



# CHAPTER IV

## JOINT PROBABILITY DISTRIBUTIONS

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2021-2022

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- 1 Jointly Distributed Random Variables
- 2 Expected Values, Covariance, and Correlation
- 3 The Distribution of the Sample Mean
- 4 The Distribution of a Linear Combination

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- 1 Jointly Distributed Random Variables
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## Two Discrete Random Variables

- ①  $D_X =$  the set of all possible values of rv  $X$ .
- ②  $D = \{(x, y) : x \in D_X, y \in D_Y\}$

### Definition 1

Let  $X$  and  $Y$  be two drv's defined on the sample space  $\mathcal{S}$ . The probability that  $X = x$  and  $Y = y$  is denoted by

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

The function  $p(x, y)$  is called **the joint probability mass function** (joint pmf) of  $X$  and  $Y$  and has the following properties:

- ①  $0 \leq p(x, y) \leq 1$ .
- ②  $\sum_{(x,y) \in D} p(x, y) = 1$ .
- ③  $P[(X, Y) \in A] = \sum_{(x,y) \in A} p(x, y)$ , where  $A \subseteq D$ .

## Two Discrete Random Variables

### Example 2

Roll a pair of fair dice. For each of the 36 sample points with probability  $1/36$ , let  $X$  denote the smaller and  $Y$  the larger outcome on the dice. The joint pmf of  $X$  and  $Y$  is given by the probabilities

$$p(x, y) = \begin{cases} \frac{1}{36}, & 1 \leq x = y \leq 6 \\ \frac{2}{36}, & 1 \leq x < y \leq 6. \end{cases}$$

## Two Discrete Random Variables

### Definition 3

The **marginal probability mass function of  $X$** , denoted by  $p_X(x)$ , is given by

$$p_X(x) = \sum_{y \in D_y} p(x, y) \quad \text{for each possible value } x.$$

Similarly, the **marginal probability mass function of  $Y$**  is

$$p_Y(y) = \sum_{x \in D_x} p(x, y) \quad \text{for each possible value } y.$$

## Two Discrete Random Variables

### Example 4

Let the joint pmf of  $X$  and  $Y$  be defined by

$$p(x, y) = \frac{x + y}{21}, \quad x = 1, 2, 3, \quad y = 1, 2.$$

Then

$$p_X(x) = \frac{2x + 3}{21}, \quad x = 1, 2, 3,$$

and

$$p_Y(y) = \frac{2 + y}{7}, \quad y = 1, 2.$$

# Two Continuous Random Variables

## Definition 5

Let  $X$  and  $Y$  be two crv's. A **joint probability density function** (joint pdf) for these two variables is a function  $f(x, y)$  satisfying  $f(x, y) \geq 0$  and  $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx dy = 1$ . Then for any (measurable) set  $A \subseteq \mathbb{R}^2$ ,

$$P((X, Y) \in A) = \iint_A f(x, y) dx dy.$$

In particular, if  $A = \{(x, y) : a \leq x \leq b, c \leq y \leq d\}$ , then

$$P((X, Y) \in A) = P(a \leq X \leq b, c \leq Y \leq d) = \int_a^b \int_c^d f(x, y) dx dy.$$



## Two Continuous Random Variables

### Definition 6

The **marginal probability density functions of  $X$  and  $Y$** , denoted by  $f_X(x)$  and  $f_Y(y)$ , respectively, are given by

$$f_X(x) = \int_{-\infty}^{\infty} f(x, y) dy \quad \text{for } -\infty < x < \infty$$

$$f_Y(y) = \int_{-\infty}^{\infty} f(x, y) dx \quad \text{for } -\infty < y < \infty$$

### Example 7

Let  $X$  and  $Y$  have the joint pdf

$$f(x, y) = \frac{4}{3}(1 - xy), \quad 0 \leq x \leq 1, \quad 0 \leq y \leq 1.$$

Find the marginal pdfs of  $X$  and of  $Y$ .

# Independent Random Variables

## Definition 8

Two random variables  $X$  and  $Y$  are said to be **independent** if for every pair of  $x$  and  $y$  values

$$p(x, y) = p_X(x) \cdot p_Y(y) \quad X, Y \text{ are discrete}$$

or

$$f(x, y) = f_X(x) \cdot f_Y(y) \quad X, Y \text{ are continuous.}$$

Otherwise,  $X$  and  $Y$  are said to be **dependent**.

## More Than Two Random Variables

### Definition 9

If  $X_1, X_2, \dots, X_n$  are all discrete rv's, the joint pmf of the variables is the function

$$p(x_1, x_2, \dots, x_n) = P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n).$$

If the variables are continuous, the joint pdf of  $X_1, \dots, X_n$  is the function  $f(x_1, x_2, \dots, x_n)$  such that for any  $n$  intervals  $[a_1, b_1], \dots, [a_n, b_n]$ ,

$$P(a_1 \leq x_1 \leq b_1, \dots, a_n \leq x_n \leq b_n) = \int_{a_1}^{b_1} \dots \int_{a_n}^{b_n} f(x_1, \dots, x_n) dx_n \dots dx_1.$$

## More Than Two Random Variables

### Example 10

Consider an experiment consisting of  $n$  independent and identical trials, in which each trial can result in any one of  $r$  possible outcomes. Let  $p_i = P(\text{outcome } i \text{ on any particular trial})$ , and define random variables by  $X_i = \text{the number of trials resulting in outcome } i (i = 1, \dots, r)$ . Such an experiment is called a **multinomial experiment**, and the joint pmf of  $X_1, \dots, X_r$  is called the **multinomial distribution**. By using a counting argument analogous to the one used in deriving the binomial distribution, the joint pmf of  $X_1, \dots, X_r$  can be shown to be

$$p(x_1, \dots, x_r) = \begin{cases} \frac{n!}{(x_1!)(x_2!) \dots (x_r)!} p_1^{x_1} \dots p_r^{x_r}, & x_i = 0, 1, 2, \dots \\ 0, & \text{otherwise,} \end{cases}$$

where  $x_1 + \dots + x_r = n$ .

## Definition 11

The random variables  $X_1, X_2, \dots, X_n$  are said to be **independent** if for every subset  $X_{i_1}, X_{i_2}, \dots, X_{i_k}$  of the variables (each pair, each triple, and so on), the joint pmf or pdf of the subset is equal to the product of the marginal pmf's or pdf's.

## Example 12

An electronic device runs until one of its three components fails. The lifetimes (in weeks),  $X_1, X_2, X_3$ , of these components are independent, and each has the Weibull pdf

$$f(x) = \frac{2x}{25} e^{(-\frac{x}{5})^2}, \quad 0 < x < \infty.$$

The probability that the device stops running in the first three weeks is equal to  $1 - P(X_i > 3, i = 1, 2, 3) = 1 - \prod_{i=1}^3 P(X_i > 3) = 0.66$ .

# Conditional Distributions

## Definition 13

Let  $X$  and  $Y$  be two crv's with joint pdf  $f(x, y)$  and marginal pdf  $f_X(x)$ . Then for any  $x$  for which  $f_X(x) > 0$ , the **conditional probability density function of  $Y$  given that  $X = x$**  is

$$f_{Y|X}(y|x) = \frac{f(x, y)}{f_X(x)}, \quad -\infty < y < \infty.$$

If  $X$  and  $Y$  are discrete, replacing pdf's by pmf's in this definition gives the **conditional probability mass function of  $Y$  when  $X = x$** .

### Example 14

Two components of a minicomputer have the following joint pdf for their useful lifetimes  $X$  and  $Y$ :

$$f(x) = \begin{cases} xe^{-x(1+y)}, & x \geq 0 \text{ and } y \geq 0 \\ 0, & \text{otherwise.} \end{cases}$$

- ❶ What is the probability that the lifetime  $X$  of the first component exceeds 3?
- ❷ What are the marginal pdf's of  $X$  and  $Y$ ? Are the two lifetimes independent? Explain.
- ❸ What is the probability that the lifetime of at least one component exceeds 3?
- ❹ What is the probability that the lifetime  $X$  exceeds 3, knowing that the lifetime  $Y$  is 4?

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# Expected Values, Covariance, and Correlation

## Definition 15

Let  $X$  and  $Y$  be jointly distributed rv's with pmf  $p(x, y)$  or pdf  $f(x, y)$  according to whether the variables are discrete or continuous. Then the expected value of a function  $h(X, Y)$ , denoted by  $E[h(X, Y)]$  or  $\mu_{h(X, Y)}$ , is given by

$$E[h(X, Y)] = \begin{cases} \sum_x \sum_y h(x, y)p(x, y), & X, Y \text{ are discrete} \\ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x, y)f(x, y)dx dy, & X, Y \text{ are continuous} \end{cases}$$

# Covariance

**Note:**  $\mu_X = E(X)$

## Definition 16

The **covariance between two rv's  $X$  and  $Y$**  is

$$\text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]$$

$$= \begin{cases} \sum_x \sum_y (x - \mu_X)(y - \mu_Y)p(x, y), & X, Y \text{ discrete} \\ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_X)(y - \mu_Y)p(x, y)dx dy, & X, Y \text{ continuous} \end{cases}$$

## Theorem 1

$$\text{Cov}(X, Y) = E(XY) - \mu_X \cdot \mu_Y.$$

# Correlation

## Definition 17

The **correlation coefficient of  $X$  and  $Y$** , denoted by  $\text{Corr}(X, Y)$ ,  $\rho_{X,Y}$ , or just  $\rho$ , is defined by

$$\rho_{X,Y} = \frac{\text{Cov}(X, Y)}{\sigma_X \cdot \sigma_Y}.$$

## Theorem 2

- ① If  $a$  and  $c$  are either both positive or both negative,  

$$\text{Corr}(aX + b, cY + d) = \text{Corr}(X, Y).$$
- ② For any two rv's  $X$  and  $Y$ ,  $-1 \leq \text{Corr}(X, Y) \leq 1$ .
- ③ If  $X$  and  $Y$  are independent, then  $\rho = 0$ .
- ④  $\rho = 1$  or  $-1$  iff  $Y = aX + b$  for some numbers  $a$  and  $b$  with  $a \neq 0$ .

### Example 18

An instructor has given a short quiz consisting of two parts. For a randomly selected student, let  $X$  = the number of points earned on the first part and  $Y$  = the number of points earned on the second part. Suppose that the joint pmf of  $X$  and  $Y$  is given the table

		$y$			
$p(x, y)$		0	5	10	15
$x$	0	.02	.06	.02	.10
	5	.04	.15	.20	.10
	10	.01	.15	.14	.01

- 1 What is the total expected score  $E(X + Y)$ ?
- 2 If the maximum of the two scores is recorded, what is the expected recorded score?
- 3 Compute the covariance and correlation for  $X$  and  $Y$ .

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# The Distribution of the Sample Mean

## Definition 19

The rv's  $X_1, X_2, \dots, X_n$  are said to form a (simple) **random sample** of size  $n$  if

- ① The  $X_i$ 's are independent random variables.
- ② Every  $X_i$  has the same probability distribution.

## Theorem 3

Let  $X_1, X_2, \dots, X_n$  be a random sample from a distribution with mean value  $\mu$  and standard deviation  $\sigma$  and let  $\bar{X} = (X_1 + \dots + X_n)/n$  (sample mean). Then

- ①  $E(\bar{X}) = \mu_{\bar{X}} = \mu$
- ②  $V(\bar{X}) = \sigma_{\bar{X}}^2 = \sigma^2/n$  and  $\sigma_{\bar{X}} = \sigma/\sqrt{n}$

In addition, with  $T_0 = X_1 + \dots + X_n$  (the sample total),

$$E(T_0) = n\mu, \quad V(T_0) = n\sigma^2, \quad \text{and} \quad \sigma_{T_0} = \sqrt{n}\sigma$$

# The Central Limit Theorem

## Theorem 4

If  $X_1, X_2, \dots, X_n \sim N(\mu, \sigma^2)$ , then

$$\bar{X} \sim N(\mu, \sigma^2/n).$$

## Theorem 5 (The Central Limit Theorem (CLT))

Let  $X_1, X_2, \dots, X_n$  be a random sample from a distribution with mean  $\mu$  and variance  $\sigma^2$ . Then if  $n$  is sufficiently large,  $\bar{X}$  has approximately a normal distribution with  $\mu_{\bar{X}} = \mu$  and  $\sigma_{\bar{X}}^2 = \sigma^2/n$ , and  $T_0$  also has approximately a normal distribution with  $\mu_{T_0} = n\mu$ ,  $\sigma_{T_0}^2 = n\sigma^2$ . The larger the value of  $n$ , the better the approximation.

## Rule of Thumb

If  $n > 30$ , the CLT can be applied.

# The Central Limit Theorem

## Example 20

The amount of a particular impurity in a batch of a certain chemical product is a random variable with mean value 4.0g and standard deviation 1.5g. If 50 batches are independently prepared, what is the (approximate) probability that the sample average amount of impurity  $\bar{X}$  is between 3.5 and 3.8g?



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# The Distribution of a Linear Combination

## Definition 21

Given a collection of  $n$  random variables  $X_1, \dots, X_n$  and  $n$  numerical constants  $a_1, \dots, a_n$ , the rv

$$Y = a_1X_1 + \dots + a_nX_n = \sum_{i=1}^n a_iX_i$$

is called the **linear combination** of the  $X_i$ 's.

# The Distribution of a Linear Combination

## Theorem 6

Let  $X_1, X_2, \dots, X_n$  have mean values  $\mu_1, \dots, \mu_n$ , respectively, and variances  $\sigma_1^2, \dots, \sigma_n^2$ , respectively.

- 1 Whether or not the  $X_i$ 's are independent,

$$E(a_1X_1 + \dots + a_nX_n) = a_1E(X_1) + \dots + a_nE(X_n).$$

- 2 If  $X_1, \dots, X_n$  are independent,

$$V(a_1X_1 + \dots + a_nX_n) = a_1^2 V(X_1) + \dots + a_n^2 V(X_n)$$

$$\sigma_{a_1X_1 + \dots + a_nX_n} = \sqrt{a_1^2\sigma_1^2 + \dots + a_n^2\sigma_n^2}.$$

- 3 For any  $X_1, \dots, X_n$ ,

$$V(a_1X_1 + \dots + a_nX_n) = \sum_{i=1}^n \sum_{j=1}^n a_i a_j \text{Cov}(X_i, X_j).$$

# The Case of Normal Random Variables

## Theorem 7

If  $X_1, X_2, \dots, X_n$  are independent, normally distributed rv's (with possibly different means and/or variances), then any linear combination of the  $X_i$ 's also has a normal distribution.

## Example 22

A gas station sells three grades of gasoline: regular, extra, and super. These are priced at \$3.00, \$3.20, and \$3.40 per gallon, respectively. Let  $X_1, X_2$ , and  $X_3$  denote the amounts of these grades purchased (gallons) on a particular day. Suppose the  $X_i$ 's are independent with  $\mu_1 = 1000, \mu_2 = 500, \mu_3 = 300, \sigma_1 = 100, \sigma_2 = 80$ , and  $\sigma_3 = 50$ . Suppose that the revenue from sales is  $Y = 3.0X_1 + 3.2X_2 + 3.4X_3$ . Find  $P(Y > 4500)$ ?