} - \left(\frac{7}{12}\right)^2 = \frac{11}{144} = \text{Var}(Y) = \sigma_2^2$$

$$E(XY) = \int_x \int_y xy f(x, y) dx dy = \int_0^1 \int_0^1 xy(x+y) dy dx = \int_0^1 \int_0^1 (x^2y + xy^2) dy dx$$

$$= \int_0^1 \left( \frac{x^2 y^2}{2} + \frac{xy^3}{3} \Big|_0^1 \right) dx = \int_0^1 \left( \frac{x^2}{2} + \frac{x}{3} \right) dx = \frac{x^3}{6} + \frac{x^2}{6} \Big|_0^1 = \frac{1}{3}$$

~~$\mu_1, \mu_2$~~

$$\text{Cov}(X, Y) = E(XY) - \mu_1 \mu_2 = \frac{1}{3} - \left(\frac{7}{12}\right)\left(\frac{7}{12}\right) = -\frac{1}{144}$$

$$\rho = \frac{\text{Cov}(X, Y)}{\sigma_1 \sigma_2} = \frac{-\frac{1}{144}}{\sqrt{\frac{11}{144}} \sqrt{\frac{11}{144}}} = -\frac{1}{11}$$

Joint Moment Generating Function "In two-D case"

Let  $f(x, y)$  be the joint p.d.f of r.v's  $X, Y$ . The mathematical expectation  $E(e^{t_1 X + t_2 Y})$ , if it exists for  $-h_1 < t_1 < h_1, -h_2 < t_2 < h_2$ , is called the joint m.g.f of  $X$  and  $Y$ , and denoted by  $M(t_1, t_2)$ . That is

$$M(t_1, t_2) = E(e^{t_1 X + t_2 Y}) = \begin{cases} \sum_x \sum_y e^{t_1 x + t_2 y} f(x, y) & \text{for disc. case} \\ \int_x \int_y e^{t_1 x + t_2 y} f(x, y) dx dy & \text{for cont. case} \end{cases}$$

If we set  $t_1 = t_2 = 0$ , we have  $M(0, 0) = 1$

Notes

(i) The marginal m.g.f of  $X$  and the marginal m.g.f of  $Y$  can be obtained as

$$M(t_1, 0) = E(e^{t_1 X}) = M_1(t_1)$$

$$M(0, t_2) = E(e^{t_2 Y}) = M_2(t_2)$$

(ii) If we differentiate  $M(t_1, t_2)$  partially  $k$  times w.r. to  $t_1$  and  $m$  times w.r. to  $t_2$ , we have

$$\frac{\partial^{k+m} M(t_1, t_2)}{\partial t_2^m \partial t_1^k} = \begin{cases} \sum_x \sum_y x^k y^m e^{t_1 x + t_2 y} f(x, y) & \text{for disc case} \\ \int_x \int_y x^k y^m e^{t_1 x + t_2 y} f(x, y) dx dy & \text{for cont. case} \end{cases}$$

set  $t_1 = t_2 = 0$ , we have

$$\frac{\partial^{k+m} M(t_1, t_2)}{\partial t_2^m \partial t_1^k} \Big|_{t_1=t_2=0} = \begin{cases} \sum_x \sum_y x^k y^m f(x, y) \\ \int_x \int_y x^k y^m f(x, y) dx dy \end{cases} \rightarrow = E(X^k Y^m)$$



In particular

$$\frac{\partial M(t_1, t_2)}{\partial t_1} \Big|_{t_1=t_2=0} = \frac{\partial M(0,0)}{\partial t_1} = E(X) = \mu_1$$

$$\frac{\partial M(t_1, t_2)}{\partial t_2} \Big|_{t_1=t_2=0} = \frac{\partial M(0,0)}{\partial t_2} = E(Y) = \mu_2$$

$$\frac{\partial^2 M(t_1, t_2)}{\partial t_1^2} \Big|_{t_1=t_2=0} = \frac{\partial^2 M(0,0)}{\partial t_1^2} = E(X^2) \Rightarrow \text{Var}(X) = \sigma_1^2 = E(X^2) - \mu_1^2$$

$$\frac{\partial^2 M(t_1, t_2)}{\partial t_2^2} \Big|_{t_1=t_2=0} = \frac{\partial^2 M(0,0)}{\partial t_2^2} = E(Y^2) \Rightarrow \text{Var}(Y) = \sigma_2^2 = E(Y^2) - \mu_2^2$$

$$\frac{\partial^2 M(t_1, t_2)}{\partial t_2 \partial t_1} \Big|_{t_1=t_2=0} = \frac{\partial^2 M(0,0)}{\partial t_2 \partial t_1} = E(XY)$$

Then

$$\text{Cov}(X, Y) = E(XY) - \mu_1 \mu_2 \quad \text{and} \quad \rho = \rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma_1 \sigma_2}$$

(iii) If we set  $\psi(t_1, t_2) = \ln M(t_1, t_2)$ , then

$$\frac{\partial \psi(t_1, t_2)}{\partial t_i} = \frac{\frac{\partial M(t_1, t_2)}{\partial t_i}}{M(t_1, t_2)}, \quad i=1, 2$$

$$\Rightarrow \frac{\partial \psi(0,0)}{\partial t_i} = \frac{\frac{\partial M(0,0)}{\partial t_i}}{M(0,0)} = \frac{\mu_i}{1} = \mu_i, \quad i=1, 2$$

$$\frac{\partial^2 \psi(t_1, t_2)}{\partial t_i^2} = \frac{M(t_1, t_2) \frac{\partial^2 M(t_1, t_2)}{\partial t_i^2} - \frac{\partial M(t_1, t_2)}{\partial t_i} \cdot \frac{\partial M(t_1, t_2)}{\partial t_i}}{[M(t_1, t_2)]^2}, \quad i=1, 2$$

$$\begin{aligned} \frac{\partial^2 \psi(0,0)}{\partial t_i^2} &= \frac{M(0,0) \frac{\partial^2 M(0,0)}{\partial t_i^2} - \frac{\partial M(0,0)}{\partial t_i} \cdot \frac{\partial M(0,0)}{\partial t_i}}{[M(0,0)]^2} \\ &= \frac{(1) E(X_i^2) - E(X_i) \cdot E(X_i)}{(1)^2} = \sigma_i^2, \quad i=1, 2 \end{aligned}$$

$$\frac{\partial^2 M(t_1, t_2)}{\partial t_2 \partial t_1} = \frac{M(t_1, t_2) \frac{\partial^2 M(t_1, t_2)}{\partial t_2 \partial t_1} - \frac{\partial M(t_1, t_2)}{\partial t_1} \cdot \frac{\partial M(t_1, t_2)}{\partial t_2}}{[M(t_1, t_2)]^2}$$

$$\frac{\partial^2 \psi(0,0)}{\partial t_2 \partial t_1} = \frac{(1) E(XY) - E(X) \cdot E(Y)}{(1)^2} = \text{Cov}(X, Y)$$

Example (4) Let the joint p.d.f of r.v X and Y be

$$f(x, y) = e^{-y}, \quad 0 < x < y < \infty$$

$$= 0, \quad \text{r.w.}$$

- (1) Find the marginal p.d.f of X and the marginal p.d.f of Y.
- (2) Find  $\mu_1 = E(X)$ ,  $\sigma_1^2 = \text{var}(X)$ ,  $\mu_2 = E(Y)$ ,  $\sigma_2^2 = \text{var}(Y)$ ,  $E(XY)$ ,  $\text{Cov}(X, Y)$ , and  $\rho(X, Y)$  by using direct expectation approach.
- (3) Find the joint c.d.f of X and Y.
- (4) Find the marginal c.d.f of X and the marginal c.d.f of Y.
- (5) Find the joint m.g.f of X and Y.
- (6) Find the marginal m.g.f of X and the marginal m.g.f of Y.
- (7) Use the joint m.g.f and find  $E(X)$ ,  $\text{var}(X)$ ,  $E(Y)$ ,  $\text{var}(Y)$ ,  $\text{Cov}(X, Y)$  and  $\rho(X, Y)$ .

Solution

(1) The marginal p.d.f of X is  $f_1(x) = \int_y f(x, y) dy = \int_{y=x}^{\infty} e^{-y} dy$

$$f_1(x) = -e^{-y} \Big|_x^{\infty} = -(e^{-\infty} - e^{-x}) = e^{-x}, \quad 0 < x < \infty$$

$$= 0, \quad \text{r.w.}$$

The marginal p.d.f of Y is  $f_2(y) = \int_x f(x, y) dx = \int_{x=0}^y e^{-y} dx = e^{-y} x \Big|_0^y$

$$f_2(y) = e^{-y} (y - 0) = y e^{-y}, \quad 0 < y < \infty$$

$$= 0, \quad \text{r.w.}$$

(2)  $\mu_1 = E(X) = \int_x x f_1(x) dx = \int_0^{\infty} x e^{-x} dx = 1$

$$E(X^2) = \int_x x^2 f_1(x) dx = \int_0^{\infty} x^2 e^{-x} dx = 2$$

$$\Rightarrow \sigma_1^2 = \text{var}(X) = E(X^2) - \mu_1^2 = 2 - (1)^2 = 1$$

$$\mu_2 = E(Y) = \int_y y f_2(y) dy = \int_0^{\infty} y \cdot y e^{-y} dy = \int_0^{\infty} y^2 e^{-y} dy = 2$$

$$E(Y^2) = \int_y y^2 f_2(y) dy = \int_0^{\infty} y^2 \cdot y e^{-y} dy = \int_0^{\infty} y^3 e^{-y} dy = 6$$

$$\Rightarrow \sigma_2^2 = \text{Var}(Y) = E(Y^2) - \mu_2^2 = 6 - (2)^2 = 2$$

$$E(XY) = \int_x \int_y xy f(x,y) dx dy = \int_{x=0}^{\infty} \int_{y=x}^{\infty} xy e^{-y} dy dx \quad \text{or} \quad \int_{y=0}^{\infty} \int_{x=0}^y xy e^{-y} dx dy$$

$$= \int_{y=0}^{\infty} y e^{-y} \left( \frac{x^2}{2} \Big|_0^y \right) dy = \frac{1}{2} \int_0^{\infty} y^3 e^{-y} dy = \frac{6}{2} = 3$$

$$\text{Cov}(X, Y) = E(XY) - \mu_1 \mu_2 = 3 - (1)(2) = 1$$

$$\rho = \rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma_1 \sigma_2} = \frac{1}{\sqrt{1} \sqrt{2}} = \frac{1}{\sqrt{2}}$$

(3) The joint c.d.f of X and Y is

$$\begin{aligned} F(x, y) &= P_r(X \leq x, Y \leq y) = \int_{-\infty}^x \int_{-\infty}^y f(t, s) dt ds = \int_{t=0}^x \int_{s=t}^y e^{-s} ds dt \\ &= \int_{t=0}^x \left( -e^{-s} \Big|_t^y \right) dt = \int_{t=0}^x (e^{-t} - e^{-y}) dt = -e^{-t} - e^{-y} t \Big|_0^x \\ &= (-e^{-x} - x e^{-y}) - (-1 - 0) = \begin{cases} 1 - e^{-x} - x e^{-y}, & 0 < x < y < \infty \\ 1, & x = y, y = \infty \end{cases} \end{aligned}$$

(4) The marginal c.d.f of X and the marginal c.d.f of Y are:-

$$F_1(x) = F(x, \infty) = \begin{cases} 0, & x < 0 \\ 1 - e^{-x}, & 0 < x < \infty \\ 1, & x = \infty \end{cases}, \quad F_2(y) = F(y, y) = \begin{cases} 0, & y < 0 \\ 1 - e^{-y} - y e^{-y}, & 0 < y < \infty \\ 1, & y = \infty \end{cases}$$

(5) The joint m.g.f of X and Y is



$$M(t_1, t_2) = E(e^{t_1 X + t_2 Y}) = \int_x \int_y e^{t_1 x + t_2 y} f(x, y) dx dy = \int_{x=0}^{\infty} \int_{y=x}^{\infty} e^{t_1 x + t_2 y} e^{-y} dy dx$$

$$= \int_{x=0}^{\infty} e^{t_1 x} \left\{ \int_{y=x}^{\infty} e^{-(1-t_2)y} dy \right\} dx = \int_{x=0}^{\infty} e^{t_1 x} \left( -\frac{1}{1-t_2} e^{-(1-t_2)y} \right) \Big|_x^{\infty} dx$$

$$= -\frac{1}{1-t_2} \int_{x=0}^{\infty} e^{t_1 x} [0 - e^{-(1-t_2)x}] dx = \frac{1}{1-t_2} \int_{x=0}^{\infty} e^{-(1-t_1-t_2)x} dx$$

$$= -\frac{1}{(1-t_2)(1-t_1-t_2)} e^{-(1-t_1-t_2)x} \Big|_0^{\infty} = -\frac{1}{(1-t_2)(1-t_1-t_2)} (0-1)$$

$$\therefore M(t_1, t_2) = \frac{1}{(1-t_2)(1-t_1-t_2)} = (1-t_2)^{-1} (1-t_1-t_2)^{-1}, \quad t_2 < 1 \text{ and } t_1 + t_2 < 1$$

check:  $M(0, 0) = 1$

(6) The marginal m.g.f of  $X$  and the marginal m.g.f of  $Y$  are:-

$$M_1(t_1) = M(t_1, 0) = \frac{1}{(1-t_1)} = (1-t_1)^{-1}, \quad M_2(t_2) = M(0, t_2) = \frac{1}{(1-t_2)^2} = (1-t_2)^{-2}$$

$$(7) \frac{\partial M(t_1, t_2)}{\partial t_1} = (1-t_2)^{-1} (1-t_1-t_2)^{-2} \Rightarrow \frac{\partial M(0, 0)}{\partial t_1} = 1 = E(X) = \mu_1$$

$$\frac{\partial^2 M(t_1, t_2)}{\partial t_1^2} = 2(1-t_2)^{-1} (1-t_1-t_2)^{-3} \Rightarrow \frac{\partial^2 M(0, 0)}{\partial t_1^2} = 2 = E(X^2)$$

$$\Rightarrow \sigma_1^2 = \text{Var}(X) = E(X^2) - \mu_1^2 = 2 - (1)^2 = 1$$

$$\frac{\partial M(t_1, t_2)}{\partial t_2} = (1-t_2)^{-1} (1-t_1-t_2)^{-2} + (1-t_1-t_2)^{-1} (1-t_2)^{-2} \Rightarrow \frac{\partial M(0, 0)}{\partial t_2} = 1+1=2 = E(Y)$$

$$\frac{\partial^2 M(t_1, t_2)}{\partial t_2^2} = 2(1-t_2)^{-1} (1-t_1-t_2)^{-3} + (1-t_1-t_2)^{-2} (1-t_2)^{-2} + 2(1-t_1-t_2)^{-1} (1-t_2)^{-3} + (1-t_2)^{-2} (1-t_1-t_2)^{-2}$$

and defn Lec - The marg

$$\Rightarrow \frac{\partial^2 M(0,0)}{\partial t_2^2} = 2+1+2+1 = 6 = E(\gamma^2)$$

$$\Rightarrow \sigma_2^2 = \text{Var}(\gamma) = E(\gamma^2) - \mu_2^2 = 6 - (2)^2 = 2$$

$$\frac{\partial^2 M(t_1, t_2)}{\partial t_2 \partial t_1} = \frac{\partial^2 M(t_1, t_2)}{\partial t_1 \partial t_2} = 2(1-t_2)^{-1}(1-t_1-t_2)^{-3} + (1-t_1-t_2)^{-2}(1-t_2)^{-2}$$

$$\Rightarrow \frac{\partial^2 \psi(0,0)}{\partial t_2 \partial t_1} = 2+1 = 3 = E(X\gamma)$$

$$\Rightarrow \text{Cov}(X, \gamma) = E(X\gamma) - \mu_1 \mu_2 = 3 - (1)(2) = 1$$

$$\Rightarrow \rho = \rho(X, \gamma) = \frac{\text{Cov}(X, \gamma)}{\sigma_1 \sigma_2} = \frac{1}{\sqrt{1} \sqrt{2}} = \frac{1}{\sqrt{2}}$$

OR

$$\psi(t_1, t_2) = \ln M(t_1, t_2) = -\ln(1-t_2) - \ln(1-t_1-t_2)$$

$$\frac{\partial \psi(t_1, t_2)}{\partial t_1} = -\frac{(-1)}{1-t_1-t_2} = (1-t_1-t_2)^{-1} \Rightarrow \frac{\partial \psi(0,0)}{\partial t_1} = 1 = E(X) = \mu_1$$

$$\frac{\partial^2 \psi(t_1, t_2)}{\partial t_1^2} = (1-t_1-t_2)^{-2} \Rightarrow \frac{\partial^2 \psi(0,0)}{\partial t_1^2} = 1 = \text{Var}(X) = \sigma_1^2$$

$$\frac{\partial \psi(t_1, t_2)}{\partial t_2} = -\frac{(-1)}{(1-t_2)} - \frac{(-1)}{1-t_1-t_2} = (1-t_2)^{-1} + (1-t_1-t_2)^{-1}$$

$$\Rightarrow \frac{\partial \psi(0,0)}{\partial t_2} = 1+1 = 2 = E(\gamma) = \mu_2$$

$$\frac{\partial^2 \psi(t_1, t_2)}{\partial t_2^2} = (1-t_2)^{-2} + (1-t_1-t_2)^{-2} \Rightarrow \frac{\partial^2 \psi(0,0)}{\partial t_2^2} = 1+1 = 2 = \text{Var}(\gamma) = \sigma_2^2$$

$$\frac{\partial^2 \psi(t_1, t_2)}{\partial t_2 \partial t_1} = \frac{\partial^2 \psi(t_1, t_2)}{\partial t_1 \partial t_2} = (1-t_1-t_2)^{-2} \Rightarrow \frac{\partial^2 \psi(0,0)}{\partial t_2 \partial t_1} = 1 = \text{Cov}(X, \gamma)$$

$$\Rightarrow \rho = \rho(X, \gamma) = \frac{\text{Cov}(X, \gamma)}{\sigma_1 \sigma_2} = \frac{1}{\sqrt{1} \sqrt{2}} = \frac{1}{\sqrt{2}}$$

Conditional DistributionDefn

Let  $f_1(x)$ ,  $f_2(y)$ , and  $f(x,y)$  be respectively the marginal p.d.f of  $X$ , the marginal p.d.f of  $Y$ , and the joint p.d.f of  $X$  and  $Y$ . We define the conditional p.d.f of  $X$  given  $Y=y$  as

$$f_1(x|y) = \frac{f(x,y)}{f_2(y)}, \quad f_2(y) \neq 0$$

and the conditional p.d.f of  $Y$  given  $X=x$  as

$$f_2(y|x) = \frac{f(x,y)}{f_1(x)}, \quad f_1(x) \neq 0$$

To show that  $f_1(x|y)$  is valid p.d.f, we note that

(i)  $f_1(x|y) \geq 0$ , because  $f(x,y) \geq 0$  and  $f_2(y) > 0$

$$(ii) \sum_x f_1(x|y) = \sum_x \frac{f(x,y)}{f_2(y)} = \frac{1}{f_2(y)} \sum_x f(x,y) = \frac{f_2(y)}{f_2(y)} = 1$$

or

$$\int_x f_1(x|y) dx = \int_x \frac{f(x,y)}{f_2(y)} dx = \frac{1}{f_2(y)} \int_x f(x,y) dx = \frac{f_2(y)}{f_2(y)} = 1$$

Notes

$$(1) \Pr(a \leq X \leq b | Y=y) = \begin{cases} \sum_{x=a}^b f_1(x|y) & , \text{ for disc. case} \\ \int_{x=a}^b f_1(x|y) dx & , \text{ for cont. case} \end{cases}$$

$$\Pr(c \leq Y \leq d | X=x) = \begin{cases} \sum_{y=c}^d f_2(y|x) & , \text{ disc} \\ \int_{y=c}^d f_2(y|x) dy & , \text{ cont.} \end{cases}$$

(2) If  $u(X)$  is a function of  $X$  alone, then the conditional expectation of  $u(X)$  given  $Y=y$  is

$$E[u(X) | Y=y] = \begin{cases} \sum_x u(x) f_1(x|y) & , \text{ disc} \\ \int_x u(x) f_1(x|y) dx & , \text{ cont.} \end{cases}$$



If  $u(Y)$  is a function of  $Y$  alone, then the conditional  
 of  $u(Y)$  given  $X=x$  is

$$E[u(Y)|X=x] = \begin{cases} \sum_y u(y) f_2(y|x) & , \text{ disc} \\ \int u(y) f_2(y|x) dy & , \text{ cont.} \end{cases}$$

In particular the conditional mean and the conditional variance  
 of  $X$  given  $Y=y$

$$E[X|Y=y] = M_{x|y} = \begin{cases} \sum_x x f_1(x|y) & , \text{ disc} \\ \int x f_1(x|y) dx & , \text{ cont.} \end{cases}$$

$$E[X^2|Y=y] = \begin{cases} \sum_x x^2 f_1(x|y) & , \text{ disc} \\ \int x^2 f_1(x|y) dx & , \text{ cont.} \end{cases}$$

and

$$\text{Var}(X|Y=y) = \sigma_{x|y}^2 = E[X^2|Y=y] - M_{x|y}^2$$

Similarly the conditional mean and the conditional variance of  
 $Y$  given  $X=x$

$$E[Y|X=x] = M_{y|x} = \begin{cases} \sum_y y f_2(y|x) & , \text{ disc} \\ \int y f_2(y|x) dy & , \text{ cont.} \end{cases}$$

$$E[Y^2|X=x] = \begin{cases} \sum_y y^2 f_2(y|x) & , \text{ disc} \\ \int y^2 f_2(y|x) dy & , \text{ cont.} \end{cases}$$

and

$$\text{Var}(Y|X=x) = \sigma_{y|x}^2 = E[Y^2|X=x] - M_{y|x}^2$$

Q1

2) =

- Example (5) Back to Example (4) and find
- (1) The conditional p-d-f of  $X$  given  $Y=y$
  - (2) The conditional p-d-f of  $Y$  given  $X=x$
  - (3)  $E(X|Y=y)$  and  $Var(X|Y=y)$
  - (4)  $E(Y|X=x)$  and  $Var(Y|X=x)$ , (5)  $P(1 < X < 2)$  and  $P(1 < X < 2 | Y=2)$

Solution

We have  $f(x,y) = e^{-y}$ ,  $0 < x < y < \infty$

= 0, e.w

$$f_1(x) = e^{-x}, 0 < x < \infty, \quad f_2(y) = y e^{-y}, 0 < y < \infty$$

= 0, e.w

= 0, e.w

(1) The conditional p-d-f of  $X$  given  $Y=y$  is

$$f_1(x|y) = \frac{f(x,y)}{f_2(y)} = \frac{e^{-y}}{y e^{-y}} = \frac{1}{y}, \quad 0 < x < y \text{ for any } 0 < y < \infty$$

= 0, e.w

(2) The conditional p-d-f of  $Y$  given  $X=x$  is

$$f_2(y|x) = \frac{f(x,y)}{f_1(x)} = \frac{e^{-y}}{e^{-x}} = e^{-(y-x)}, \quad x < y < \infty \text{ for any } 0 < x < \infty$$

= 0, e.w

$$(3) \mu_{x|y} = E(X|Y=y) = \int_x^y x f_1(x|y) dx = \int_{x=0}^y x \frac{1}{y} dx = \frac{1}{y} \left( \frac{x^2}{2} \Big|_0^y \right) = \frac{y}{2}$$

$$E(X^2|Y=y) = \int_x^y x^2 f_1(x|y) dx = \int_{x=0}^y x^2 \frac{1}{y} dx = \frac{1}{y} \left( \frac{x^3}{3} \Big|_0^y \right) = \frac{y^2}{3}$$

$$\sigma_{x|y}^2 = Var(X|Y=y) = E(X^2|Y=y) - \mu_{x|y}^2 = \frac{y^2}{3} - \left( \frac{y}{2} \right)^2 = \frac{y^2}{12}$$

$$(4) \mu_{y|x} = E(Y|X=x) = \int_y^{\infty} y f_2(y|x) dy = \int_{y=x}^{\infty} y e^{-(y-x)} dx = e^x \int_x^{\infty} y e^{-y} dy$$

$$= e^x \left( -y e^{-y} - e^{-y} \Big|_x^{\infty} \right) = e^x \left( x e^{-x} + e^{-x} \right) = x + 1$$

$$E(Y^2|X=x) = \int_y^{\infty} y^2 f_2(y|x) dy = \int_{y=x}^{\infty} y^2 e^{-(y-x)} dy = e^x \int_x^{\infty} y^2 e^{-y} dy$$

$$= e^x \left( -y^2 e^{-y} - 2y e^{-y} - 2e^{-y} \Big|_x^{\infty} \right) = e^x \left( x^2 e^{-x} + 2x e^{-x} + 2e^{-x} \right) = x^2 + 2x + 2$$

$$\sigma_{Y|X}^2 = \text{Var}(Y|X=x) = E(Y^2|X=x) - \mu_{Y|X}^2 = x^2 + 2x + 2 - (x+1)^2 = x^2 + 2x + 2 - x^2 - 2x - 1 = 1$$

$$(5) \Pr(1 \leq X \leq 2) = \int_{x=1}^2 f_1(x) dx = \int_1^2 e^{-x} dx = -e^{-x} \Big|_1^2 = e^{-1} - e^{-2}$$

$$\Pr(1 \leq X \leq 2 | Y=2) = \int_{x=1}^2 f_1(x|Y=2) dx = \int_1^2 \frac{1}{2} dx = \frac{x}{2} \Big|_1^2 = \frac{1}{2}(2-1) = \frac{1}{2}$$

Example (6) Let the r.v.  $X$  has p.d.f  $f(x)$  and c.d.f  $F(x)$ .

Define  $f(x|X > x_0) = \frac{f(x)}{1-F(x_0)}$ ,  $x_0 < x < \infty$ ,  $x_0$  fixed number  
 $= 0$ , e.w,  $F(x_0) \neq 1$

(a) Show that  $f(x|X > x_0)$  be a conditional p.d.f of  $X$  given  $X > x_0$

(b) Let  $f(x) = e^{-x}$ ,  $0 < x < \infty$   
 $= 0$ , e.w. Compute  $\Pr(X > 2 | X > 1)$

Solution

(a) (i)  $f(x|X > x_0) \geq 0$ , yes, because  $f(x) \geq 0$  and  $1-F(x_0) > 0$

$$(ii) \int_{x_0}^{\infty} f(x|X > x_0) dx = \int_{x_0}^{\infty} \frac{f(x)}{1-F(x_0)} dx = \frac{1}{1-F(x_0)} \int_{x_0}^{\infty} f(x) dx$$

$$= \frac{1}{1-F(x_0)} F(x) \Big|_{x_0}^{\infty} = \frac{F(\infty) - F(x_0)}{1-F(x_0)} = \frac{1 - F(x_0)}{1-F(x_0)} = 1$$

(b)  $f(x) = e^{-x}$ ,  $0 < x < \infty$   $\Rightarrow$   $F(x) = \int_{-\infty}^x f(t) dt = \int_0^x e^{-t} dt = -e^{-t} \Big|_0^x = 1 - e^{-x}$   
 $= 0$ , e.w

$$f(x|X > 1) = \frac{f(x)}{1-F(1)} = \frac{e^{-x}}{1 - (1 - e^{-1})} = e \cdot e^{-x}, \quad 1 < x < \infty$$

$$= 0 \text{ e.w}$$

$$\Pr(X > 2 | X > 1) = \int_2^{\infty} f(x|X > 1) dx = \int_2^{\infty} e \cdot e^{-x} dx = -e(e^{-x}) \Big|_2^{\infty}$$

$$= -e(0 - e^{-2}) = e^{-1}$$



## Stochastic Independent

Defn Let  $X_1$  and  $X_2$  be two r.v.'s having joint p.d.f  $f(x_1, x_2)$  and marginal p.d.f's  $f_1(x_1)$  and  $f_2(x_2)$  respectively. The r.v.'s  $X_1$  and  $X_2$  are said to be sto. indep. if and only if  $f(x_1, x_2) = f_1(x_1) \cdot f_2(x_2)$ . otherwise  $X_1$  and  $X_2$  are said to be sto. dep.

Note If the r.v.'s  $X_1$  and  $X_2$  are sto. indep, we have

$$f_1(x_1|x_2) = \frac{f(x_1, x_2)}{f_2(x_2)} = \frac{f_1(x_1) \cdot f_2(x_2)}{f_2(x_2)} = f_1(x_1)$$

and

$$f_2(x_2|x_1) = \frac{f(x_1, x_2)}{f_1(x_1)} = \frac{f_1(x_1) \cdot f_2(x_2)}{f_1(x_1)} = f_2(x_2)$$

An alternative definition for sto. indep is as follows:-  
Let the r.v.'s  $X_1$  and  $X_2$  have the joint e.d.f  $F(x_1, x_2)$  and the marginals e.d.f's  $F_1(x_1)$  and  $F_2(x_2)$  respectively. The r.v.'s  $X_1$  and  $X_2$  are said to be sto. indep iff  $F(x_1, x_2) = F_1(x_1) \cdot F_2(x_2)$

Example (7) Back to Examples (1), (2), (3), and (4)

In Example (1), we have

(i)  $f(x, y) = \frac{1}{21}(x+y)$ ,  $x=1, 2, 3$ ;  $y=1, 2$   
 $= 0$ , e.w

and  $f_1(x) = \frac{1}{21}(2x+3)$ ,  $x=1, 2, 3$ ,  $f_2(y) = \frac{1}{7}(y+2)$ ,  $y=1, 2$   
 $= 0$ , e.w  $= 0$ , e.w

$$f_1(x) \cdot f_2(y) = \frac{1}{21 \cdot 7}(2x+3)(y+2) \neq \frac{1}{21}(x+y) = f(x, y)$$

and that implies the r.v.'s  $X$  and  $Y$  are sto. dep.

(ii)  $f(x, y) = e^{-(x+y)}$ ,  $0 < x < \infty$   
 $= 0$ , e.w

and  $f_1(x) = e^{-x}$ ,  $0 < x < \infty$ ,  $f_2(y) = e^{-y}$ ,  $0 < y < \infty$   
 $= 0$ , e.w  $= 0$ , e.w

$$f_1(x) \cdot f_2(y) = e^{-x} \cdot e^{-y} = e^{-(x+y)} = f(x, y) \Rightarrow X \text{ and } Y \text{ are sto. indep}$$

Example (2), we have

$$F(x, y) = \frac{1}{42} xy(x+y+2), \quad F_1(x) = \frac{1}{21} x(x+4), \quad F_2(y) = \frac{1}{14} y(y+5)$$

$$F_1(x) \cdot F_2(y) = \frac{1}{294} xy(x+4)(y+5) \neq \frac{1}{42} xy(x+y+2) = F(x, y) \\ \Rightarrow X \text{ and } Y \text{ are sto. dep}$$

(iii)  $F(x, y) = (1 - e^{-x}) / (1 - e^{-y})$ ,  $F_1(x) = 1 - e^{-x}$ ,  $F_2(y) = 1 - e^{-y}$

$$F_1(x) \cdot F_2(y) = (1 - e^{-x})(1 - e^{-y}) = F(x, y) \Rightarrow X \text{ and } Y \text{ are sto. indep.}$$

In Example (3), we have

$$f(x, y) = x + y, \quad f_1(x) = x + \frac{1}{2}, \quad f_2(y) = y + \frac{1}{2}$$

$$f_1(x) \cdot f_2(y) = (x + \frac{1}{2})(y + \frac{1}{2}) \neq x + y = f(x, y) \Rightarrow X \text{ and } Y \text{ are sto. dep.}$$

In Example (4), we have

$$f(x, y) = e^{-y}, \quad f_1(x) = e^{-x}, \quad f_2(y) = y e^{-y}$$

$$f_1(x) \cdot f_2(y) = e^{-x} \cdot y e^{-y} = y e^{-(x+y)} \neq e^{-y} = f(x, y) \Rightarrow X \text{ and } Y \text{ are sto. dep.}$$

Theorem (1) Let  $f(x_1, x_2)$  be the joint p.d.f of r.v.'s  $X_1$  and  $X_2$ . The r.v.'s  $X_1$  and  $X_2$  are sto. indep iff  $f(x_1, x_2)$  can be written as a product of a non-negative function of  $x_1$  alone and a non-negative function of  $x_2$  alone, that is

$$f(x_1, x_2) = g(x_1) \cdot h(x_2) \text{ where } g(x_1) > 0 \text{ and } h(x_2) > 0$$

proof

$\Rightarrow$  Let the r.v.'s  $X_1$  and  $X_2$  are sto. indep, then

$f(x_1, x_2) = f_1(x_1) \cdot f_2(x_2)$ , where  $f_1(x_1)$  is the marginal p.d.f of r.v.  $X_1$  which is a function of  $x_1$  alone and  $f_2(x_2)$  is the marginal p.d.f of  $X_2$  which is a function of  $x_2$  alone.

Thus, the condition  $f(x_1, x_2) = g(x_1) h(x_2)$  is fulfilled.

$\Leftarrow$  Let  $f(x_1, x_2) = g(x_1) h(x_2)$ , where  $g(x_1) > 0$  is a function of  $x_1$  alone and  $h(x_2) > 0$  is a function of  $x_2$  alone.

Consider the cont. case

$$f_1(x_1) = \int_{x_2} f(x_1, x_2) dx_2 = \int_{x_2} g(x_1) h(x_2) dx_2 = g(x_1) \int_{x_2} h(x_2) dx_2 = c_1 g(x_1)$$

and

$$f_2(x_2) = \int_{x_1} f(x_1, x_2) dx_1 = \int_{x_1} g(x_1) h(x_2) dx_1 = h(x_2) \int_{x_1} g(x_1) dx_1 = c_2 h(x_2)$$

$$\begin{aligned} \text{but } 1 &= \int_{x_1} \int_{x_2} f(x_1, x_2) dx_1 dx_2 = \int_{x_1} \int_{x_2} g(x_1) h(x_2) dx_1 dx_2 \\ &= \left( \int_{x_1} g(x_1) dx_1 \right) \cdot \left( \int_{x_2} h(x_2) dx_2 \right) = c_1 c_2 \end{aligned}$$

$\therefore f(x_1, x_2) = g(x_1) \cdot h(x_2) = c_1 g(x_1) \cdot c_2 h(x_2) = f_1(x_1) \cdot f_2(x_2)$   
 $\therefore$  The r.v.'s  $X_1$  and  $X_2$  are st. indep.

Theorem (2) If the r.v.'s  $X_1$  and  $X_2$  are st. indep., then

- (1)  $Pr(a \leq X_1 \leq b, c \leq X_2 \leq d) = Pr(a \leq X_1 \leq b) \cdot Pr(c \leq X_2 \leq d)$
- (2)  $E[u(X_1) \cdot v(X_2)] = E[u(X_1)] \cdot E[v(X_2)]$ , where  $u(x_1)$  is a function of  $x_1$  alone and  $v(x_2)$  is a function of  $x_2$  alone.

proof

Consider the cont. case

$$\begin{aligned} (1) Pr(a \leq X_1 \leq b, c \leq X_2 \leq d) &= \int_a^b \int_c^d f(x_1, x_2) dx_1 dx_2 \\ &= \int_a^b \int_c^d f_1(x_1) \cdot f_2(x_2) dx_1 dx_2 \\ &= \left( \int_a^b f_1(x_1) dx_1 \right) \cdot \left( \int_c^d f_2(x_2) dx_2 \right) \\ &= Pr(a \leq X_1 \leq b) \cdot Pr(c \leq X_2 \leq d) \end{aligned}$$

$$\begin{aligned} (2) E[u(X_1) \cdot v(X_2)] &= \int_{x_1} \int_{x_2} u(x_1) \cdot v(x_2) f(x_1, x_2) dx_1 dx_2 \\ &= \int_{x_1} \int_{x_2} u(x_1) \cdot v(x_2) f_1(x_1) \cdot f_2(x_2) dx_1 dx_2 \\ &= \left( \int_{x_1} u(x_1) f_1(x_1) dx_1 \right) \cdot \left( \int_{x_2} v(x_2) f_2(x_2) dx_2 \right) \\ &= E[u(X_1)] \cdot E[v(X_2)] \end{aligned}$$



If the r.v.'s  $X$  and  $Y$  are stochastically independent, then

$$E(XY) = E(X) \cdot E(Y) = \mu_1 \mu_2$$

$$Cov(X, Y) = E(XY) - \mu_1 \mu_2 = E(X) \cdot E(Y) - \mu_1 \mu_2 = \mu_1 \mu_2 - \mu_1 \mu_2 = 0$$

$\Rightarrow P = P(X, Y) = 0$ , but the converse is not true. That is if  $P = 0$  does not imply that  $X$  and  $Y$  are stochastically independent.

Theorem (4) - Let  $f(x_1, x_2)$  be the joint p.d.f of r.v.'s  $X_1$  and  $X_2$  with marginals p.d.f's  $f_1(x_1)$  and  $f_2(x_2)$  and let  $M(t_1, t_2)$  be the joint m.g.f of r.v.'s  $X_1$  and  $X_2$  with marginals m.g.f's  $M_1(t_1)$  and  $M_2(t_2)$ . The r.v.'s  $X_1$  and  $X_2$  are stochastically independent iff  $M(t_1, t_2) = M_1(t_1) M_2(t_2)$

Proof

$\Rightarrow$  Let the r.v.'s  $X_1$  and  $X_2$  be stochastically independent, then

$$M(t_1, t_2) = E(e^{t_1 X_1 + t_2 X_2}) = E(e^{t_1 X_1} \cdot e^{t_2 X_2}) \stackrel{\text{by Theorem (3) part (2)}}{=} E(e^{t_1 X_1}) \cdot E(e^{t_2 X_2}) = M_1(t_1) \cdot M_2(t_2)$$

$\Leftarrow$  Let  $M(t_1, t_2) = M_1(t_1) \cdot M_2(t_2)$  and consider the cont. case

$$M_1(t_1) = E(e^{t_1 X_1}) = \int_{x_1} e^{t_1 x_1} f_1(x_1) dx_1 \quad \text{and} \quad M_2(t_2) = E(e^{t_2 X_2}) = \int_{x_2} e^{t_2 x_2} f_2(x_2) dx_2$$

$$\begin{aligned} \text{So} \quad M_1(t_1) \cdot M_2(t_2) &= \left( \int_{x_1} e^{t_1 x_1} f_1(x_1) dx_1 \right) \left( \int_{x_2} e^{t_2 x_2} f_2(x_2) dx_2 \right) \\ &= \iint_{x_1, x_2} e^{t_1 x_1 + t_2 x_2} f_1(x_1) f_2(x_2) dx_1 dx_2 \end{aligned}$$

But

$$M(t_1, t_2) = E(e^{t_1 X_1 + t_2 X_2}) = \iint_{x_1, x_2} e^{t_1 x_1 + t_2 x_2} f(x_1, x_2) dx_1 dx_2$$

and  $M(t_1, t_2) = M_1(t_1) \cdot M_2(t_2)$ , then

$$\iint_{x_1, x_2} e^{t_1 x_1 + t_2 x_2} f_1(x_1) f_2(x_2) dx_1 dx_2 = \iint_{x_1, x_2} e^{t_1 x_1 + t_2 x_2} f(x_1, x_2) dx_1 dx_2$$

that implies  $f(x_1, x_2) = f_1(x_1) \cdot f_2(x_2)$

$\therefore$  the r.v.'s  $X_1$  and  $X_2$  are stochastically independent

Example (8) Back to Example (4), we have  
 $M(t_1, t_2) = (1-t_2)^{-1} (1-t_1-t_2)^{-1}$ ,  $M_1(t_1) = (1-t_1)^{-1}$ ,  $M_2(t_2) = (1-t_2)^{-1}$

$$M_1(t_1) \cdot M_2(t_2) = (1-t_1)^{-1} (1-t_2)^{-1} \neq (1-t_1-t_2)^{-1} = M(t_1, t_2)$$

$\therefore$  the r.v.'s  $X$  and  $Y$  are stochastically dependent.

Example (9) Let the joint m.g.f of r.v.'s  $X$  and  $Y$  be  $M(t_1, t_2) = \frac{e^{t_1^2}}{1-2t_2}$

- (1) Find the marginal m.g.f of  $X$  and the marginal m.g.f of  $Y$ .
- (2) Test whether or not  $X$  and  $Y$  are stochastically independent.
- (3) Find the correlation coefficient between  $X$  and  $Y$ .

Solution

(1) The marginal m.g.f of  $X$  and the marginal p.d.f of  $Y$  are

$$M_1(t_1) = M(t_1, 0) = e^{t_1^2}, \quad M_2(t_2) = M(0, t_2) = (1-2t_2)^{-1}$$

$$(2) M_1(t_1) \cdot M_2(t_2) = \frac{e^{t_1^2}}{1-2t_2} \neq M(t_1, t_2) \Rightarrow X \text{ and } Y \text{ are stochastically dependent.}$$

$$(3) \text{ Let } \psi(t_1) = \ln M_1(t_1) = t_1^2 \Rightarrow \frac{\partial \psi(t_1)}{\partial t_1} = 2t_1 \Rightarrow \left. \frac{\partial \psi(t_1)}{\partial t_1} \right|_{t_1=0} = 0 = E(X)$$

$$\frac{\partial^2 \psi(t_1)}{\partial t_1^2} = 2 \Rightarrow \left. \frac{\partial^2 \psi(t_1)}{\partial t_1^2} \right|_{t_1=0} = 2 = \text{Var}(X) = \sigma_1^2$$

$$\text{Let } \psi(t_2) = \ln M_2(t_2) = -\ln(1-2t_2) \Rightarrow \frac{\partial \psi(t_2)}{\partial t_2} = \frac{2}{1-2t_2} = 2(1-2t_2)^{-1}$$

$$\Rightarrow \left. \frac{\partial \psi(t_2)}{\partial t_2} \right|_{t_2=0} = 2 = E(Y) = \mu_2, \quad \frac{\partial^2 \psi(t_2)}{\partial t_2^2} = 4(1-2t_2)^{-2}$$

$$\left. \frac{\partial^2 \psi(t_2)}{\partial t_2^2} \right|_{t_2=0} = 4 = \text{Var}(Y) = \sigma_2^2$$

$$\text{Let } \psi(t_1, t_2) = \ln M(t_1, t_2) = t_1^2 (1-2t_2)^{-1} - \ln(1-2t_2)$$

$$\frac{\partial \psi(t_1, t_2)}{\partial t_1} = 2t_1 (1-2t_2)^{-1} \Rightarrow \frac{\partial^2 \psi(t_1, t_2)}{\partial t_2 \partial t_1} = 4t_1 (1-2t_2)^{-2}$$

$$\left. \frac{\partial^2 \psi(t_1, t_2)}{\partial t_2 \partial t_1} \right|_{t_1=t_2=0} = 0 = \text{Cov}(X, Y) \Rightarrow \rho = \frac{\text{Cov}(X, Y)}{\sigma_1 \sigma_2} = \frac{0}{2\sqrt{2}} = 0$$