

## Section 2.4 The Correlation Coefficient

Let  $X$  and  $Y$  be two random variables. The correlation coefficient of  $X$  and  $Y$  is defined to be the covariance of  $X$  and  $Y$ , divided by the  $\sqrt{\sigma_1^2 \sigma_2^2}$ .  $\rho_{xy} = \frac{\text{Cov}(x, y)}{\sqrt{\sigma_1^2 \sigma_2^2}} = \frac{E((x - \mu_1)(y - \mu_2))}{\sigma_1 \sigma_2} = \frac{E(XY) - \mu_1 \mu_2}{\sigma_1 \sigma_2}$

Note:  $\text{Cov}(x, y) = E(XY) - \mu_1 \mu_2$  or  $E(XY) = \text{Cov}(x, y) + \mu_1 \mu_2$

**Example 1:** Consider  $f(x, y) = x + y$ ; where  $0 < x < 1$  and  $0 < y < 1$ .

$$f(x) = \int_0^1 x + y \, dy = x + \frac{y^2}{2} \Big|_0^1 = x + \frac{1}{2}; \quad 0 < x < 1;$$

$$f(x) = x + \frac{1}{2}; \quad 0 < x < 1$$

$$E(X) = \int_0^1 x(x + \frac{1}{2}) \, dx = \frac{x^3}{3} + \frac{x^2}{4} \Big|_0^1 = \frac{1}{3} + \frac{1}{4} = \frac{7}{12};$$

$$E(X) = \frac{7}{12} = \mu_1. \quad \text{Similarly, } E(Y) = \frac{7}{12} = \mu_2$$

$$E(X^2) = \int_0^1 x^2(x + \frac{1}{2}) \, dx = \frac{x^4}{4} + \frac{x^3}{6} \Big|_0^1 = \frac{1}{4} + \frac{1}{6} = \frac{10}{24} = \frac{5}{12};$$

$$E(X^2) = \frac{5}{12}. \quad \text{Similarly, } E(Y^2) = \frac{5}{12}$$

$$\sigma_1^2 = E(X^2) - (E(X))^2 = \frac{5}{12} - \left(\frac{7}{12}\right)^2 = \frac{60-49}{144} = \frac{11}{144};$$

$$\sigma_1^2 = \frac{11}{144}. \quad \text{Similarly, } \sigma_2^2 = \frac{11}{144}$$

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

$$\rho_{xy} = \frac{\text{Cov}(x, y)}{\sqrt{\sigma_1^2 \sigma_2^2}} = \frac{E(XY) - \mu_1 \mu_2}{\sqrt{\sigma_1^2 \sigma_2^2}} = \frac{\frac{2}{6} - \frac{7}{12} \cdot \frac{7}{12}}{\sqrt{\frac{11}{144} \cdot \frac{11}{144}}} = \frac{-\frac{1}{144}}{\frac{11}{144}} = -\frac{1}{11} = -0.090909; \quad \rho_{xy} = -0.090909$$

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

If  $\rho = 1$ , there is a line with equation  $y = a + bx$ ,  $b > 0$ . Hence, the probability for the distribution of  $X$  and  $Y$  comes from the points on the straight line, so  $P(y = a + bx) = 1$ .

If  $\rho = -1$ , we have the same thing but  $b < 0$ .

**Question:** Is there a line in the  $XY$ -plane such that the probability for  $X$  and  $Y$  tends to concentrate around this line?

If  $y$  has a linear conditional mean, that is,  $E(Y|x) = \int_{-\infty}^{\infty} y f(y|x) \, dy = a + bx$ , we can find the constants

$a$ , and  $b$ . Mathematics shows that  $b = \rho \frac{\sigma_2}{\sigma_1}$  and  $a = \mu_2 - \rho \frac{\sigma_2}{\sigma_1} \mu_1$ .

$$E(Y|x) = \int_{-\infty}^{\infty} y f(y|x) \, dy = a + bx = \mu_2 - \rho \frac{\sigma_2}{\sigma_1} \mu_1 + \rho \frac{\sigma_2}{\sigma_1} x = \mu_2 + \rho \frac{\sigma_2}{\sigma_1} (x - \mu_1)$$

Hence, the linear conditional mean of

$$E(Y|x) = \mu_2 + \rho \frac{\sigma_2}{\sigma_1} (x - \mu_1)$$

and

$$E(X|y) = \mu_1 + \rho \frac{\sigma_1}{\sigma_2} (y - \mu_2)$$

If Y has a linear conditional mean:  $E(Y|x) = \mu_2 + \rho \frac{\sigma_2}{\sigma_1} (x - \mu_1)$ , then the variance of the conditional distribution is  $\sigma_{Y|x}^2 = \sigma_2^2 (1 - \rho^2)$ .

Results from the conditional variance of Y given X. Note: Since the variance is greater or equal to zero, it implies that

$$1. (1 - \rho^2) \geq 0 \Rightarrow \rho^2 \leq 1 \Rightarrow -1 \leq \rho \leq 1$$

$$2. \sigma_{Y|x}^2 = \sigma_2^2 (1 - \rho^2); \text{ Note: If } \rho = 0, \text{ then } \sigma_{Y|x}^2 = \sigma_2^2$$

$$3. \text{ If } \rho > 0, \text{ then } \sigma_{Y|x}^2 < \sigma_2^2$$

$$4. \text{ Note: } \rho \frac{\sigma_2}{\sigma_1} \times \rho \frac{\sigma_1}{\sigma_2} = \rho^2$$

5. If  $\rho^2$  is near one then  $\sigma_{Y|x}^2$  is relatively small, meaning there is a high concentration of the probability for this conditional distribution near the conditional mean of Y given X;  $E(Y|x) = \mu_2 + \rho \frac{\sigma_2}{\sigma_1} (x - \mu_1)$ .

Note: If the random variables are discrete the results will still hold.

**Example 2:** Given the conditional means  $E(Y|x) = 4x + 3$  and  $E(X|y) = \frac{1}{16}y - 3$ , find  $\mu_1$ ,  $\mu_2$ , and  $\rho$ .

$$\begin{array}{l|l} E(E(Y|x)) = E(4x + 3) & E(E(X|y)) = E(\frac{1}{16}y - 3) \\ \mu_2 = 4\mu_1 + 3 & \mu_1 = \frac{1}{16}\mu_2 - 3 \end{array}$$

$$\text{Hence, } \mu_2 = 4(\frac{1}{16}\mu_2 - 3) + 3 = \frac{1}{4}\mu_2 - 12 + 3 \Rightarrow \mu_2 = \frac{1}{4}\mu_2 - 9 \Rightarrow 4\mu_2 = \mu_2 - 36 \Rightarrow \mu_2 = -12$$

$$\mu_1 = \frac{1}{16}(-12) - 3 \Rightarrow \mu_1 = -\frac{15}{4}$$

Note:  $E(Y|x) = a_2 + b_2x$  and  $E(X|y) = a_1 + b_1y \Rightarrow \rho^2 = b_1b_2$ . Hence,  $\rho^2 = 4 \times \frac{1}{16} = \frac{1}{4}$

$\rho = \pm\sqrt{\frac{1}{4}} \Rightarrow \rho = \pm\frac{1}{2}$ . Since the coefficients of X and Y are both positive,  $\rho = \frac{1}{2}$ .

**Example 3:** Consider the pdf  $f(x, y) = e^{-y}$ ;  $0 < x < y < \infty$ .

$$\begin{aligned} M(t_1, t_2) &= E(e^{t_1x+t_2y}) = \int_0^\infty \int_x^\infty e^{t_1x+t_2y} e^{-y} dy dx = \int_0^\infty \int_x^\infty e^{t_1x} e^{-y(1-t_2)} dy dx = \int_0^\infty e^{t_1x} \left( -\frac{1}{1-t_2} e^{-y(1-t_2)} \Big|_x^\infty \right) dx \\ &= \int_0^\infty e^{t_1x} \frac{e^{-x(1-t_2)}}{(1-t_2)} dx = \int_0^\infty \frac{e^{-x(1-t_1-t_2)}}{(1-t_2)} dx = \frac{1}{(1-t_2)} \Gamma(1) \left( \frac{1}{(1-t_1-t_2)} \right)^1 = \frac{1}{(1-t_2)(1-t_1-t_2)} \end{aligned}$$

Hence,  $M(t_1, t_2) = \frac{1}{(1-t_2)(1-t_1-t_2)}$ ; where  $t_2 < 1$  and  $t_1 + t_2 < 1$ . Now, using this mgf verify that  $\mu_1 = 1$ ,  $\mu_2 = 2$ ,  $\sigma_1^2 = 1$ ,  $\sigma_2^2 = 2$ , and  $E((X - \mu_1)(Y - \mu_2)) = 1$ .

$$M(t_1) = M(t_1, 0) = \frac{1}{(1-0)(1-t_1-0)} = \frac{1}{1-t_1} = (1-t_1)^{-1}.$$

$$\mu_1 = M'(t_1=0) = -1(1-t_1)^{-2}(-1) \Big|_{t_1=0} = 1$$

$$M(t_2) = M(0, t_2) = \frac{1}{(1-t_2)(1-0-t_2)} = \frac{1}{(1-t_2)^2} = (1-t_2)^{-2}.$$

$$\mu_2 = M'(t_2=0) = -2(1-t_2)^{-3}(-1) \Big|_{t_2=0} = 2$$

$$E(X^2) = M''(t_1) = -2(1-t_1)^{-3}(-1) \Big|_{t_1=0} = 2 \quad \text{and}$$

$$\sigma_1^2 = E(X^2) - (\mu_1)^2 = 2 - (1)^2 = 1$$

$$E(Y^2) = M''(t_2) = 2(-3)(1-t_1)^{-4}(-1) \Big|_{t_2=0} = 6 \quad \text{and}$$

$$\sigma_2^2 = E(Y^2) - (\mu_2)^2 = 6 - (2)^2 = 2$$

To compute the expected value of,  $E(XY) = \frac{\partial^2 M(0,0)}{\partial t_1^1 \partial t_2^1}$ , first we take the derivative w.r.t.  $t_1$ ; i.e.

$$\frac{\partial}{\partial t_1} \left( (1-t_2)^{-1} (1-t_1-t_2)^{-1} \right) = (1-t_2)^{-1} (-1)(1-t_1-t_2)^{-2} (-1) = (1-t_2)^{-1} (1-t_1-t_2)^{-2}.$$

Next, we use the derivative w.r.t.  $t_1$  to take the derivative with respect to  $t_2$ ; i.e

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

$$\text{Hence, } E(XY) = \frac{\partial^2 M(0,0)}{\partial t_1^1 \partial t_2^1} = (1-t_2)^{-2} (1-t_1-t_2)^2 + (1-t_2)^{-1} (2)(1-t_1-t_2)^{-3} \Big|_{t_1=t_2=0} = 1 + 2 = 3$$

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

$$\text{Finally, } \rho_{xy} = \frac{\text{Cov}(x, y)}{\sqrt{\sigma_1^2 \sigma_2^2}} = \frac{1}{\sqrt{1 \times 2}} = \frac{1}{\sqrt{2}}$$

**Example 4:** Consider the joint pdf  $f(x, y) = e^{-y}$ ;  $0 < x < y < \infty$ . From **Example 3** we know that  $\mu_1 = 1, \mu_2 = 2, \sigma_1^2 = 1, \sigma_2^2 = 2$ , and  $\rho = \frac{1}{\sqrt{2}}$ ;  $f(x) = e^{-x}$ ;  $0 < x < \infty$  and  $f(y) = ye^{-y}$ ;  $0 < y < \infty$ . The conditional pdfs are  $f(x|y) = \frac{1}{y}$ ;  $0 < x < y$  and  $f(y|x) = \frac{e^{-y}}{e^{-x}}$ ;  $x < y < \infty$ .

$$E(X|y) = \int_0^y \frac{x}{y} dx = \frac{x^2}{2y} \Big|_0^y = \frac{y}{2} ; \text{ Hence, } E(X|y) = \frac{y}{2} ; 0 < y < \infty$$

$$E(Y|x) = \int_x^\infty \frac{ye^{-y}}{e^{-x}} dy = \frac{1}{e^{-x}} \left[ -ye^{-y} \Big|_x^\infty - \int_x^\infty -e^{-y} dy \right] = \frac{1}{e^{-x}} \left[ 0 + xe^{-x} - e^{-x} \Big|_x^\infty \right] = \frac{1}{e^{-x}} \left[ 0 + xe^{-x} + e^{-x} \right] = x + 1$$

$$E(Y|x) = x + 1 ; 0 < x < \infty$$

Since the conditional means are linear we can use  $\rho^2 = b_1 b_2$  to find the correlation  $\rho$ .

$$\rho^2 = 1 \times \frac{1}{2} = \frac{1}{2} \Rightarrow \rho = \pm \sqrt{\frac{1}{2}} \Rightarrow \rho = \frac{1}{\sqrt{2}}. \text{ Same answer as in Example 3.}$$

Now use the information given in this example to compute

$$E(Y|x) = \mu_2 + \rho \frac{\sigma_2}{\sigma_1} (x - \mu_1) = 2 + \frac{1}{\sqrt{2}} \frac{\sqrt{2}}{1} (x - 1) = 2 + x - 1 = x + 1;$$

$$E(Y|x) = x + 1$$

$$E(X|y) = \mu_1 + \rho \frac{\sigma_1}{\sigma_2} (y - \mu_2) = 1 + \frac{1}{\sqrt{2}} \frac{1}{\sqrt{2}} (y - 2) = 1 + \frac{1}{2} (y - 2) = 1 + \frac{y}{2} - 1 = \frac{y}{2};$$

$$E(X|y) = \frac{y}{2}$$

[Redacted]

### Homework 2.4

1. If the pdf of X and Y is given by  $f(x, y)$  and  $0 < x < y < 1$ , give the formulas for the following.

a.  $\rho_{xy} =$

b.  $E(E(X|y)) =$

c.  $Cov(X, Y) =$

d. If X and Y have linear conditional means, then  $E(X|y) =$

$$E(Y|x) =$$

e. If X has a linear conditional mean, then  $\sigma_{X|y}^2 =$

2. Given the conditional means  $E(Y|x) = -2x - 1$  and  $E(X|y) = -\frac{1}{5}y + 2$ , find  $\mu_1$ ,  $\mu_2$ , and  $\rho$ .

3. Consider the pdf  $f(x, y) = \frac{1}{2}x^2e^{-y}$ ;  $0 < x < y < \infty$ . Compute the correlation between X and Y.

4. Consider the joint pdf  $f(x, y) = 4e^{-2y}$ ;  $0 < x < y < \infty$ .

Given  $\mu_1 = \frac{1}{2}$ ,  $\mu_2 = 1$ ,  $\sigma_1^2 = \frac{1}{4}$ ,  $\sigma_2^2 = \frac{1}{2}$ ,  $E(XY) = \frac{3}{4}$ ,  $E(X|y) = \frac{y}{2}$ , and  $E(Y|x) = x + \frac{1}{2}$ .

a. Compute  $\rho_{xy} =$

b. Use the conditional linear means,  $E(X|y) = \frac{y}{2}$  and  $E(Y|x) = x + \frac{1}{2}$  to compute  $\rho_{xy}$ .

c. Use the information given in the problem to compute the

$$E(Y|x) = \mu_2 + \rho \frac{\sigma_2}{\sigma_1} (x - \mu_1) =$$

$$E(X|y) = \mu_1 + \rho \frac{\sigma_1}{\sigma_2} (y - \mu_2) =$$