

# Conditional Distributions and Independent random variables

## 1. CONDITIONAL DISTRIBUTIONS

**Definition 1.** Let  $\underline{Z} = (X, Y)$  be a random vector of discrete type with support  $E_{\underline{Z}}$ , joint d.f.  $F_{\underline{Z}}$  and joint p.m.f.  $f_{\underline{Z}}$ . Then  $X$  and  $Y$  are discrete type random variables.

For a fixed  $y$  with  $P(Y = y) > 0$ , the function  $f_{X|Y}(\cdot|y) : \mathbb{R} \rightarrow \mathbb{R}$  defined as

$$f_{X|Y}(x|y) = P(X = x|Y = y), \quad \forall x \in \mathbb{R},$$

is called the conditional probability mass function of  $X$ , given  $Y = y$ . Thus, the conditional probability mass function of  $X$ , given  $Y = y$ , is

$$\begin{aligned} f_{X|Y}(x|y) &= P(X = x|Y = y) = \frac{P(X = x, Y = y)}{P(Y = y)} = \frac{f_{\underline{Z}}(x, y)}{f_Y(y)} \\ &= \begin{cases} \frac{f_{\underline{Z}}(x, y)}{f_Y(y)}, & \text{if } x \in E_{X|Y=y} \\ 0, & \text{otherwise,} \end{cases} \end{aligned}$$

where  $E_{X|Y=y} = \{x \in \mathbb{R} \mid (x, y) \in E_{\underline{Z}}\}$  and  $f_Y$  is the marginal p.m.f. of  $Y$ .

The conditional cumulative distribution function of  $X$ , given  $Y = y$ , is defined as

$$\begin{aligned} F_{X|Y}(x|y) &= P(X \leq x|Y = y) \\ &= \frac{P(X \leq x, Y = y)}{P(Y = y)} \\ &= \sum_{x_i \in E_{X|Y=y} \cap (-\infty, x]} \frac{f_{\underline{Z}}(x_i, y)}{f_Y(y)} \\ &= \sum_{x_i \leq x} f_{X|Y}(x_i|y), \quad \text{where } x_i \in E_{X|Y=y}. \end{aligned}$$

In the similar manner, we can define the conditional probability mass function and conditional cumulative distribution function of  $Y$ , given  $X = x$ , provided  $P(X = x) > 0$ .

**Definition 2.** Let  $\underline{Z} = (X, Y)$  be a random vector of continuous type with joint c.d.f.  $F_{\underline{Z}}$  and joint p.d.f.  $f_{\underline{Z}}$ . Then  $X$  and  $Y$  are continuous type random variables. Let  $y \in \mathbb{R}$  be such that  $f_Y(y) > 0$ , where  $f_Y(y) > 0$  is the marginal p.d.f. of  $Y$ .

The function  $f_{X|Y}(\cdot|y) : \mathbb{R} \rightarrow \mathbb{R}$  defined as

$$f_{X|Y}(x|y) = \frac{f_{\underline{Z}}(x, y)}{f_Y(y)}, \quad \forall x \in \mathbb{R},$$

is called the conditional probability density function of  $X$ , given  $Y = y$ .

Also, the conditional cumulative distribution function of  $X$ , given  $Y = y$ , is defined as

$$\begin{aligned} F_{X|Y}(x|y) &= \int_{-\infty}^x f_{X|Y}(t|y) dt \\ &= \int_{-\infty}^x \frac{f_{\underline{Z}}(t, y)}{f_Y(y)} dt \end{aligned}$$

In the similar manner, we can define the conditional probability density function and conditional cumulative distribution function of  $Y$ , given  $\{X = x\}$ , provided  $f_X(x) > 0$ , where  $f_X(x) > 0$  is the marginal p.d.f. of  $X$ .

**Note:** Definition 1 and 2 can be generalized if we replace random variables  $X$  and  $Y$  by random vectors  $\underline{X}$  and  $\underline{Y}$ .

**Example 3.** Let  $\underline{Z} = (X, Y)$  be a random vector with joint p.d.f.

$$f(x, y) = \begin{cases} 6xy(2 - x - y), & \text{if } 0 < x < 1, 0 < y < 1 \\ 0, & \text{otherwise} \end{cases}$$

Then find the conditional p.d.f. of  $X$ , given  $Y = y$ , where  $0 < y < 1$ .

**Solution:** The conditional p.d.f. of  $X$ , given  $Y = y$ , is

$$\begin{aligned} f_{X|Y}(x|y) &= \frac{f(x, y)}{f_Y(y)} \\ &= \begin{cases} \frac{6xy(2-x-y)}{\int_0^1 6xy(2-x-y)dx}, & \text{if } 0 < x < 1 \\ 0, & \text{otherwise} \end{cases} \\ &= \begin{cases} \frac{6x(2-x-y)}{4-3y}, & \text{if } 0 < x < 1 \\ 0, & \text{otherwise} \end{cases} \end{aligned}$$

**Example 4.** Let  $\underline{Z} = (X, Y, Z)$  be a random vector with joint p.m.f.

$$f(x, y, z) = \begin{cases} \frac{xyz}{72}, & \text{if } (x, y, z) \in \{1, 2\} \times \{1, 2, 3\} \times \{1, 3\} \\ 0, & \text{otherwise} \end{cases}$$

- (1) Find the conditional p.m.f. of  $X$ , given  $(Y, Z) = (2, 1)$ .
- (2) Find the conditional p.m.f. of  $(X, Z)$ , given  $Y = 3$ .

**Solution:**

- (1) The conditional p.m.f. of  $X$ , given  $(Y, Z) = (2, 1)$ , is

$$\begin{aligned} f_{X|(Y,Z)}(x|(2, 1)) &= \frac{f(x, 2, 1)}{P((Y, Z) = (2, 1))} \\ &= \begin{cases} \frac{2x}{72P(Y=2, Z=1)}, & \text{if } x \in E_{X|(Y,Z)=(2,1)} = \{x \in \mathbb{R} \mid (x, 2, 1) \in E_{\underline{Z}}\} \\ 0, & \text{otherwise} \end{cases} \\ &= \begin{cases} \frac{2x}{72P(Y=2, Z=1)}, & \text{if } x \in \{1, 2\} \\ 0, & \text{otherwise} \end{cases} \end{aligned}$$

Now,  $P(Y = 2, Z = 1) = \sum_{x \in R_{(2,1)}} f(x, 2, 1)$ , where  $R_{(2,1)} = \{x \in \mathbb{R} \mid (x, 2, 1) \in E_{\underline{Z}}\} = \{1, 2\}$ . Hence,  $P(Y = 2, Z = 1) = f(1, 2, 1) + f(2, 2, 1) = \frac{1}{12}$ . Therefore,

$$f_{X|(Y,Z)}(x|(2, 1)) = \begin{cases} \frac{x}{3}, & \text{if } x \in \{1, 2\} \\ 0, & \text{otherwise} \end{cases}$$

(2) The conditional p.m.f. of  $(X, Z)$ , given  $Y = 3$ , is

$$\begin{aligned} f_{(X,Z)|Y}((x, z)|3) &= \frac{f(x, 3, z)}{P(Y = 3)} \\ &= \begin{cases} \frac{3xz}{72P(Y=3)}, & \text{if } x \in E_{X,Z|Y=3} = \{(x, z) \in \mathbb{R} \mid (x, 3, z) \in E_{\underline{Z}}\} \\ 0, & \text{otherwise} \end{cases} \\ &= \begin{cases} \frac{3xz}{72P(Y=3)}, & \text{if } (x, z) \in \{1, 2\} \times \{1, 3\} \\ 0, & \text{otherwise} \end{cases} \end{aligned}$$

Now,  $P(Y = 3) = \sum_{(x,z) \in R_3} f(x, 3, z)$ , where  $R_3 = \{(x, z) \in \mathbb{R} \mid (x, 3, z) \in E_{\underline{Z}}\} = \{1, 2\} \times \{1, 3\}$ . Hence,  $P(Y = 3) = f(1, 3, 1) + f(1, 3, 3) + f(2, 3, 1) + f(2, 3, 3) = \frac{1}{2}$ . Therefore,

$$f_{(X,Z)|Y}((x, z)|3) = \begin{cases} \frac{xz}{12}, & \text{if } x \in \{1, 2\} \times \{1, 3\} \\ 0, & \text{otherwise} \end{cases}$$

## 2. INDEPENDENT RANDOM VARIABLES

**Definition 5.** The random variables  $X_1, X_2, \dots, X_n$  are said to be independent if for any sub-collection  $\{X_{i_1}, X_{i_2}, \dots, X_{i_k}\}$ ,  $2 \leq k \leq n$ , we have

$$F_{X_{i_1}, \dots, X_{i_k}}(x_1, x_2, \dots, x_k) = \prod_{j=1}^k F_{X_{i_j}}(x_j), \quad \forall (x_1, x_2, \dots, x_k) \in \mathbb{R}^k$$

where  $F_{X_{i_1}, \dots, X_{i_k}}$  is the joint c.d.f. of  $(X_{i_1}, X_{i_2}, \dots, X_{i_k})$  and  $F_{X_{i_j}}$  is the marginal c.d.f. of  $X_{i_j}$ , for  $1 \leq j \leq k$ .

**Theorem 6.** Let  $\underline{X} = (X_1, X_2, \dots, X_n) : \mathcal{S} \rightarrow \mathbb{R}^n$  be a  $n$ -dimensional ( $n \geq 2$ ) random vector with joint c.d.f.  $F_{\underline{X}}$ . Let  $F_{X_i}$  be the marginal c.d.f. of  $X_i$ , for  $1 \leq i \leq n$ . Then the random variables  $X_1, X_2, \dots, X_n$  are independent if and only if

$$F_{\underline{X}}(x_1, x_2, \dots, x_n) = \prod_{i=1}^n F_{X_i}(x_i), \quad \forall (x_1, x_2, \dots, x_n) \in \mathbb{R}^n.$$

**Theorem 7.** Let  $\underline{X} = (X_1, X_2, \dots, X_n) : \mathcal{S} \rightarrow \mathbb{R}^n$  be a  $n$ -dimensional ( $n \geq 2$ ) random vector of either discrete or continuous type. Let  $f_{\underline{X}}$  be the joint p.m.f. (or p.d.f.) of  $\underline{X}$  and  $f_{X_i}$  be the marginal p.m.f. (or p.d.f.) of random variable  $X_i$ , for  $1 \leq i \leq n$ . Then

(1) the random variables  $X_1, X_2, \dots, X_n$  are independent if and only if

$$f_{\underline{X}}(x_1, x_2, \dots, x_n) = \prod_{i=1}^n f_{X_i}(x_i), \quad \forall (x_1, x_2, \dots, x_n) \in \mathbb{R}^n.$$

(2) the random variables  $X_1, X_2, \dots, X_n$  are independent  $\Rightarrow E_{\underline{X}} = \prod_{i=1}^n E_{X_i}$ , where  $E_{\underline{X}}$  is the support of random vector  $\underline{X}$  and  $E_{X_i}$  is the support of random variable  $X_i$ , for  $1 \leq i \leq n$ .

**Theorem 8.** Let  $X_1, X_2, \dots, X_n$  be the independent random variables.

(1) Let  $\psi_i : \mathbb{R} \rightarrow \mathbb{R}$  be a function such that  $\psi_i^{-1}(A) \in \mathbb{B}_{\mathbb{R}}$ , for all  $A \in \mathbb{B}_{\mathbb{R}}$ , for  $i = 1, 2, \dots, n$ . Then the random variables  $\psi_1(X_1), \psi_2(X_2), \dots, \psi_n(X_n)$  are independent.

(2) For  $A_i \in \mathbb{B}_{\mathbb{R}}$ ,  $i = 1, 2, \dots, n$ , we have

$$P(\{X_i \in A_i, i = 1, 2, \dots, n\}) = \prod_{i=1}^n P(\{X_i \in A_i\}).$$

**Remark 9.**  $\underline{X} = (X_1, X_2)$  be a random vector of either discrete or continuous type. Let  $D = \{x_2 \in \mathbb{R} \mid f_{X_1|X_2}(\cdot|x_2) \text{ is defined}\}$ . Then for  $x_2 \in D$ ,  $X_1$  and  $X_2$  are independent if and only if  $f_{X_1|X_2}(x_1|x_2) = f_{X_1}(x_1)$ , for all  $x_1 \in \mathbb{R}$ ,

i.e.,

$X_1$  and  $X_2$  are independent if and only if  $\forall x_2 \in D$ , the conditional distribution of  $X_1$ , given  $X_2 = x_2$ , is the same as unconditional distribution of  $X_1$ .

**Example 10.** Let  $\underline{Z} = (X, Y, Z)$  be a random vector with joint p.m.f.

$$f(x, y, z) = \begin{cases} \frac{xyz}{72}, & \text{if } (x, y, z) \in \{1, 2\} \times \{1, 2, 3\} \times \{1, 3\} \\ 0, & \text{otherwise} \end{cases}$$

(1) Are  $X, Y$  and  $Z$  independent random variables?

(2) Are  $X$  and  $Z$  independent random variables?

**Solution:**

(1) The supports of  $X, Y$  and  $Z$  are

$$E_X = \{x \in \mathbb{R} \mid (x, y, z) \in E_{\underline{Z}} \text{ for some } (y, z) \in \mathbb{R}^2\} = \{1, 2\}$$

$$E_Y = \{y \in \mathbb{R} \mid (x, y, z) \in E_{\underline{Z}} \text{ for some } (x, z) \in \mathbb{R}^2\} = \{1, 2, 3\}$$

and

$$E_Z = \{z \in \mathbb{R} \mid (x, y, z) \in E_{\underline{Z}} \text{ for some } (x, y) \in \mathbb{R}^2\} = \{1, 3\},$$

respectively. For  $x \in E_X$ ,  $R_x = \{(y, z) \in \mathbb{R}^2 \mid (x, y, z) \in E_{\underline{Z}}\} = \{1, 2, 3\} \times \{1, 3\}$ . So the marginal p.m.f. of  $X$  is

$$\begin{aligned} f_X(x) &= \begin{cases} \sum_{(y,z) \in R_x} f(x, y, z), & \text{if } x \in E_X \\ 0, & \text{otherwise} \end{cases} \\ &= \begin{cases} \frac{x}{3}, & \text{if } x \in \{1, 2\} \\ 0, & \text{otherwise} \end{cases} \end{aligned}$$

Similarly the marginal p.m.f. of  $Y$  and  $Z$  are

$$f_Y(y) = \begin{cases} \frac{y}{6}, & \text{if } y \in \{1, 2, 3\} \\ 0, & \text{otherwise} \end{cases}$$

and

$$f_Z(z) = \begin{cases} \frac{z}{4}, & \text{if } z \in \{1, 3\} \\ 0, & \text{otherwise} \end{cases}$$

respectively. Clearly  $f(x, y, z) = f_X(x)f_Y(y)f_Z(z)$ , for all  $(x, y, z) \in \mathbb{R}^3$ . Thus  $X, Y$  and  $Z$  are independent.

(2) Let  $\underline{X} = (X, Y)$ . The support of  $\underline{X}$  is  $E_{\underline{X}} = \{(x, z) \in \mathbb{R}^2 \mid (x, y, z) \in E_{\underline{Z}} \text{ for some } y \in \mathbb{R}\} = \{1, 2\} \times \{1, 3\}$ . For  $(x, z) \in E_{\underline{X}}$ ,  $R_{(x,z)} = \{y \in \mathbb{R} \mid (x, y, z) \in E_{\underline{Z}}\} = \{1, 2, 3\}$ .

So the marginal p.m.f. of  $\underline{X}$  is

$$f_{\underline{X}}(x, z) = \begin{cases} \sum_{y \in R(x, z)} f(x, y, z), & \text{if } (x, z) \in E_{\underline{X}} \\ 0, & \text{otherwise} \end{cases}$$

$$= \begin{cases} \frac{xz}{12}, & \text{if } (x, z) \in \{1, 2\} \times \{1, 3\} \\ 0, & \text{otherwise} \end{cases}$$

Thus  $f_{\underline{X}}(x, z) = f_X(x)f_Z(z)$ , for all  $(x, z) \in \mathbb{R}^2$ . Thus  $X$  and  $Z$  are independent.

**Example 11.** Let  $\underline{Z} = (X, Y)$  be a random vector with joint p.d.f.

$$f_{\underline{Z}}(x, y) = \begin{cases} \frac{1}{x}, & \text{if } 0 < y < x < 1 \\ 0, & \text{otherwise.} \end{cases}$$

Are  $X$  and  $Y$  independent?

**Solution:** By Example 7 of Lecture 14, the marginal p.d.f. of  $X$  and  $Y$  are

$$f_X(x) = \begin{cases} 1, & \text{if } 0 < x < 1 \\ 0, & \text{otherwise} \end{cases}$$

and

$$f_Y(y) = \begin{cases} -\ln y, & \text{if } 0 < y < 1 \\ 0, & \text{otherwise} \end{cases}$$

Clearly,  $f_{\underline{Z}}(x, y) \neq f_X(x)f_Y(y)$ . Hence,  $X$  and  $Y$  are not independent.

**Alternative solution:** The support of  $\underline{Z}$  is  $E_{\underline{Z}} = \{(x, y) \in \mathbb{R}^2 \mid 0 < y < x < 1\}$ , and the support of  $X$  and  $Y$  are  $(0, 1)$ . Hence,  $E_{\underline{Z}} \neq E_X \times E_Y$ . Therefore,  $X$  and  $Y$  are not independent.