

# ST 501: Fundamentals of Statistical Inference

## Multivariate probability distributions (Part I)

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# Bivariate discrete random variable

## Definition

Let  $X = (X_1, X_2)$  where the  $X_1$  and  $X_2$  are discrete random variables. Then  $X$  is said to be a discrete bivariate random variable. The **joint** pmf for  $X = (X_1, X_2)$  is defined as

$$p(x_1, x_2) = P(X_1 = x_1, X_2 = x_2)$$

**Note** If  $X = (X_1, X_2)$  is a discrete bivariate rv then

1.  $p(x_1, x_2) \geq 0$  for all  $x_1, x_2$ .
2.  $\sum p(x_1, x_2) = 1$  where the summation is over all  $(x_1, x_2)$  with  $p(x_1, x_2) > 0$ .
3. For any subset  $A \subset \mathbb{R}^2$ ,  $P(A) = \sum p(x_1, x_2)$  where the sum is over all pairs  $(x_1, x_2) \in A$  with  $p(x_1, x_2) > 0$ .

**Example** We roll a fair die twice. Let  $X_1$  and  $X_2$  be the faces shown on the first and second roll, respectively. Then  $X = (X_1, X_2)$  takes on  $6 \times 6 = 36$  possible values with

$$p(x_1, x_2) \equiv \frac{1}{36}, \quad (x_1, x_2) \in \{1, 2, \dots, 6\} \times \{1, 2, \dots, 6\}.$$

**Example** We toss a fair coin 6 times. Let  $X_1$  and  $X_2$  be the number of heads and tails (in these 6 tosses), respectively. Then  $X = (X_1, X_2)$  takes on 7 possible values, namely

$$X \in \mathcal{S} = \{(0, 6), (1, 5), (2, 4), (3, 3), (4, 2), (5, 1), (6, 0)\}$$

and that

$$p(x_1, x_2) = \binom{6}{x_1} 2^{-6}, \quad (x_1, x_2) \in \mathcal{S}.$$

# Joint cumulative distribution function

## Definition

For any **bivariate** random variable  $X = (X_1, X_2)$ , the *joint* cdf for  $X$  is.

$$F(x) = P(X_1 \leq x_1, X_2 \leq x_2), \quad x = (x_1, x_2) \in \mathbb{R}^2.$$

**Note** If  $X = (X_1, X_2)$  is a bivariate **discrete** rv then

$$F(x) = P(X_1 \leq x_1, X_2 \leq x_2) = \sum_{y \leq x} p(y_1, y_2)$$

where the sum is over all  $y = (y_1, y_2) \leq x$  with  $p(y_1, y_2) > 0$ .

**Example** When tossing a fair die twice, for  $x = (2, 4)$  we have

$$\begin{aligned} P(X \leq x) &= p(1, 1) + p(1, 2) + p(1, 3) + p(1, 4) \\ &\quad + p(2, 1) + p(2, 2) + p(2, 3) + p(2, 4) = \frac{8}{36}. \end{aligned}$$

**Example** When tossing a fair coin six times with  $X_1$  and  $X_2$  being the number of heads and tails, if  $x = (3, 5)$  then

$$P(X \leq x) = p(1, 5) + p(2, 4) + p(3, 3) = 2^{-6} \left( \binom{6}{1} + \binom{6}{2} + \binom{6}{3} \right) = \frac{41}{64}.$$

A joint cdf is monotone increasing in each argument.

**Proposition**

Let  $X = (X_1, X_2)$  be a bivariate rv with *joint* cdf  $F$ . Then

$$\lim_{x_1 \rightarrow -\infty} F(x_1, x_2) = \lim_{x_2 \rightarrow -\infty} F(x_1, x_2) = 0, \quad \text{for all } x_1, x_2 \in \mathbb{R}$$

$$\lim_{x_1 \rightarrow \infty} \lim_{x_2 \rightarrow \infty} F(x_1, x_2) = 1,$$

$$F(x_1^*, x_2^*) - F(x_1, x_2^*) - F(x_1^*, x_2) + F(x_1, x_2) \geq 0, \quad x_1^* \geq x_1, x_2^* \geq x_2.$$

# Marginal pmf

## Definition

Let  $X = (X_1, X_2)$  be a discrete bivariate random variable with joint pmf  $p(x_1, x_2)$ . The **marginal** pmf of  $X_1$  (respectively  $X_2$ ) is defined as

$$p_1(x_1) = \sum_z p(x_1, z), \quad p_2(x_2) = \sum_z p(z, x_2)$$

where the sum is over all  $(x_1, z)$  (respectively  $(z, x_2)$ ) pairs with  $p(x_1, z) > 0$  (respectively  $p(z, x_2) > 0$ ).

**Example** When rolling a fair die twice (with  $X_1$  and  $X_2$  being the face shown on the first and second roll), we have

$$p_1(x_1) \equiv \frac{1}{6}, \quad x_1 \in \{1, 2, \dots, 6\}; \quad p_2(x_2) \equiv \frac{1}{6}, \quad x_2 \in \{1, 2, \dots, 6\}.$$

**Example** In the setting of tossing a fair coin six times (with  $X_1$  and  $X_2$  being the number of heads and the number of tails), we have

$$p_1(x_1) = \binom{6}{x_1} 2^{-6}, \quad p_2(x_2) = \binom{6}{x_2} 2^{-6}$$



**Example** From a group of three Republicans, two Democrats, and two independent, two people are randomly selected to form a committee. Let  $Y_1$  and  $Y_2$  be the number of Republicans and Democrats on the committee, respectively. Find the joint pmf for  $Y = (Y_1, Y_2)$  and the marginal pmf for  $Y_1$  and  $Y_2$ .

**Example** From a group of three Republicans, two Democrats, and two independent, two people are randomly selected to form a committee. Let  $Y_1$  and  $Y_2$  be the number of Republicans and Democrats on the committee, respectively. Find the joint pmf for  $Y = (Y_1, Y_2)$  and the marginal pmf for  $Y_1$  and  $Y_2$ .

The joint pmf for  $Y = (Y_1, Y_2)$  is

$$p(y_1, y_2) = \frac{\binom{3}{y_1} \binom{2}{y_2} \binom{2}{2-y_1-y_2}}{\binom{7}{2}}, \quad y_1 \geq 0, y_2 \geq 0, y_1 + y_2 \leq 2.$$

The following table gives the joint and the marginal pmf.

	$y_1 = 0$	$y_1 = 1$	$y_1 = 2$	$p_2$
$y_2 = 0$	1/21	4/21	1/21	6/21
$y_2 = 1$	6/21	6/21	0	12/21
$y_2 = 2$	3/21	0	0	3/21
$p_1$	10/21	10/21	1/21	

# Bivariate continuous random variable

A univariate continuous rv is defined using an integral.

Analogously, a bivariate continuous rv is defined in terms of a bivariate integral.

## Definition

Let  $X = (X_1, X_2)$  be a bivariate random variable with joint cdf  $F$ . Then  $X$  is said to be a bivariate continuous rv if and only if there exists a function  $f$  such that

$$F(x_1, x_2) = P(X_1 \leq x_1, X_2 \leq x_2) = \int_{-\infty}^{x_1} \int_{-\infty}^{x_2} f(y_1, y_2) dy_2 dy_1$$

Any function  $f$  with the above property is a joint pdf for  $X$ .

1. For a bivariate continuous rv  $X = (X_1, X_2)$ ,

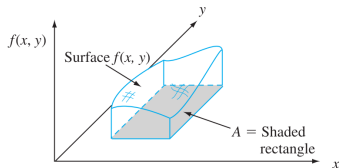
$$P(X = x) = 0 \quad \text{for all } x = (x_1, x_2).$$

2.  $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x_1, x_2) dx_1 dx_2 = 1$

3. For any set  $A$  that is a countable union (or countable intersection) of rectangles

$$P(X \in A) = \int_{(x_1, x_2) \in A} f(x_1, x_2) dx_1 dx_2$$

We can visualize  $f(x, y)$  as specifying a surface at height  $f(x, y)$  above the point  $(x, y)$  in a three-dimensional coordinate system. Then  $P[(X, Y) \in A]$  is the volume underneath this surface and above the region  $A$ , analogous to the area under a curve in the case of a single rv. This is illustrated in Figure 5.1.



**Figure 5.1**  $P[(X, Y) \in A] = \text{volume under density surface above } A$

**Example** Suppose  $X = (X_1, X_2)$  has joint pdf

$$f(x_1, x_2) = \begin{cases} \frac{6}{5}(x_1 + x_2^2) & \text{for } 0 \leq x_1 \leq 1, 0 \leq x_2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Compute  $P(0 \leq X_1 \leq \frac{1}{4}, 0 \leq X_2 \leq \frac{1}{4})$ .

**Example** Suppose  $X = (X_1, X_2)$  has joint pdf

$$f(x_1, x_2) = \begin{cases} \frac{6}{5}(x_1 + x_2^2) & \text{for } 0 \leq x_1 \leq 1, 0 \leq x_2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Compute  $P(0 \leq X_1 \leq \frac{1}{4}, 0 \leq X_2 \leq \frac{1}{4})$ .

$$\begin{aligned} P(0 \leq X_1 \leq 1/4, 0 \leq X_2 \leq 1/4) &= \int_0^{1/4} \int_0^{1/4} \frac{6}{5}(x_1 + x_2^2) dx_1 dx_2 \\ &= \frac{6}{20} \int_0^{1/4} x_1 dx_1 + \frac{6}{20} \int_0^{1/4} x_2^2 dx_2 \\ &= \frac{6}{40} x_1^2 \Big|_0^{1/4} + \frac{1}{10} x_2^3 \Big|_0^{1/4} \\ &= \frac{6}{640} + \frac{1}{640} = \frac{7}{640} \end{aligned}$$

**EXAMPLE 5.4** Gasoline is to be stocked in a bulk tank once at the beginning of each week and then sold to individual customers. Let  $Y_1$  denote the proportion of the capacity of the bulk tank that is available after the tank is stocked at the beginning of the week. Because of the limited supplies,  $Y_1$  varies from week to week. Let  $Y_2$  denote the proportion of the capacity of the bulk tank that is sold during the week. Because  $Y_1$  and  $Y_2$  are both proportions, both variables take on values between 0 and 1. Further, the amount sold,  $y_2$ , cannot exceed the amount available,  $y_1$ . Suppose that the joint density function for  $Y_1$  and  $Y_2$  is given by

$$f(y_1, y_2) = \begin{cases} 3y_1, & 0 \leq y_2 \leq y_1 \leq 1, \\ 0, & \text{elsewhere.} \end{cases}$$

A sketch of this function is given in Figure 5.4.

Find the probability that less than one-half of the tank will be stocked and more than one-quarter of the tank will be sold.



**EXAMPLE 5.4** Gasoline is to be stocked in a bulk tank once at the beginning of each week and then sold to individual customers. Let  $Y_1$  denote the proportion of the capacity of the bulk tank that is available after the tank is stocked at the beginning of the week. Because of the limited supplies,  $Y_1$  varies from week to week. Let  $Y_2$  denote the proportion of the capacity of the bulk tank that is sold during the week. Because  $Y_1$  and  $Y_2$  are both proportions, both variables take on values between 0 and 1. Further, the amount sold,  $y_2$ , cannot exceed the amount available,  $y_1$ . Suppose that the joint density function for  $Y_1$  and  $Y_2$  is given by

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A sketch of this function is given in Figure 5.4.

Find the probability that less than one-half of the tank will be stocked and more than one-quarter of the tank will be sold.

We are interested in  $P(Y_1 \leq 0.5, Y_2 \geq 0.25)$ , i.e.,

$$\begin{aligned} P(Y_1 \leq 0.5, Y_2 \geq 0.25) &= \int_0^{0.5} \int_{0.25}^1 f(y_1, y_2) \, dy_2 \, dy_1 \\ &= \int_{0.25}^{0.5} \int_{0.25}^{y_1} 3y_1 \, dy_2 \, dy_1 \\ &= y_1^3 - \frac{3}{8}y_1^2 \Big|_{0.25}^{0.5} = \frac{5}{128} \end{aligned}$$

## Definition

Let  $X = (X_1, X_2)$  be a continuous bivariate rv with joint pdf  $f(x_1, x_2)$ . The **marginal** pdf of  $X_1$  (respectively  $X_2$ ) is defined as

$$f_1(x_1) = \int_{-\infty}^{\infty} f(x_1, z) \, dz, \quad f_2(x_2) = \int_{-\infty}^{\infty} f(z, x_2) \, dz.$$

**Note** Once again,  $f_1(x_1)$  and  $f_2(x_2)$  are not probabilities, i.e.,  $f_1(x_1) \neq P(X_1 = x_1)$  as  $P(X_1 = x_1) = 0$  for all  $x_1$ . Rather

$$P(X_1 \in A) = \int_{x_1 \in A} f_1(x_1) \, dx_1.$$

**Example** Let  $X = (X_1, X_2)$  be a bivariate rv with joint pdf

$$f(x_1, x_2) = 2, \quad x_1 \geq 0, x_2 \geq 0, x_1 + x_2 \leq 1.$$

$f$  is a valid joint pdf as

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x_1, x_2) dx_1 dx_2 = \int_0^1 \int_0^{1-x_2} 2 dx_1 dx_2 = \int_0^1 2(1-x_2) dx_2 = 1$$

Q. What is the marginal pdf of  $X_1$  and  $X_2$  ?

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The marginal pdf of  $X_1$  and  $X_2$  are

$$f_1(x_1) = \int_{-\infty}^{\infty} f(x_1, z) dz = \int_0^{1-x_1} 2 dz = 2(1-x_1), \quad x_1 \in [0, 1]$$

$$f_2(x_2) = \int_{-\infty}^{\infty} f(z, x_2) dz = \int_0^{1-x_2} 2 dz = 2(1-x_2), \quad x_2 \in [0, 1]$$

**Example** Let  $X = (X_1, X_2)$  be a bivariate rv with joint pdf

$$f(x_1, x_2) = c - 2(c - 1)(x_1 + x_2 - 2x_1x_2) \quad x_1 \in [0, 1], x_2 \in [0, 1]$$

Here  $c \in (0, 2)$  is a constant.

Q. What is the marginal pdf of  $X_1$  and  $X_2$  ?

**Example** Let  $X = (X_1, X_2)$  be a bivariate rv with joint pdf

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Here  $c \in (0, 2)$  is a constant.

Q. What is the marginal pdf of  $X_1$  and  $X_2$  ?

The marginal pdf for  $X_1$  and  $X_2$  are

$$f_1(x_1) = \int_0^1 c - 2(c - 1)(x_1 + z - 2x_1z) dz = 1$$

$$f_2(x_2) = \int_0^1 c - 2(c - 1)(z + x_2 - 2zx_2) dz = 1$$

**Note** Both  $X_1$  and  $X_2$  are, **marginally**  $\text{Unif}(0, 1)$ . However  $X = (X_1, X_2)$  is **not** uniform on  $[0, 1] \times [0, 1]$ .

# Multivariate random variable

It is straightforward to generalize the definition of a bivariate rv to a multivariate rv.

## Definition

Let  $X = (X_1, X_2, \dots, X_m)$  where each of the  $X_i$  are discrete random variables. Then  $X$  is a discrete (multivariate) rv with joint pmf denoted by

$$p(x) = p(x_1, \dots, x_m) = P(X = x) = P(X_1 = x_1, \dots, X_m = x_m)$$

where  $x = (x_1, x_2, \dots, x_m) \in \mathbb{R}^m$ .

**Note** For any  $A \subset \mathbb{R}^m$ ,

$$P(A) = \sum_{x \in A} p(x)$$

where the summation is over all  $x \in A$  for which  $p(x) > 0$ .

## Definition

Let  $X = (X_1, X_2, \dots, X_m)$ . Then  $X$  is said to be a continuous (multivariate) rv if there exists a function  $f: \mathbb{R}^m \mapsto [0, 1]$  such that for all  $x = (x_1, \dots, x_m) \in \mathbb{R}^m$ ,

$$\begin{aligned} F(x) &= P(X \leq x) = P(X_1 \leq x_1, X_2 \leq x_2, \dots, X_m \leq x_m) \\ &= \int_{-\infty}^{x_1} \int_{-\infty}^{x_2} \cdots \int_{-\infty}^{x_m} f(z_1, z_2, \dots, z_m) \, dz_1 dz_2 \cdots dz_m. \end{aligned}$$

**Note** For any set  $A \subset \mathbb{R}^m$  for which  $A$  is a countable union (or countable intersection) of hyper-rectangles

$$P(A) = \int_{(x_1, \dots, x_m) \in A} f(x_1, x_2, \dots, x_m) \, dx_1 dx_2 \cdots dx_m.$$



**Note** We rarely, if ever, need to compute the probability of an event for a (general) multivariate rv by **explicitly** summing or integrating over a set.

Rather, for a multivariate rv, most probability calculations are done via transforming the multivariate rv to some function (or functions) of simpler random variables (such as a collection of independent random variables).

# Independent Random Variables

We revisit the topic of independent random variables (as previously discussed in the lecture slides for Chapter 4).

## Definition

Let  $X_1$  and  $X_2$  be random variables with **marginal** cdf  $F_1$  and  $F_2$ . Let  $X = (X_1, X_2)$  has *joint* cdf  $F$ . Then  $X_1$  and  $X_2$  are **independent** if and only if **for all**  $(x_1, x_2) \in \mathbb{R}^2$

$$F(x_1, x_2) = F_1(x_1)F_2(x_2).$$

Two rvs are said to be **dependent** if they are **not** independent.

We first characterize independence of two discrete rvs.

**Proposition**

*Let  $X_1$  and  $X_2$  be discrete random variables with marginal pmf  $p_1$  and  $p_2$ . Let  $X = (X_1, X_2)$  has joint pmf  $p$ . Then  $X_1$  and  $X_2$  are independent if and only if for all  $(x_1, x_2) \in \mathbb{R}^2$*

$$p(x_1, x_2) = p_1(x_1)p_2(x_2).$$

We next characterize independence of two continuous rvs

**Proposition**

*Let  $X_1$  and  $X_2$  be continuous rvs with marginal pdf  $f_1$  and  $f_2$ . Suppose  $X = (X_1, X_2)$  has joint pdf  $f$ . Then  $X_1$  and  $X_2$  are independent if and only if for all  $(x_1, x_2) \in \mathbb{R}^2$*

$$f(x_1, x_2) = f_1(x_1)f_2(x_2).$$

Generalizations of the previous ideas to three or more random variables are straightforward, e.g.,  $X_1, X_2, \dots, X_m$  are mutually independent if and only if, for all  $(x_1, x_2, \dots, x_m)$

$$\begin{aligned} F(x_1, x_2, \dots, x_m) &= P(X_1 \leq x_1, X_2 \leq x_2, \dots, X_m \leq x_m) \\ &= F_1(x_1)F_2(x_2) \cdots F_m(x_m) \end{aligned}$$

where the  $F_i$  are the marginal cdf.

Therefore, if the  $X_1, X_2, \dots, X_m$  are all discrete random variables, then they are mutually independent if and only if, for all  $(x_1, x_2, \dots, x_m)$ ,

$$p(x_1, x_2, \dots, x_m) = p_1(x_1)p_2(x_2) \dots p_m(x_m)$$

Similarly, if the  $X_1, X_2, \dots, X_m$  are all continuous random variables then they are mutually independent if and only if, for all  $(x_1, x_2, \dots, x_m)$ ,

$$f(x_1, x_2, \dots, x_m) = f_1(x_1)f_2(x_2) \dots f_m(x_m)$$

**Example** Let  $Y = (Y_1, Y_2)$  has joint pdf

$$f(y_1, y_2) = \begin{cases} 6y_1y_2^2 & 0 \leq y_1 \leq 1, 0 \leq y_2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Show that  $Y_1$  and  $Y_2$  are independent.

**Example** Let  $Y = (Y_1, Y_2)$  has joint pdf

$$f(y_1, y_2) = \begin{cases} 6y_1y_2^2 & 0 \leq y_1 \leq 1, 0 \leq y_2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Show that  $Y_1$  and  $Y_2$  are independent.

We first compute  $f_1(y_1)$  and  $f_2(y_2)$ , i.e.,

$$f_1(y_1) = \int_0^1 6y_1y_2^2 \, dy_2 = 2y_1y_2^3 \Big|_0^1 = 2y_1$$

$$f_2(y_2) = \int_0^1 6y_1y_2^2 \, dy_1 = 3y_1^2y_2^2 \Big|_0^1 = 3y_2^2$$

and so  $f(y_1, y_2) = f_1(y_1)f_2(y_2)$  for all  $(y_1, y_2)$ .



The previous example generalizes to yield a quite useful result.

**Proposition**

*Suppose  $X = (X_1, X_2)$  has joint pdf  $f$  satisfying the conditions*

- 1.  $f(x_1, x_2)$  is positive if and only if  $(x_1, x_2) \in [a, b] \times [c, d]$ .*
- 2. There exists functions  $g$  and  $h$  such that*

$$f(x_1, x_2) = g(x_1)h(x_2)$$

*for all  $(x_1, x_2) \in [a, b] \times [c, d]$ .*

*Then  $X_1$  and  $X_2$  are independent.*

**Example** Let  $Y = (Y_1, Y_2)$  has joint pdf

$$f(y_1, y_2) = \begin{cases} 2 & 0 \leq y_2 \leq y_1 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Show that  $Y_1$  and  $Y_2$  are not independent.

**Example** Let  $Y = (Y_1, Y_2)$  has joint pdf

$$f(y_1, y_2) = \begin{cases} 2 & 0 \leq y_2 \leq y_1 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Show that  $Y_1$  and  $Y_2$  are not independent.

Let  $y_2 = 0.5$  and  $y_1 = 0.3$ . Note that  $f_1(y_1) > 0$  and  $f_2(y_2) > 0$ .

However,  $f(y_1, y_2) = 0 \neq f_1(y_1)f_2(y_2)$ .

In fact there exists (an uncountable number) of points  $(y_1, y_2)$  with  $f(y_1, y_2) \neq f_1(y_1)f_2(y_2)$ .

Therefore  $Y_1$  and  $Y_2$  are not independent.

- 10.** Annie and Alvie have agreed to meet between 5:00 P.M. and 6:00 P.M. for dinner at a local health-food restaurant. Let  $X$  = Annie's arrival time and  $Y$  = Alvie's arrival time. Suppose  $X$  and  $Y$  are independent with each uniformly distributed on the interval  $[5, 6]$ .
- a.** What is the joint pdf of  $X$  and  $Y$ ?
  - b.** What is the probability that they both arrive between 5:15 and 5:45?
  - c.** If the first one to arrive will wait only 10 min before leaving to eat elsewhere, what is the probability that they have dinner at the health-food restaurant? [*Hint:* The event of interest is  $A = \{(x, y): |x - y| \leq 1/6\}$ .]

For part (b) the answer is  $1/4$  as  $X$  and  $Y$  are independent and  $P(5.25 \leq X \leq 5.75) = P(5.25 \leq Y \leq 5.75) = 1/2$ .

For part (c) we first define  $U = X - 5$  and  $V = Y - 5$ . We are interested in  $p_* = P(|X - Y| \leq 1/6) = P(|U - V| \leq 1/6)$ , i.e.,

$$\begin{aligned} p_* &= \int_0^{1/6} \int_0^{u+1/6} dv du + \int_{1/6}^{5/6} \int_{v-1/6}^{v+1/6} dv du + \int_{5/6}^1 \int_{v-1/6}^1 dv du \\ &= \int_0^{1/6} (v + 1/6) dv + \int_{1/6}^{5/6} \frac{2}{6} dv + \int_{5/6}^1 (7/6 - v) dv \\ &= \left( \frac{v^2}{2} + \frac{v}{6} \Big|_0^{1/6} \right) + \left( \frac{v}{6} - \frac{v^2}{2} \Big|_{5/6}^1 \right) + \frac{2}{9} = \frac{11}{36}. \end{aligned}$$

## Example: Independent Exponential Random Variables

Q1a. Let  $X$  and  $Y$  be independent exponential rvs with rate parameters  $\lambda$  and  $\nu$ , respectively. Find  $P(X \leq Y)$ .

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Q1a. Let  $X$  and  $Y$  be independent exponential rvs with rate parameters  $\lambda$  and  $\nu$ , respectively. Find  $P(X \leq Y)$ .

$$\begin{aligned}P(X \leq Y) &= \int_0^{\infty} \int_0^y \lambda \nu e^{-\lambda x} e^{-\nu y} dx dy \\&= \int_0^{\infty} \nu e^{-\nu y} (1 - e^{-\lambda y}) dy \\&= \int_0^{\infty} \nu e^{-\nu y} - \nu e^{-(\lambda+\nu)y} dy \\&= -e^{-\nu y} + \frac{\nu}{\lambda + \nu} e^{-(\lambda+\nu)y} \Big|_0^{\infty} \\&= 1 - \frac{\nu}{\lambda + \nu} = \frac{\lambda}{\lambda + \nu}.\end{aligned}$$

Q1b. Let  $X$  and  $Y$  be independent exponential rvs with rates  $\lambda$  and  $\nu$ , respectively. Find the distribution of  $X - Y$ .



Q1b. Let  $X$  and  $Y$  be independent exponential rvs with rates  $\lambda$  and  $\nu$ , respectively. Find the distribution of  $X - Y$ .

Let  $Z = X - Y \in (-\infty, \infty)$ . We now compute  $P(Z \leq z)$ .

First suppose  $z \leq 0$ . Then

$$\begin{aligned}P(X - Y \leq z) &= P(Y \geq X - z) \\&= P(Y \geq X - z \mid Y \geq X) \times P(Y \geq X) \\&= P(Y \geq -z)P(Y \geq X) = \frac{\lambda e^{\nu z}}{\lambda + \nu}\end{aligned}$$

Next suppose  $z \geq 0$ . Then

$$\begin{aligned}P(X - Y \leq z) &= P(Y - X \geq -z) \\&= 1 - P(Y - X \leq -z) = 1 - \frac{\nu e^{-\lambda z}}{\lambda + \nu}\end{aligned}$$

The cdf for  $Z$  is then

$$F(z) = \begin{cases} \frac{\lambda e^{\nu z}}{\lambda + \nu} & \text{if } z \leq 0 \\ 1 - \frac{\nu e^{-\lambda z}}{\lambda + \nu} & \text{if } z \geq 0 \end{cases}$$

Taking the derivative of  $F(z)$  wrt  $z$  yields

$$f_Z(z) = \begin{cases} \frac{\lambda \nu e^{\nu z}}{\lambda + \nu} & \text{if } z \leq 0 \\ \frac{\lambda \nu e^{-\lambda z}}{\lambda + \nu} & \text{if } z \geq 0 \end{cases}$$

When  $\lambda = \nu$  the previous cdf and pdf reduces to

$$F(z) = \begin{cases} \frac{1}{2}e^{\lambda z} & \text{if } z \leq 0 \\ 1 - \frac{1}{2}e^{-\lambda z} & \text{if } z \geq 0 \end{cases}, \quad f(z) = \frac{\lambda}{2}e^{-\lambda|z|}.$$

which is the Laplace distribution with mean 0 and scale  $\lambda^{-1}$ .

- 112.** The article “**Error Distribution in Navigation**” (*J. of the Institute of Navigation*, 1971: 429–442) suggests that the frequency distribution of positive errors (magnitudes of errors) is well approximated by an exponential distribution. Let  $X$  = the lateral position error (nautical miles), which can be either negative or positive. Suppose the pdf of  $X$  is

$$f(x) = (.1)e^{-.2|x|} \quad -\infty < x < \infty$$

**Example** Let  $X$  and  $Y$  be independent exponential rvs with rate parameters  $\lambda \neq \nu$ . What is the distribution of  $X + Y$  ?

**Example** Let  $X$  and  $Y$  be independent exponential rvs with rate parameters  $\lambda \neq \nu$ . What is the distribution of  $X + Y$  ?

Let  $Z = X + Y \in [0, \infty)$ . Then for any  $z \geq 0$ ,

$$\begin{aligned} P(Z \leq z) &= \int_0^z \int_0^{z-x} \lambda \nu e^{-\lambda x} e^{-\nu y} dy dx \\ &= \int_0^z \lambda e^{-\lambda x} (1 - e^{-\nu(z-x)}) dx \\ &= 1 - e^{-\lambda z} - e^{-\nu z} \int_0^z \lambda e^{-(\lambda-\nu)x} dx \\ &= 1 - e^{-\lambda z} + e^{-\nu z} \left( \frac{\lambda e^{-(\lambda-\nu)x}}{\lambda - \nu} \Big|_0^z \right) \\ &= 1 - e^{-\lambda z} + \frac{\lambda}{\lambda - \nu} e^{-\lambda z} - \frac{\lambda}{\lambda - \nu} e^{-\nu z} \\ &= 1 + \frac{\nu}{\lambda - \nu} e^{-\lambda z} - \frac{\lambda}{\lambda - \nu} e^{-\nu z} \end{aligned}$$

Taking derivative of  $P(Z \leq z)$  wrt  $z$  we obtain

$$f(z) = \frac{d}{dz}P(Z \leq z) = \frac{\lambda\nu}{\lambda - \nu}(e^{-\nu z} - e^{-\lambda z}).$$

This is known as the **hypoexponential** distribution.

# Independence of discrete and continuous rv

Recall that we defined independence of random variables in terms of the cdf and not pmf or pdf.

The use of cdf allows us to mix discrete and continuous rvs.

**Example** Let  $X \sim \text{Exp}(\lambda)$  and  $Y \sim \text{Bernoulli}(1/2)$  be independent rvs. What is the distribution of  $Z = X(2Y - 1)$  ?

# Independence of discrete and continuous rv

Recall that we defined independence of random variables in terms of the cdf and not pmf or pdf.

The use of cdf allows us to mix discrete and continuous rvs.

**Example** Let  $X \sim \text{Exp}(\lambda)$  and  $Y \sim \text{Bernoulli}(1/2)$  be independent rvs. What is the distribution of  $Z = X(2Y - 1)$  ?

It is obvious that  $(X, Y)$  is a bivariate rv but there is neither a joint pmf nor a joint pdf.



Nevertheless, we have

$$\begin{aligned}P(Z \leq z) &= P(X(2Y - 1) \leq z, Y = 0) + P(X(2Y - 1) \leq z, Y = 1) \\&= \frac{1}{2}P(X \geq -z) + \frac{1}{2}P(X \leq z) \quad (\text{Why ?})\end{aligned}$$

Now suppose  $z \leq 0$ . Then  $P(X \leq z) = 0$  and hence

$$P(Z \leq z) = \frac{1}{2}P(X \geq -z) = e^{\lambda z}$$

Similarly, if  $z \geq 0$  then  $P(X \geq -z) = 1$  and

$$P(Z \leq z) = \frac{1}{2} + \frac{1}{2}(1 - e^{-\lambda z}) = 1 - \frac{1}{2}e^{-\lambda z}$$

This is once again the cdf of a **Laplace** rv.

# Conditional probability distributions

We first recall the definition of a conditional probability for discrete random variables.

## Definition (Conditional pmf)

Let  $X = (X_1, X_2)$  be a discrete bivariate random variable. The conditional pmf of  $X_1$  given  $X_2$  is the function

$$p(x_1 | x_2) = \frac{P(X_1 = x_1, X_2 = x_2)}{P(X_2 = x_2)} = \frac{p(x_1, x_2)}{p_2(x_2)}, \quad p_2(x_2) > 0.$$

where  $p$  and  $p_2$  are the joint pmf and the marginal pmf of  $X_2$ , respectively. Note that  $p(x_1, | x_2) = P(X_1 = x_1 | X_2 = x_2)$ .

**Note** The above definition implies the following obvious yet important claims.

1. For any  $A \subset \mathbb{R}$

$$P(X_1 \in A \mid X_2 = x_2) = \sum_{x_1} p(x_1 \mid x_2)$$

where the sum is over all  $x_1$  with  $p(x_1, x_2) > 0$ .

2. For any  $B \subset \mathbb{R}^2$

$$P((X_1, X_2) \in B) = \sum_{x_1} \sum_{x_2} p(x_1 \mid x_2) p_2(x_2)$$

where the sum is over all  $(x_1, x_2) \in B$  with  $p(x_1, x_2) > 0$ .

**Example** Let  $X_1 \sim \text{Pois}(\lambda)$  and  $X_2 \sim \text{Pois}(\mu)$  be independent. Then  $X_1 + X_2 \sim \text{Pois}(\lambda + \mu)$ . The conditional pmf of  $X_1$  given  $Z = X_1 + X_2$  is

$$\begin{aligned} p(x_1 | z) &= P(X_1 = x_1 | X_1 + X_2 = z) \\ &= \frac{P(X_1 = x_1, X_2 = z - x_1)}{P(X_1 + X_2 = z)} \\ &= \frac{(e^{-\lambda} \lambda^{x_1} / x_1!)(e^{-\mu} \mu^{z-x_1} / (z-x_1)!)}{e^{-(\lambda+\mu)} (\lambda + \mu)^z / z!} \\ &= \frac{z!}{x_1!(z-x_1)!} \left( \frac{\lambda}{\lambda + \mu} \right)^{x_1} \left( \frac{\mu}{\lambda + \mu} \right)^{z-x_1} \end{aligned}$$

which is the pmf of a  $\text{Bin}(z, \lambda/(\lambda + \mu))$  random variable.

When  $X = (X_1, X_2)$  is a continuous bivariate random variable, the quantity  $P(X_1 = x_1 | X_2 = x_2)$  is possibly **ill-defined** as  $P(X_2 = x_2) = 0$ , i.e., we cannot define

$$P(X_1 = x_1 | X_2 = x_2) = \frac{P(X_1 = x_1, X_2 = x_2)}{P(X_2 = x_2)}$$

as both the numerator and the denominator are equal to 0.

Q. What interpretation for  $P(X_1 = x_1 | X_2 = x_2)$  ?

A. Let  $P(X_1 = x_1 | X_2 = x_2)$  be a function  $f(x_1 | x_2)$  such that for all  $B \subset \mathbb{R}^2$

$$P((X_1, X_2) \in B) = \iint_B f(x_1 | x_2) f_2(x_2) dx_1 dx_2$$

### Definition

Let  $X = (X_1, X_2)$  be a continuous bivariate random variable.

The **conditional pdf** of  $X_1$  given  $X_2 = x_2$  is a function  $f(x_1 | x_2)$  such that, for all  $B \subset \mathbb{R}^2$  with  $P((X_1, X_2) \in B) > 0$

$$P((X_1, X_2) \in B) = \iint_B f(x_1 | x_2) f_2(x_2) dx_1 dx_2 \quad (*)$$

where  $f_2$  is the marginal pdf of  $X_2$ .

**Important** Using this definition with  $B = [-\infty, z] \times \mathbb{R}$  we have

$$\int_{-\infty}^z f_1(x_1) dx_1 = P(X_1 \leq z) = \int_{-\infty}^z \int_{-\infty}^{\infty} f(x_1 | x_2) f_2(x_2) dx_2 dx_1$$

We therefore should have

$$f_1(x_1) = \int_{-\infty}^{\infty} f(x_1, x_2) dx_2 = \int_{-\infty}^{\infty} f(x_1 | x_2) f(x_2) dx_2$$

and thus

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

as **one possible** definition for  $f(x_1 | x_2)$ .

This definition turns out to be valid, i.e.,  $f(x_1 | x_2)$  as defined does satisfy condition (\*).

**Summary** For a continuous bivariate rv  $X = (X_1, X_2)$ ,  $f(x_1 | x_2)$  is different from  $P(X_1 = x_1 | X_2 = x_2)$  as  $P(X_1 = x_1 | X_2 = x_2)$  is **ill-defined**

Rather,  $f(x_1 | x_2)$  is any function satisfying

$$\iint_B f(x_1, x_2) \, dx_1 dx_2 = \iint_B f(x_1 | x_2) f_2(x_2) \, dx_1 dx_2$$

for all  $B \subset \mathbb{R}^2$  with  $P((X_1, X_2) \in B) > 0$ .

**Canonical** choice is  $f(x_1 | x_2) = f(x_1, x_2)/f_2(x_2)$  for  $f_2(x_2) > 0$ .



**EXAMPLE 5.8** A soft-drink machine has a random amount  $Y_2$  in supply at the beginning of a given day and dispenses a random amount  $Y_1$  during the day (with measurements in gallons). It is not resupplied during the day, and hence  $Y_1 \leq Y_2$ . It has been observed that  $Y_1$  and  $Y_2$  have a joint density given by

$$f(y_1, y_2) = \begin{cases} 1/2, & 0 \leq y_1 \leq y_2 \leq 2, \\ 0 & \text{elsewhere.} \end{cases}$$

That is, the points  $(y_1, y_2)$  are uniformly distributed over the triangle with the given boundaries. Find the conditional density of  $Y_1$  given  $Y_2 = y_2$ . Evaluate the probability that less than 1/2 gallon will be sold, given that the machine contains 1.5 gallons at the start of the day.

We are interested in the conditional pdf of  $Y_1$  given  $Y_2$ . We first need to find  $f_2(y_2)$ , i.e.,

$$f_2(y_2) = \int_{-\infty}^{\infty} f(z, y_2) \, dz = \int_0^{y_2} \frac{1}{2} \, dz = \frac{y_2}{2}$$

The conditional pdf of  $Y_1$  given  $Y_2$  is then

$$f(y_1 \mid y_2) = \frac{f(y_1, y_2)}{f_2(y_2)} = \frac{1/2}{y_2/2} = \frac{1}{y_2}.$$

## Expected value for functions of multivariate rvs

We now formally define expected value for functions of multiple rvs. Note that we have used these ideas previously when considering the expectation of a sum of independent rvs.

### Definition

Let  $X = (X_1, X_2, \dots, X_m)$  be a discrete multivariate r.v. with joint pmf  $p(x_1, x_2, \dots, x_m)$ . Then for any function  $g: \mathbb{R}^m \mapsto \mathbb{R}$ ,

$$\mathbb{E}[g(X_1, \dots, X_m)] = \sum_{(x_1, \dots, x_m)} g(x_1, \dots, x_m) p(x_1, \dots, x_m)$$

where the sum is over all  $(x_1, \dots, x_m)$  with  $p(x_1, \dots, x_m) > 0$ .

### Definition

Let  $X = (X_1, X_2, \dots, X_m)$  be a continuous multivariate rv with joint pdf  $f(x_1, x_2, \dots, x_m)$ . Then for any function  $g: \mathbb{R}^m \mapsto \mathbb{R}$ ,

$$\mathbb{E}[g(X_1, \dots, X_m)] = \int_{\mathbb{R}} \cdots \int_{\mathbb{R}} g(x_1, \dots, x_m) f(x_1, \dots, x_m) dx_1 \dots dx_m$$

Q. How do you define  $\mathbb{E}[g(X_1, \dots, X_m)]$  when the  $(X_1, \dots, X_m)$  is a **mix** of discrete and continuous rvs ?

In any case, we have the following important, albeit simple, results (mantra: expectation is a linear operation).

Let  $X = (X_1, X_2, \dots, X_m)$ , then

1.  $\mathbb{E}[c] = c$  for all constant  $c$ .
2.  $\mathbb{E}[cg(X_1, \dots, X_m)] = c\mathbb{E}[g(X_1, \dots, X_m)]$  for all constant  $c$  and all functions  $g$ .
3. For any functions  $g_1, g_2, \dots, g_K$ ,

$$\mathbb{E}[g_1(X_1, \dots, X_m) + \dots + g_K(X_1, \dots, X_m)] = \sum_k \mathbb{E}[g_k(X_1, \dots, X_m)]$$

Finally when  $X$  and  $Y$  are independent (possibly multivariate) random variables then, for any functions  $g$  and  $h$

$$\mathbb{E}[g(X)h(Y)] = \mathbb{E}[g(X)]\mathbb{E}[h(Y)]$$

**Example** Let  $X$  and  $Y$  be independent  $\text{Unif}(0, 1)$  random variables. What is  $\mathbb{E}[|X - Y|]$  ?

$$\begin{aligned}\mathbb{E}[|X - Y|] &= \int_0^1 \int_0^1 |x - y| \, dx dy \\ &= \int_0^1 \left( \int_0^y (y - x) \, dx + \int_y^1 (x - y) \, dx \right) dy \\ &= \int_0^1 \left( y^2/2 + (1 - y^2)/2 - y(1 - y) \right) dy = 1/3\end{aligned}$$