

## Lecture - 6 ①

Expected Values  $\rightarrow$  Let  $X$  and  $Y$  be jointly r.v with pmf  $p_{X,Y}(x,y)$  or pdf  $f_{X,Y}(x,y)$  then the expected values of a function  $h(X,Y)$  is denoted as  $E(h(X,Y))$  and defined as

$$E(h(X,Y)) = \begin{cases} \sum_{x \in R_X} \sum_{y \in R_Y} h(x,y) \cdot p_{X,Y}(x,y); & \text{discrete} \\ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x,y) \cdot f_{X,Y}(x,y) dx dy; & \text{continuous} \end{cases}$$

Covariance : In covariance, we are discussing that, how two r.v  $X$  and  $Y$  related.

~~It is a measure of the degree to which two variables are related. It is calculated as the product of the deviation of each variable from its mean, divided by the product of their standard deviations. It ranges from -1 to 1. A value of 1 means perfect positive correlation, -1 means perfect negative correlation, and 0 means no correlation.~~

(\*) If covariance between two r.v is positive, it means they are positively related. That is by increasing one variable, other is also increased.

e.g population and pollution are positively related.

(xx) If covariance between two r.v is negative, it means they are negatively related i.e by increasing one variable other is decreases.

e.g plantation and pollution are negatively related.

Def'n

(2)

Let  $X$  and  $Y$  be the r.v then covariance between  $X$  and  $Y$  is denoted as  $\text{cov}(X, Y)$  and defined as

$$\begin{aligned}\text{cov}(X, Y) &= E[(X - E(X))(Y - E(Y))] \\ &= E[XY - \underset{\substack{\downarrow \\ \text{constant}}}{X E(Y)} - \underset{\substack{\downarrow \\ \text{constant}}}{Y E(X)} + \underbrace{E(X) \cdot E(Y)}_{\text{constant}}]\end{aligned}$$

$$\therefore E(X) = \begin{cases} \sum x \cdot p_X(x); \text{ discrete} \\ \int_{-\infty}^{\infty} x \cdot f_X(x) dx; \text{ continuous} \end{cases}$$

and  $E(Y)$  are constant values and  $E(aX + b) = aE(X) + b$  then

$$\text{cov}(X, Y) = E(XY) - E(X) \cdot E(Y) - \cancel{E(Y) \cdot E(X)} + \cancel{E(X) \cdot E(Y)}$$

$$\text{cov}(X, Y) = E(XY) - E(X) \cdot E(Y)$$

See Example  
S.16; (in book)

Note 1

if  $\text{cov}(X, Y) > 0 \rightarrow$  positively related

$< 0 \rightarrow$  Negatively related

~~if  $\text{cov}(X, Y) = 0$  then  $X$  and  $Y$  are independent.~~

Note :

if  $X$  and  $Y$  are independent then

$$E(XY) = E(X) \cdot E(Y).$$

in this case  $\text{cov}(X, Y) = 0$ . But converse of this statement need not be true. i.e. if  $\text{cov}(X, Y) = 0$  then  $X$  and  $Y$  may be dependent.

(3)  
 Let  $X \sim U[-1, 1]$  (Uniform dist<sup>n</sup>)  
 and  $Y = X^2$  then we need to show that  
 $\text{cov}(X, Y) = 0$  but  $X$  and  $Y$  are not independent

Sol<sup>n</sup>

$$\because X \sim U[-1, 1]$$

$$f_X(x) = \frac{1}{1-(-1)} = \frac{1}{2}; \quad x \in [-1, 1]$$

$$E(X) = \frac{1+(-1)}{2} = 0$$

$$\text{cov}(X, Y) = E(XY) - E(X) \cdot E(Y)$$

$X \sim U[a, b]$   
 $f_X(x) = \frac{1}{b-a}; a \leq x \leq b$   
 $E(X) = \frac{a+b}{2}$   
 $V(X) = \frac{(b-a)^2}{12}$

Now;  $E(XY) = E(X \cdot X^2) \quad (\because Y = X^2)$   
 $= E(X^3) = \int_{-1}^1 x^3 \cdot \frac{1}{2} dx = 0$   
 $\rightarrow$  odd integral

Thus  $\text{cov}(X, Y) = 0 - 0 \cdot E(Y)$   
 $= 0$

but  $X$  and  $Y$  are not independent as they are  
 written in terms of each other i.e.  $Y = X^2$ .

Correlation: The correlation or correlation coefficient  
 between two r.v  $X$  and  $Y$  is defined as

$$\text{Corr}(X, Y) \text{ or } \rho_{X,Y} = \frac{\text{cov}(X, Y)}{\sigma_X \cdot \sigma_Y}$$

$\downarrow$   
 standard deviation of  $X$        $\downarrow$  standard deviation of  $Y$

$\text{corr}(X, Y) = 1 \rightarrow$  perfectly linear correlated in +ve direction  
 $= -1 \rightarrow$  perfectly linear correlation in -ve direction

**Example 5.15** The joint and marginal pmf's for  $X$  = automobile policy deductible amount and  $Y$  = homeowner policy deductible amount in Example 5.1 were

		$y$					$y$		
$p(x, y)$		0	100	200	$x$		0	100	200
$x$	100	.20	.10	.20	$p_X(x)$	100	$p_Y(y)$	.25	.25
	250	.05	.15	.30		250		.25	.5

from which  $\mu_X = \sum x p_X(x) = 175$  and  $\mu_Y = 125$ . Therefore,

$$\begin{aligned}
 \text{Cov}(X, Y) &= \sum_{(x, y)} (x - 175)(y - 125)p(x, y) \\
 &= (100 - 175)(0 - 125)(.20) + \dots \\
 &\quad + (250 - 175)(200 - 125)(.30) \\
 &= 1875
 \end{aligned}$$



**Example 5.16** The joint and marginal pdf's of  $X$  = amount of almonds and  $Y$  = amount of cashews were)  
(Example 5.5 continued)

$$f(x, y) = \begin{cases} 24xy & 0 \leq x \leq 1, 0 \leq y \leq 1, x + y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$f_X(x) = \begin{cases} 12x(1 - x)^2 & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

with  $f_Y(y)$  obtained by replacing  $x$  by  $y$  in  $f_X(x)$ . It is easily verified that  $\mu_X = \mu_Y = \frac{2}{5}$ , and

$$\begin{aligned} E(XY) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f(x, y) dx dy = \int_0^1 \int_0^{1-x} xy \cdot 24xy dy dx \\ &= 8 \int_0^1 x^2(1 - x)^3 dx = \frac{2}{15} \end{aligned}$$

Thus  $\text{Cov}(X, Y) = \frac{2}{15} - \left(\frac{2}{5}\right)\left(\frac{2}{5}\right) = \frac{2}{15} - \frac{4}{25} = -\frac{2}{75}$ . A negative covariance is reasonable here because more almonds in the can implies fewer cashews. ■

It might appear that the relationship in the insurance example is quite strong since  $\text{Cov}(X, Y) = 1875$ , whereas  $\text{Cov}(X, Y) = -\frac{2}{75}$  in the nut example would seem to imply quite a weak relationship. Unfortunately, the covariance has a serious defect that makes it impossible to interpret a computed value. In the insurance example, suppose we had expressed the deductible amount in cents rather than in dollars. Then  $100X$  would replace  $X$ ,  $100Y$  would replace  $Y$ , and the resulting covariance would be  $\text{Cov}(100X, 100Y) = (100)(100)\text{Cov}(X, Y) = 18,750,000$ . If, on the other hand, the deductible amount had been expressed in hundreds of dollars, the computed covariance would have been  $(.01)(.01)(1875) = .1875$ . *The defect of covariance is that its computed value depends critically on the units of measurement.* Ideally, the choice of units should have no effect on a measure of strength of relationship. This is achieved by scaling the covariance.