

Statistics I:

Chapter 4: Multivariate Random Variables

Carlos Oliveira

E-mail: carlosoliveira@iseg.ulisboa.pt

ISEG - Lisbon School of Economics and Management

Multivariate random variable: A random variable k - dimensional is a function with domain \mathbf{S} and codomain \mathbb{R}^k :

$$(X_1, \dots, X_k) : s \in \mathbf{S} \rightarrow (X_1(s), \dots, X_k(s)) \in \mathbb{R}^k .$$

The function $(X_1(s), \dots, X_k(s))$ is usually written for simplicity as (X_1, \dots, X_k) .

Remark: If $k = 2$ we have the bivariate random variable or two dimensional random variable

$$(X, Y) : s \in \mathbf{S} \rightarrow (X(s), Y(s)) \in \mathbb{R}^2 .$$

Joint cumulative distribution function: Let (X, Y) be a bivariate random variable. The real function of two real variables with domain \mathbb{R}^2 and defined by

$$F_{X,Y}(x, y) = P(X \leq x, Y \leq y)$$

is the joint cumulative distribution function of the two dimensional random variable (X, Y) .

Example (Dice casting)

Random Experiment: Roll two different dice (one red and one green) and write down the number of dots on the upper face of each die.

Random vector: (X_{red}, X_{green}) , where X_i is the of dots the i die, with $i = \text{green or red}$.

Some probabilities:

$$P(X_{red} = 2, X_{green} = 4) = \frac{1}{36}$$

$$P(X_{red} + X_{green} > 10) = \frac{1}{12}$$

$$\begin{aligned} P\left(\frac{X_{red}}{X_{green}} \leq 2\right) &= P\left(\frac{X_{red}}{X_{green}} = 1\right) + P\left(\frac{X_{red}}{X_{green}} = 2\right) \\ &= \frac{6}{36} + \frac{3}{36} = \frac{1}{4} \end{aligned}$$

Example (Coin Tossing)

Random experiment: Two different and fair coins are tossed once.

Random vector: (X_1, X_2) , where X_i represents the number of heads obtained with coin i , with $i = 1, 2$.

Some probabilities:

$$\begin{aligned}P(X_1 = 0, X_2 = 0) &= P(X_1 = 0, X_2 = 1) = P(X_1 = 1, X_2 = 0) \\ &= P(X_1 = 1, X_2 = 1) = \frac{1}{4}\end{aligned}$$

$$P(X_1 + X_2 \geq 1) = \frac{3}{4}$$

Properties of the joint cumulative distribution function:

- $0 \leq F_{X,Y}(x, y) \leq 1$
- $F_{X,Y}(x, y)$ is non decreasing with respect to x and y :
 - $\Delta_x > 0 \Rightarrow F_{X,Y}(x + \Delta x, y) \geq F_{X,Y}(x, y)$
 - $\Delta_y > 0 \Rightarrow F_{X,Y}(x, y + \Delta y) \geq F_{X,Y}(x, y)$
- $\lim_{x \rightarrow -\infty} F_{X,Y}(x, y) = 0$, $\lim_{y \rightarrow -\infty} F_{X,Y}(x, y) = 0$ and
 $\lim_{x \rightarrow +\infty, y \rightarrow +\infty} F_{X,Y}(x, y) = 1$
- $P(x_1 < X \leq x_2, y_1 < Y \leq y_2) =$
 $F_{X,Y}(x_2, y_2) - F_{X,Y}(x_1, y_2) - F_{X,Y}(x_2, y_1) + F_{X,Y}(x_1, y_1).$
- $F_{X,Y}(x, y)$ is right continuous with respect to x and y :
 $\lim_{x \rightarrow a^+} F_{X,Y}(x, y) = F_{X,Y}(a, y)$ and $\lim_{y \rightarrow b^+} F_{X,Y}(x, y) = F_{X,Y}(x, b).$

Example (Coin Tossing)

Random experiment: Two different and fair coins are tossed once.

Random vector: (X_1, X_2) , where X_i represents the number of heads obtained with coin i , with $i = 1, 2$.

Joint cumulative distribution function:

$$F_{X_1, X_2}(x_1, x_2) = P(X_1 \leq x_1, X_2 \leq x_2) = \begin{cases} 0, & x_1 < 0 \\ 0, & x_2 < 0 \\ \frac{1}{4}, & 0 \leq x_1 < 1, 0 \leq x_2 < 1 \\ \frac{1}{2}, & 0 \leq x_1 < 1, x_2 \geq 1 \\ \frac{1}{2}, & 0 \leq x_2 < 1, 0 \leq x_1 < 1 \\ 1, & x_1 \geq 1, x_2 \geq 1 \end{cases}$$

The (marginal) cumulative distribution functions of X and Y can be obtained from the Joint cumulative distribution functions of (X, Y) :

- The Marginal cumulative distribution function of X :
$$F_X(x) = P(X \leq x) = P(X \leq x, Y \leq +\infty) = \lim_{y \rightarrow +\infty} F_{X,Y}(x, y).$$
- The Marginal cumulative distribution function of Y :
$$F_Y(y) = P(Y \leq y) = P(X \leq +\infty, Y \leq y) = \lim_{x \rightarrow +\infty} F_{X,Y}(x, y).$$

Remark: The joint distribution uniquely determines the marginal distributions, but the inverse is not true.

Example (Coin Tossing)

Random experiment: Two different and fair coins are tossed once.

Random vector: (X_1, X_2) , where X_i represents the number of heads obtained with coin i , with $i = 1, 2$.

Joint distribution function:

$$F_{X_1, X_2}(x_1, x_2) = \begin{cases} 0, & x_1 < 0 \text{ or } x_2 < 0 \\ \frac{1}{4}, & 0 \leq x_1 < 1, 0 \leq x_2 < 1 \\ \frac{1}{2}, & 0 \leq x_1 < 1, x_2 \geq 1 \\ \frac{1}{2}, & 0 \leq x_2 < 1, 0 \leq x_1 < 1 \\ 1, & x_1 \geq 1, x_2 \geq 1 \end{cases}$$

Marginal distribution function for X_1 :

$$F_{X_1}(x_1) = \lim_{x_2 \rightarrow +\infty} F_{X_1, X_2}(x_1, x_2) = \begin{cases} 0, & x_1 < 0 \\ \frac{1}{2}, & 0 \leq x_1 < 1 \\ 1, & x_1 \geq 1 \end{cases}$$

Example

Let (X, Y) be a jointly distributed random variable with CDF:

$$F_{X,Y}(x, y) = \begin{cases} 1 - e^{-x} - e^{-y} + e^{-x-y}, & x \geq 0, y \geq 0 \\ 0, & x < 0, y < 0 \end{cases}.$$

Marginal cumulative distribution function of the random variable X is:

$$F_X(x) = \begin{cases} 1 - e^{-x}, & x \geq 0 \\ 0, & x < 0 \end{cases}.$$

Marginal cumulative distribution function of the random variable Y is:

$$F_Y(y) = \begin{cases} 1 - e^{-y}, & y \geq 0 \\ 0, & y < 0 \end{cases}.$$

Independence of jointly distributed random variables

Definition: The jointly distributed random variables X and Y are said to be independent if and only if for any two sets $B_1 \in \mathbb{R}$, $B_2 \in \mathbb{R}$ we have

$$P(X \in B_1, Y \in B_2) = P(X \in B_1)P(Y \in B_2)$$

Remark: Independence implies that $F_{X,Y}(x, y) = F_X(x)F_Y(y)$, for any $(x, y) \in \mathbb{R}^2$.

Theorem: If X and Y are independent random variables and if $h(X)$ and $g(Y)$ are two functions of X and Y respectively, then the random variables $U = h(X)$ and $V = g(Y)$ are also independent random variables.

Example (Coin Tossing)

Random experiment: Two different and fair coins are tossed once.

Random vector: (X_1, X_2) , where X_i represents the number of heads obtained with coin i , with $i = 1, 2$.

Are these random variables independent?

$$F_{X_1}(x_1) = \begin{cases} 0, & x_1 < 0 \\ \frac{1}{2}, & 0 \leq x_1 < 1 \\ 1, & x_1 \geq 1 \end{cases}, \quad F_{X_2}(x_2) = \begin{cases} 0, & x_2 < 0 \\ \frac{1}{2}, & 0 \leq x_2 < 1 \\ 1, & x_2 \geq 1 \end{cases}$$

One can easily verify that $F_{X_1, X_2}(x_1, x_2) = F_{X_1}(x_1) \times F_{X_2}(x_2)$.

$$F_{X_1, X_2}(x_1, x_2) = \begin{cases} 0, & x_1 < 0 \text{ or } x_2 < 0 \\ \frac{1}{4}, & 0 \leq x_1 < 1, 0 \leq x_2 < 1 \\ \frac{1}{2}, & 0 \leq x_1 < 1, x_2 \geq 1 \\ \frac{1}{2}, & 0 \leq x_2 < 1, 0 \leq x_1 < 1 \\ 1, & x_1 \geq 1, x_2 \geq 1 \end{cases}$$

Example

Let (X, Y) be a jointly distributed random variable with CDF:

$$F_{X,Y}(x, y) = \begin{cases} 1 - e^{-x} - e^{-y} + e^{-x-y}, & x \geq 0, y \geq 0 \\ 0, & x < 0, y < 0 \end{cases}.$$

Marginal cumulative distribution function of the random variable X and Y are:

$$F_X(x) = \lim_{y \rightarrow +\infty} F_{X,Y}(x, y) = \begin{cases} 1 - e^{-x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

$$F_Y(y) = \lim_{x \rightarrow +\infty} F_{X,Y}(x, y) = \begin{cases} 1 - e^{-y}, & y \geq 0 \\ 0, & y < 0 \end{cases}.$$

X and Y are independent random variables because:

$$F_{X,Y}(x, y) = F_X(x)F_Y(y)$$

since

$$1 - e^{-x} - e^{-y} + e^{-x-y} = (1 - e^{-y})(1 - e^{-x}).$$

Let $D_{(X,Y)}$ be the set of discontinuities of the joint cumulative distribution function $F_{(X,Y)}(x,y)$, that is

$$D_{(X,Y)} = \{(x,y) \in \mathbb{R}^2 : P(X = x, Y = y) > 0\}$$

Definition: (X, Y) is a two dimensional discrete random variable if and only if

$$\sum_{(x,y) \in D_{(X,Y)}} P(X = x, Y = y) = 1.$$

Remark: As in the univariate case, a multivariate discrete random variable can take a finite number of possible values (x_i, y_j) , where $i = 1, 2, \dots, k_1$ and $j = 1, 2, \dots, k_2$, where k_1 and k_2 are finite integers, or a countably infinite (x_i, y_j) , where $i = 1, 2, \dots$ and $j = 1, 2, \dots$. For the sake of generality we consider the latter case. That is $D_{(X,Y)} = \{(x_i, y_j), i = 1, 2, \dots, j = 1, 2, \dots\}$

Joint probability distribution/ function: If X and Y are discrete random variables, then the function given by

$$f_{X,Y}(x,y) = P(X = x, Y = y)$$

for $(x,y) \in D_{(X,Y)}$ is called the joint probability function of (X, Y) or joint probability distribution of the random variables X and Y .

Theorem: A bivariate function $f_{X,Y}(x,y)$ can serve as joint probability distribution of the pair of discrete random variables X and Y if and only if its values satisfy the conditions:

- $f_{X,Y}(x,y) \geq 0$ for any $(x,y) \in \mathbb{R}^2$
- $\sum_{(x,y) \in D_{(X,Y)}} f_{X,Y}(x,y) = \sum_{i=1}^{\infty} \sum_{j=1}^{\infty} f_{X,Y}(x_i, y_j) = 1$

Remark: We can calculate any probability using this function. For instance $P((x,y) \in B) = \sum_{(x,y) \in B} f_{X,Y}(x,y)$

Example

Let X and Y be the random variables representing the population of monthly wages of husbands and wives in a particular community. Say, there are only three possible monthly wages in euros: 0, 1000, 2000. The joint probability distribution is

	X	0	1000	2000
Y				
0		0.05	0.15	0.10
1000		0.10	0.10	0.30
2000		0.05	0.05	0.10

The probability that a husband earns 2000 euros and the wife earns 1000 euros is given by

$$\begin{aligned}
 f_{X,Y}(2000, 1000) &= P(X = 2000, Y = 1000) \\
 &= 0.30
 \end{aligned}$$

Joint cumulative distribution function: If X and Y are discrete random variables, the function given by

$$F_{X,Y}(x,y) = \sum_{s \leq x} \sum_{t \leq y} f_{X,Y}(s,t)$$

for $(x,y) \in \mathbb{R}^2$ is called the joint distribution function or joint cumulative distribution of X and Y .

Marginal probability distribution/function: If Y and X are discrete random variables and $f_{X,Y}$ is the value of their joint probability distribution at (x,y) the function given by

$$P(X = x) = \begin{cases} \sum_{y \in D_y} f(x,y) = \sum_{y \in D_y} f_{X,Y}(x,y), & \text{for } x \in D_x \\ 0, & \text{for } x \notin D_x \end{cases}$$

$$P(Y = y) = \begin{cases} \sum_{x \in D_x} f(x,y) = \sum_{x \in D_x} f_{X,Y}(x,y), & \text{for } y \in D_y \\ 0, & \text{for } y \notin D_y \end{cases}$$

are respectively is the Marginal probability distribution of the r.v. X and Y , where D_x and D_y are the range of X and Y respectively.

Example

$$P(X = x) = P(X = x, Y = 0) + P(X = x, Y = 1000) \\ + P(X = x, Y = 2000)$$

$$P(Y = y) = P(X = 0, Y = y) + P(X = 1000, Y = y) \\ + P(X = 2000, Y = y)$$

Applying these formulas we have:

	X	0	1000	2000	$P(Y = y)$
Y					
0		0.05	0.15	0.10	0.30
1000		0.10	0.10	0.30	0.50
2000		0.05	0.05	0.10	0.20
$P(X = x)$		0.20	0.30	0.50	1

$$F_{X,Y}(1000, 1000) = P(X = 0, Y = 0) + P(X = 0, Y = 1000) \\ + P(X = 1000, Y = 0) + P(X = 1000, Y = 1000)$$

$$F_{X,Y}(0, 1000) = P(X = 0, Y = 0) + P(X = 0, Y = 1000)$$

Independence of random variables: Two discrete random variables X and Y are independent if and only if, for all $(x, y) \in D_{X,Y}$,

$$P(X = x, Y = y) = P(X = x)P(Y = y).$$

Example

	X	0	1000	2000	$P(Y = y)$
Y					
0		0.05	0.15	0.10	0.30
1000		0.10	0.10	0.30	0.50
2000		0.05	0.05	0.10	0.20
$P(X = x)$		0.20	0.30	0.50	1

Are these two random variables independent?

$$P(X = 2000, Y = 2000) = P(X = 2000) \times P(Y = 2000) = 0.1$$

Is this sufficient to say that X and Y are independent? **NO!**

$$P(X = 0, Y = 0) = 0.05 \text{ but } P(X = 0)P(Y = 0) = 0.06$$

thus X and Y are not independent.

Conditional probability function of Y given X : A *conditional probability function* of a discrete random variable Y given another discrete variable X taking a specific value is defined as

$$\begin{aligned}f_{Y|X=x}(y) &= P(Y = y | X = x) = \frac{P(Y = y, X = x)}{P(X = x)} \\ &= \frac{f_{X,Y}(x, y)}{f_X(x)}, \quad f_X(x) > 0, \text{ for a fixed } x.\end{aligned}$$

The *conditional probability function* of X given Y is defined by

$$f_{X|Y=y}(x) = \frac{f_{X,Y}(x, y)}{f_Y(y)}, \quad f_Y(y) > 0.$$

Remarks:

- The conditional probability functions satisfy all the properties of probability functions, and therefore $\sum_{i=1}^{\infty} f_{Y|X}(y_i) = 1$.
- If X and Y are independent $f_{Y|X=x}(y) = f_Y(y)$ and $f_{X|Y=y}(x) = f_X(x)$

Example

Consider the joint probability function

	X	0	1000	2000	$P(Y = y)$
Y					
0		0.05	0.15	0.10	0.30
1000		0.10	0.10	0.30	0.50
2000		0.05	0.05	0.10	0.20
$P(X = x)$		0.20	0.30	0.50	1

Compute $P(Y = y|X = 0)$.

$$P(Y = 0|X = 0) = \frac{P(Y = 0, X = 0)}{P(X = 0)} = \frac{0.05}{0.2} = 0.25$$

$$P(Y = 1000|X = 0) = \frac{P(Y = 1000, X = 0)}{P(X = 0)} = \frac{0.1}{0.2} = 0.5.$$

$$P(Y = 2000|X = 0) = \frac{P(Y = 2000, X = 0)}{P(X = 0)} = \frac{0.05}{0.2} = 0.25.$$

Definition: The conditional CDF of Y given X by defined by

$$F_{Y|X=x}(y) = P(Y \leq y | X = x) = \sum_{y' \in D_Y \wedge y' \leq y} \frac{P(Y = y', X = x)}{P(X = x)}$$

for a fixed x , with $P(X = x) > 0$.

Remark: It can be checked that $F_{Y|X=x}$ is indeed a CDF.

Exercise: Verify that $F_{Y|X=x}$ is non-decreasing and and

$$\lim_{y \rightarrow +\infty} F_{Y|X=x}(y) = 1.$$

Definition: The conditional CDF of Y given X by defined by

$$F_{Y|X=x}(y) = P(Y \leq y | X = x) = \sum_{y' \in D_Y \wedge y' \leq y} \frac{P(Y = y', X = x)}{P(X = x)}$$

for a fixed x , with $P(X = x) > 0$.

Remark: It can be checked that $F_{Y|X=x}$ is indeed a CDF.

Exercise: Verify that $F_{Y|X=x}$ is non-decreasing and and

$$\lim_{y \rightarrow +\infty} F_{Y|X=x}(y) = 1.$$

$$\begin{aligned} 1) \quad & F_{Y|X=x}(y + \delta) - F_{Y|X=x}(y) \\ & = P(Y \leq y + \delta, X = x) - P(Y \leq y, X = x) \geq 0. \end{aligned}$$

$$\begin{aligned} 2) \quad & \lim_{y \rightarrow +\infty} F_{Y|X=x}(y) = \lim_{y \rightarrow +\infty} P(Y \leq y | X = x) \\ & = \lim_{y \rightarrow +\infty} \frac{P(Y \leq y, X = x)}{P(X = x)} = \frac{P(Y \leq \infty, X = x)}{P(X = x)} = \frac{P(X = x)}{P(X = x)} = 1. \end{aligned}$$

Example

Consider the conditional probability of Y given that $X = 0$ previously deduced:

$$P(Y = 0|X = 0) = \frac{P(Y = 0, X = 0)}{P(X = 0)} = \frac{0.05}{0.2} = 0.25$$

$$P(Y = 1000|X = 0) = \frac{P(Y = 1000, X = 0)}{P(X = 0)} = \frac{0.1}{0.2} = 0.5.$$

$$P(Y = 2000|X = 0) = \frac{P(Y = 2000, X = 0)}{P(X = 0)} = \frac{0.05}{0.2} = 0.25.$$

Then the conditional CDF of Y given that $X = 0$ is

$$F_{Y|X=0}(y) = \begin{cases} 0, & y < 0 \\ 0.25, & 0 \leq y < 1000 \\ 0.75, & 1000 \leq y < 2000 \\ 1, & y \geq 2000 \end{cases}$$

Definition: (X, Y) is a two-dimensional continuous random variable with a joint cumulative distribution function $F_{X,Y}(x, y)$, if and only if X and Y are continuous random variables and there is a non-negative real function $f_{X,Y}(x, y)$, such that

$$F_{X,Y}(x, y) = P(X \leq x, Y \leq y) = \int_{-\infty}^y \int_{-\infty}^x f_{X,Y}(t, s) dt ds.$$

The function $f_{X,Y}(x, y)$ is the joint (probability) density of X and Y .

Remark: Let A be a set in the \mathbb{R}^2 . Then,

$$P((X, Y) \in A) = \int \int_A f_{X,Y}(t, s) dt ds.$$

Example

Joint probability density function of the two dimensional random variable (P_1, S) where P_1 represents the price and S the total sales (in 10000 units).

Joint density function:

$$f_{P_1, S}(p, s) = \begin{cases} 5pe^{-ps}, & 0.2 < p < 0.4, \quad s > 0 \\ 0, & \text{otherwise} \end{cases}$$

Joint cumulative distribution function:

$$\begin{aligned} F_{P_1, S}(p, s) &= P(P_1 \leq p, S \leq s) \\ &= \begin{cases} 0, & p < 0.2 \text{ or } s < 0 \\ -1 + 5p - 5 \frac{e^{-0.2s} - e^{-ps}}{s}, & 0.2 < p < 0.4, s \geq 0 \\ 1 - 5 \frac{e^{-0.2s} - e^{-0.4s}}{s}, & p \geq 0.4, s \geq 0 \end{cases} \end{aligned}$$

To get the CDF we need to make the following computations:

Example

- If $p < 0.2$ or $s < 0$, then $f_{P_1, S}(p, s) = 0$ and

$$P(P_1 \leq p, S \leq s) = \int_{-\infty}^p \int_{-\infty}^s f_{P_1, S}(t, u) dt du = 0$$

- If $0.2 < p < 0.4$ and $s \geq 0$, then

$$\begin{aligned} P(P_1 \leq p, S \leq s) &= \int_{-\infty}^p \int_{-\infty}^s f_{P_1, S}(t, u) dt du \\ &= \int_{0.2}^p \int_0^s f_{P_1, S}(t, u) dt du = -1 + 5p - 5 \frac{e^{-0.2s} - e^{-ps}}{s} \end{aligned}$$

- If $p \geq 0.4$ and $s \geq 0$, then

$$\begin{aligned} P(P_1 \leq p, S \leq s) &= \int_{-\infty}^p \int_{-\infty}^s f_{P_1, S}(t, u) dt du \\ &= \int_{0.2}^{0.4} \int_0^s f_{P_1, S}(t, u) dt du = 1 - 5 \frac{e^{-0.2s} - e^{-0.4s}}{s} \end{aligned}$$

Theorem: A bivariate function can serve as a joint probability density function of a pair of continuous random variables X and Y if its values, $f_{X,Y}(x, y)$, satisfy the conditions:

- $f_{X,Y}(x, y) \geq 0$, for all $(x, y) \in \mathbb{R}^2$
- $\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f_{X,Y}(x, y) dx dy = 1$.

Property: Let (X, Y) be a bivariate random variable and $B \in \mathbb{R}^2$, then

$$P((X, Y) \in B) = \int \int_B f_{X,Y}(x, y) dx dy.$$

Example

Let (X, Y) be a continuous bi-dimensional random variable with density function $f_{X,Y}$ given by

$$f_{X,Y}(x,y) = \begin{cases} kx + y, & 0 < x < 1, 0 < y < 1 \\ 0, & \text{otherwise} \end{cases}.$$

Find k .

Solution: From the first condition, we know that $f_{X,Y}(x,y) \geq 0$. Therefore $k \geq 0$. Additionally,

$$\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f_{X,Y}(x,y) dx dy = 1.$$

This is equivalent to

$$\int_0^1 \int_0^1 kx + y dx dy = 1 \Leftrightarrow \frac{1+k}{2} = 1 \Leftrightarrow k = 1.$$

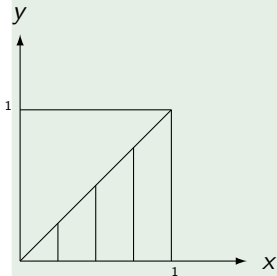
Example

Let (X, Y) be a continuous bi-dimensional random variable with density function $f_{X,Y}$ given by

$$f_{X,Y}(x, y) = \begin{cases} x + y, & 0 < x < 1, 0 < y < 1 \\ 0, & \text{otherwise} \end{cases}.$$

Compute $P(X > Y)$.

Solution: Firstly, we notice that



$$\begin{aligned} P(X > Y) &= \int_0^1 \int_0^x (x + y) dy dx \\ &= \int_0^1 \frac{3}{2} x^2 dx = \frac{1}{2} \end{aligned}$$

Properties: Let (X, Y) be a continuous bivariate random variable. If $f_{X,Y}$ represents the density function of (X, Y) and $F_{X,Y}$ represents respectively joint CDF of (X, Y) . Then,

- $f_{X,Y}(x, y) = \frac{\partial^2 F_{X,Y}(x, y)}{\partial x \partial y} = \frac{\partial^2 F_{X,Y}(x, y)}{\partial y \partial x}$, almost everywhere.
- Marginal density functions of the random variable X

$$f_X(x) = \int_{-\infty}^{+\infty} f_{X,Y}(x, v) dv,$$

- Marginal density functions of the random variable Y

$$f_Y(y) = \int_{-\infty}^{+\infty} f_{X,Y}(u, y) du.$$

- Marginal CDF of the random variable X

$$F_X(x) = \lim_{y \rightarrow +\infty} F_{X,Y}(x, y) = \int_{-\infty}^x \underbrace{\int_{-\infty}^{+\infty} f_{X,Y}(u, y) dy}_{=f_X(u)} du,$$

- Marginal CDF of the random variable Y

$$F_Y(y) = \lim_{x \rightarrow +\infty} F_{X,Y}(x, y) = \int_{-\infty}^y \underbrace{\int_{-\infty}^{+\infty} f_{X,Y}(x, v) dv}_{=f_Y(v)} dx.$$

Example

Joint density function:

$$f_{P,S}(p, s) = \begin{cases} 5pe^{-ps}, & 0.2 < p < 0.4, \quad s > 0 \\ 0, & \text{otherwise} \end{cases}$$

Marginal density function of P :

$$\begin{aligned} f_P(p) &= \int_{-\infty}^{+\infty} f_{P,S}(p, s) ds = \begin{cases} 5 \underbrace{\int_0^{+\infty} pe^{-ps} ds}_{=1}, & 0.2 < p < 0.4 \\ 0, & \text{otherwise} \end{cases} \\ &= \begin{cases} 5, & 0.2 < p < 0.4 \\ 0, & \text{otherwise} \end{cases} \end{aligned}$$

Marginal cumulative distribution function:

$$F_S(s) = \lim_{p \rightarrow +\infty} F_{P,S}(p, s) = \begin{cases} 0, & s < 0 \\ 1 - 5 \frac{e^{-0.2s} - e^{-0.4s}}{s^2}, & s \geq 0 \end{cases}$$

Definition: If $f_{X,Y}(x, y)$ is the joint probability density function of the continuous random variables X and Y and $f_Y(y)$ is the marginal density function of Y , the function given by

$$f_{X|Y=y}(x) = \frac{f_{X,Y}(x, y)}{f_Y(y)}, x \in \mathbb{R} \text{ (for fixed } y), f_Y(y) > 0$$

is the **conditional probability function of X given $\{Y = y\}$** . Similarly if $f_X(x)$ is the marginal density function of X

$$f_{Y|X=x}(y) = \frac{f_{X,Y}(x, y)}{f_X(x)}, y \in \mathbb{R} \text{ (for fixed } x), f_X(x) > 0$$

is the conditional probability function of Y given $\{X = x\}$.

Remark: Note that

$$P(X \in B | Y = y) = \int_B f_{X|Y=y}(x) dx$$

for any $B \subset \mathbb{R}$.

Example

(X, Y) is a random vector with the following joint density function:

$$f_{X,Y}(x, y) = \begin{cases} (y + x) & \text{for } (x, y) \in (0, 1) \times (0, 1) \\ 0 & \text{otherwise} \end{cases} .$$

Conditional density function of Y given that $X = x$ (with $x \in (0, 1)$):

$$\begin{aligned} f_X(x) &= \int_0^1 (y + x) dy & f_{Y|X=x}(y) &= \frac{f_{X,Y}(x, y)}{f_X(x)} \\ &= x + \frac{1}{2} & &= \frac{x + y}{x + \frac{1}{2}}, y \in (0, 1) \end{aligned}$$

Probability of $Y \geq 0.7 | X = 0.5$

$$\begin{aligned} P(Y \geq 0.7 | X = 0.5) &= \int_{0.7}^1 f_{Y|X=0.5}(y) dy \\ &= \int_{0.7}^1 (y + 0.5) dy = 0.405. \end{aligned}$$

Remark:

- The conditional density functions of X and Y verify all the properties of a density function of a univariate random variable.
- Note that we can always decompose a joint density function in the following way

$$f_{X,Y}(x,y) = f_X(x)f_{Y|X=x}(y) = f_Y(y)f_{X|Y=y}(x).$$

- If X and Y are independent $f_{Y|X=x}(y) = f_Y(y)$ and $f_{X|Y=y}(x) = f_X(x)$.

Example

Consider the conditional density function of Y given that $X = x$ (with $x \in (0, 1)$):

$$f_{Y|X=x}(y) = \frac{f_{X,Y}(x,y)}{f_X(x)} = \frac{x+y}{x+\frac{1}{2}}, y \in (0, 1).$$

$f_{Y|X=x}$ is indeed a density function:

$$f_{Y|X=x}(y) \geq 0 \quad \text{and} \quad \int_0^1 \frac{x+y}{x+\frac{1}{2}} dy = 1.$$

Example

Consider the conditional density function of Y given that $X = x$ (with $x \in (0, 1)$) and the marginal density function of Y .

$$f_{Y|X=x}(y) = \frac{f_{X,Y}(x,y)}{f_X(x)} = \frac{x+y}{x+\frac{1}{2}}, y \in (0,1)$$

$$f_Y(y) = y + \frac{1}{2}, y \in (0,1).$$

The random variables are not independent because

$$f_{Y|X=x}(y) \neq f_Y(y), \quad \text{for some } y \in (0,1).$$

Definition: The conditional CDF of Y given X by defined by

$$F_{Y|X=x}(y) = \int_{-\infty}^y f_{Y|X=x}(s) ds = \int_{-\infty}^y \frac{f_{Y,X}(s, x)}{f_X(x)} ds$$

for a fixed x , with $f_X(x) > 0$.

Remark: It can be checked that $F_{Y|X=x}$ is indeed a CDF.

Example

Consider the conditional density function of Y given that $X = x$ (with $x \in (0, 1)$):

$$f_{Y|X=x}(y) = \frac{f_{X,Y}(x, y)}{f_X(x)} = \frac{x + y}{x + \frac{1}{2}}, \quad y \in (0, 1).$$

For $x \in (0, 1)$, the conditional cumulative density function is given by:

$$F_{Y|X=x}(y) = \begin{cases} 0, & y < 0 \\ \frac{y(2x+y)}{1+2x}, & 0 \leq y < 1 \\ 1, & y \geq 1 \end{cases}$$

where, $\frac{y(2x+y)}{1+2x} = \int_0^y \frac{x+s}{x+\frac{1}{2}} ds$.