

Chapter 4 - Part 2

# Joint Probability

## Joint Probability Distribution - Example

There is a bag with 2 blue and 3 red marbles. Two marbles are drawn without replacement.

$$S = \{RR, RB, BR, BB\}$$

Let

- ▶  $X$  : number of blue marbles in both draws
- ▶  $Y$  : number of red marbles in last draw

The assignment

$$S = \{ \underbrace{RR}_{x=0,y=1}, \underbrace{RB}_{x=1,y=0}, \underbrace{BR}_{x=1,y=1}, \underbrace{BB}_{x=2,y=0} \}$$

gives the joint distribution of  $X$  and  $Y$ . Mostly, we will show this as:

| $y \backslash x$ | 0      | 1   | 2      |
|------------------|--------|-----|--------|
| 0                | no way | R B | B B    |
| 1                | R R    | B R | no way |

## Example (cont'd)

► 2 blue and 3 red marbles

$$P(RR) = \frac{3}{5} \cdot \frac{2}{4} = \frac{3}{10}$$

$$P(RB) = \frac{3}{5} \cdot \frac{2}{4} = \frac{3}{10}$$

$$P(BR) = \frac{2}{5} \cdot \frac{3}{4} = \frac{3}{10}$$

$$P(BB) = \frac{2}{5} \cdot \frac{1}{4} = \frac{1}{10}$$

| x \ y | 0      | 1   | 2      |
|-------|--------|-----|--------|
| 0     | no way | R B | B B    |
| 1     | R R    | B R | no way |

The joint probability distribution function of  $X$  and  $Y$  is given by

| x \ y    | 0   | 1   | 2   | $\Sigma$ |
|----------|-----|-----|-----|----------|
| 0        | 0   | 0.3 | 0.1 | 0.4      |
| 1        | 0.3 | 0.3 | 0   | 0.6      |
| $\Sigma$ | 0.3 | 0.6 | 0.1 | 1        |

## Example (cont'd)

The joint probability distribution function of  $X$  and  $Y$  is given by

| $\begin{array}{c} x \\ y \end{array}$ | 0   | 1   | 2   | $\Sigma$ |
|---------------------------------------|-----|-----|-----|----------|
| 0                                     | 0   | 0.3 | 0.1 | 0.4      |
| 1                                     | 0.3 | 0.3 | 0   | 0.6      |
| $\Sigma$                              | 0.3 | 0.6 | 0.1 | 1        |

$$p(0,0) = 0, \quad p(0,1) = 0.3, \quad p(1,0) = 0.3, \quad p(1,1) = 0.3, \quad p(2,0) = 0.1, \quad p(2,1) = 0$$

Another notation:

$$P(X = 2, Y = 0) = 0.1, \quad P(Y = 0) = 0.4,$$

$$P(X > 1, Y = 0) = 0.1, \quad P(X < 2, Y < 1) = 0.3$$

## Joint Probability Distribution - Definition

Given two random variables  $X$  and  $Y$  that are defined on the same sample space, the **joint probability distribution function** of them is given by

$$p(a, b) = P(X = a, Y = b) = P(X = a) \cap P(Y = b)$$

**Note:** This can also be defined for  $n > 2$  many random variables.

## Covariance - Definition

Let  $X$  and  $Y$  be two discrete random variables on the same sample space. Let the values that  $X$  can take be

$$x_1, x_2, \dots, x_n$$

and the values that  $Y$  can take be

$$y_1, y_2, \dots, y_m.$$

We define the **covariance** of  $X$  and  $Y$  as

$$\sigma_{XY} = \text{Cov}(X, Y) = \sum_{i=1}^n \sum_{j=1}^m p(x_i, y_j)(x_i - E(X))(y_j - E(Y))$$

## Example

Consider again

| $y \backslash x$ | 0   | 1   | 2   | $\Sigma$ |
|------------------|-----|-----|-----|----------|
| 0                | 0   | 0.3 | 0.1 | 0.4      |
| 1                | 0.3 | 0.3 | 0   | 0.6      |
| $\Sigma$         | 0.3 | 0.6 | 0.1 | 1        |

First,

$$E(X) = 0 \cdot 0.3 + 1 \cdot 0.6 + 2 \cdot 0.1 = 0.8, \quad E(Y) = 0 \cdot 0.4 + 1 \cdot 0.6 = 0.6$$

Hence

$$\begin{aligned} \text{Cov}(X, Y) = & \underbrace{p(0,0)}_0 (0 - 0.8)(0 - 0.6) + \underbrace{p(0,1)}_{0.3} (0 - 0.8)(1 - 0.6) \\ & + \underbrace{p(1,0)}_{0.3} (1 - 0.8)(0 - 0.6) + \underbrace{p(1,1)}_{0.3} (1 - 0.8)(1 - 0.6) \\ & + \underbrace{p(2,0)}_{0.1} (2 - 0.8)(0 - 0.6) + \underbrace{p(2,1)}_0 (2 - 0.8)(1 - 0.6) \end{aligned}$$

## Example (cont'd)

$$\begin{aligned}\text{Cov}(X, Y) &= \underbrace{p(0, 0)}_0 (0 - 0.8)(0 - 0.6) + \underbrace{p(0, 1)}_{0.3} (0 - 0.8)(1 - 0.6) \\ &\quad + \underbrace{p(1, 0)}_{0.3} (1 - 0.8)(0 - 0.6) + \underbrace{p(1, 1)}_{0.3} (1 - 0.8)(1 - 0.6) \\ &\quad + \underbrace{p(2, 0)}_{0.1} (2 - 0.8)(0 - 0.6) + \underbrace{p(2, 1)}_0 (2 - 0.8)(1 - 0.6) \\ &= (0.3) \cdot (-0.8) \cdot (0.4) + (0.3) \cdot (0.2) \cdot (-0.6) \\ &\quad + (0.3) \cdot (0.2) \cdot (0.4) + (0.1) \cdot (1.2) \cdot (-0.6) \\ &= -0.18\end{aligned}$$

## Random Variable vs Dataset

The **covariance** of the joint distribution

| $\begin{array}{c} x \\ y \end{array}$ | 0   | 1   | 2   | $\Sigma$ |
|---------------------------------------|-----|-----|-----|----------|
| 0                                     | 0   | 0.3 | 0.1 | 0.4      |
| 1                                     | 0.3 | 0.3 | 0   | 0.6      |
| $\Sigma$                              | 0.3 | 0.6 | 0.1 | 1        |

is the same as the **population covariance** of a dataset of the form

$$\underbrace{\{(0, 1), (0, 1), \dots, (0, 1)\}}_{30\%}, \underbrace{\{(1, 0), (1, 0), \dots, (1, 0)\}}_{30\%}, \underbrace{\{(1, 1), (1, 1), \dots, (1, 1)\}}_{30\%}, \underbrace{\{(2, 0), \dots, (2, 0)\}}_{10\%}$$

An example of such dataset:

$$\{(0, 1), (0, 1), (0, 1), (1, 0), (1, 0), (1, 0), (1, 1), (1, 1), (1, 1), (2, 0)\}$$

## Multivariable Function of Random Variables - Example

| $y \backslash x$ | 0   | 1   | 2   | $\Sigma$ |
|------------------|-----|-----|-----|----------|
| 0                | 0   | 0.3 | 0.1 | 0.4      |
| 1                | 0.3 | 0.3 | 0   | 0.6      |
| $\Sigma$         | 0.3 | 0.6 | 0.1 | 1        |

The function  $t = f(x, y) = 2x + 4y + 3$  gives a random variable with outcomes

| $(x, y)$   | (0,0) | (0,1) | (1,0) | (1,1) | (2,0) | (2,1) |
|------------|-------|-------|-------|-------|-------|-------|
| $t=f(x,y)$ | 3     | 7     | 5     | 9     | 7     | 11    |

$$P(T = 3) = P(X = 0, Y = 0) = 0,$$

$$P(T = 5) = P(X = 1, Y = 0) = 0.3,$$

$$P(T = 7) = P(X = 0, Y = 1) + P(X = 2, Y = 0) = 0.3 + 0.1 = 0.4,$$

$$P(T = 9) = P(X = 1, Y = 1) = 0.3,$$

$$P(T = 11) = P(X = 2, Y = 1) = 0$$

## Example (cont'd)

| $y \backslash x$ | 0   | 1   | 2   | $\Sigma$ |
|------------------|-----|-----|-----|----------|
| 0                | 0   | 0.3 | 0.1 | 0.4      |
| 1                | 0.3 | 0.3 | 0   | 0.6      |
| $\Sigma$         | 0.3 | 0.6 | 0.1 | 1        |

$$T = 2X + 4Y + 3$$

| t    | 5   | 7   | 9   |
|------|-----|-----|-----|
| p(t) | 0.3 | 0.4 | 0.3 |

$$E(T) = 5 \cdot 0.3 + 7 \cdot 0.4 + 9 \cdot 0.3 = 7$$

Also notice that

$$2E(X) + 4E(Y) + 3 = 2 \cdot 0.8 + 4 \cdot 0.6 + 3 = 7$$

## Proposition

Let  $a, b, c \in \mathbb{R}$  be constants and  $X, Y$  be random variables. Then,

$$E(aX + bY + c) = aE(X) + bE(Y) + c$$

## Example

Roll a pair of dice (one black one white). Let  $X$  be the random variable representing sum of two dice. Let's find  $E(X)$ .

Call  $X_b$  and  $X_w$  for the random variables representing the outcomes of black and white die, respectively. Then

$$X = X_b + X_w$$

We already seen that  $E(X_b) = E(X_w) = 3.5$ . Therefore

$$E(X) = E(X_b + X_w) = E(X_b) + E(X_w) = 3.5 + 3.5 = 7$$

## Proposition

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

Proof.

It follows from the definition of covariance:

$$\text{Cov}(X, Y) = \sum_{i=1}^n \sum_{j=1}^m p(x_i, y_j) (x_i - E(X))(y_j - E(Y)) = E((X - E(X))(Y - E(Y))).$$



## Proposition

$$\text{Cov}(X, X) = \text{Var}(X)$$

Proof.

$$\text{Cov}(X, X) = E[(X - E(X))(X - E(X))] = E[(X - E(X))^2] = \text{Var}(X)$$



$$\text{Cov}(X, Y) = \text{Cov}(Y, X)$$

Proof.

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



## Proposition

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y)$$

Proof.

$$\begin{aligned}\text{Cov}(X, Y) &= E[(X - E(X))(Y - E(Y))] \\&= E[XY - XE(Y) - YE(X) + E(X)E(Y)] \\&= E(XY) - E(XE(Y)) - E(YE(X)) + E(E(X)E(Y)) \\&= E(XY) - E(X)E(Y) - E(X)E(Y) + E(X)E(Y) \\&= E(XY) - E(X)E(Y)\end{aligned}$$



## Example

Let's calculate again the covariance of the following

| $y \backslash x$ | 0   | 1   | 2   | $\Sigma$ |
|------------------|-----|-----|-----|----------|
| 0                | 0   | 0.3 | 0.1 | 0.4      |
| 1                | 0.3 | 0.3 | 0   | 0.6      |
| $\Sigma$         | 0.3 | 0.6 | 0.1 | 1        |

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

Call  $T = XY$ . Then possible outcomes of  $T$  are

| $(x,y)$ | (0,1) | (1,0) | (1,1) | (2,0) |
|---------|-------|-------|-------|-------|
| $t=xy$  | 0     | 0     | 1     | 0     |

$$P(T = 0) = 0.3 + 0.3 + 0.1 = 0.7, \quad P(T = 1) = 0.3$$

## Example (cont'd)

| $y \backslash x$ | 0   | 1   | 2   | $\Sigma$ |
|------------------|-----|-----|-----|----------|
| 0                | 0   | 0.3 | 0.1 | 0.4      |
| 1                | 0.3 | 0.3 | 0   | 0.6      |
| $\Sigma$         | 0.3 | 0.6 | 0.1 | 1        |

$$T = XY$$

| t    | 0   | 1   |
|------|-----|-----|
| p(t) | 0.7 | 0.3 |

$$E(XY) = E(T) = 0.3$$

Hence

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y) = 0.3 - 0.8 \cdot 0.6 = -0.18$$

# Independence

Two random variables  $X$  and  $Y$  are called **independent** if

$$P(X = a, Y = b) = P(X = a) \cdot P(Y = b)$$

for all possible outcome  $a$  of  $X$  and  $b$  of  $Y$ .

Otherwise, they are called **dependent**.

## Example

| $y \backslash x$ | 0   | 1   | 2   | $\Sigma$ |
|------------------|-----|-----|-----|----------|
| 0                | 0   | 0.3 | 0.1 | 0.4      |
| 1                | 0.3 | 0.3 | 0   | 0.6      |
| $\Sigma$         | 0.3 | 0.6 | 0.1 | 1        |

$X$  and  $Y$  are **not independent** since for example

$$P(X = 0, Y = 1) = 0.3 \neq 0.3 \cdot 0.6 = P(X = 0) \cdot P(Y = 1)$$

## Example

| $\begin{array}{c} x \\ y \end{array}$ | 1    | 2    | $\Sigma$ |
|---------------------------------------|------|------|----------|
| 1                                     | 0.14 | 0.56 | 0.7      |
| 2                                     | 0.06 | 0.24 | 0.3      |
| $\Sigma$                              | 0.2  | 0.8  | 1        |

$X$  and  $Y$  are independent since

$$P(X = 1, Y = 1) = 0.14 = 0.2 \cdot 0.7 = P(X = 1) \cdot P(Y = 1)$$

$$P(X = 1, Y = 2) = 0.06 = 0.2 \cdot 0.3 = P(X = 1) \cdot P(Y = 2)$$

$$P(X = 2, Y = 1) = 0.56 = 0.8 \cdot 0.7 = P(X = 2) \cdot P(Y = 1)$$

$$P(X = 2, Y = 2) = 0.24 = 0.8 \cdot 0.3 = P(X = 2) \cdot P(Y = 2)$$

## Example

Roll a pair of dice (one black one white). Call  $X_b$  and  $X_w$  for the random variables representing the outcomes of black and white die, respectively.

$X_b$  and  $X_w$  are **independent** since

$$P(X_b = i, X_w = j) = \frac{1}{36} = \frac{1}{6} \cdot \frac{1}{6} = P(X_b = i) \cdot P(X_w = j)$$

for all  $i, j \in \{1, 2, 3, 4, 5, 6\}$ .

## Covariance of Independent Random Variables - Example

Roll a pair of dice (one black one white). Call  $X_b$  and  $X_w$  for the random variables representing the outcomes of black and white die, respectively.

$$\begin{aligned} E(X_b X_w) &= \sum_{j=1}^6 \sum_{i=1}^6 i \cdot j \cdot \underbrace{P(x_b = i, x_w = j)}_{\frac{1}{36}} = \frac{1}{36} \sum_{j=1}^6 \sum_{i=1}^6 i \cdot j \\ &= \frac{1}{36} (1 \cdot 1 + 1 \cdot 2 + \dots + 1 \cdot 6 + 2 \cdot 1 + 2 \cdot 2 + \dots + 2 \cdot 6 + 3 \cdot 1 + \dots + \dots + 6 \cdot 6) \\ &= \frac{1}{36} (1 \cdot (1 + 2 + \dots + 6) + 2 \cdot (1 + 2 + \dots + 6) + \dots + 6 \cdot (1 + 2 + \dots + 6)) \\ &= \frac{1}{36} \cdot \underbrace{(1 + 2 + \dots + 6)}_{21} \cdot \underbrace{(1 + 2 + \dots + 6)}_{21} = \left( \frac{21}{6} \right)^2 \end{aligned}$$

$$\Rightarrow \text{Cov}(X_b, X_w) = E(X_b X_w) - E(X_b)E(X_w) = \left( \frac{21}{6} \right)^2 - \frac{21}{6} \cdot \frac{21}{6} = 0.$$

## Covariance of Independent Random Variables - Theorem

If  $X$  and  $Y$  are independent, then

$$\text{Cov}(X, Y) = 0.$$

Proof.

If  $X$  and  $Y$  are independent,

$$\begin{aligned} E(XY) &= \sum_j \sum_i x_i \cdot y_j \cdot p(x_i, y_j) \\ &= \sum_j \sum_i x_i \cdot y_j \cdot p(x_i) p(y_j) \\ &= \left( \sum_i x_i \cdot p(x_i) \right) \left( \sum_j y_j \cdot p(y_j) \right) \\ &= E(X)E(Y) \end{aligned}$$

$$\implies \text{Cov}(X, Y) = E(XY) - E(X)E(Y) = 0$$

## Covariance of Independent Random Variables - Theorem

If  $X$  and  $Y$  are independent, then

$$\text{Cov}(X, Y) = 0.$$

**Remark:** Converse of this theorem is **not true!**  $\text{Cov}(X, Y) = 0$  does not imply  $X$  and  $Y$  being independent.

## Example

| $\begin{array}{c} x \\ y \end{array}$ | 0   | 3   | 5   | $\Sigma$ |
|---------------------------------------|-----|-----|-----|----------|
| 0                                     | 0.1 | 0.1 | 0.1 | 0.3      |
| 1                                     | 0.1 | 0.1 | 0.2 | 0.4      |
| 2                                     | 0.1 | 0.1 | 0.1 | 0.3      |
| $\Sigma$                              | 0.3 | 0.3 | 0.4 | 1        |

$$E(X) = 0 \cdot 0.3 + 3 \cdot 0.3 + 5 \cdot 0.4 = 2.9$$

$$E(Y) = 0 \cdot 0.3 + 1 \cdot 0.4 + 2 \cdot 0.3 = 1$$

$$E(XY) = 3 \cdot 0.1 + 5 \cdot 0.2 + 6 \cdot 0.1 + 10 \cdot 0.1 = 2.9$$

$$\implies \text{Cov}(X, Y) = E(XY) - E(X)E(Y) = 0$$

But  $X$  and  $Y$  are not independent since for example

$$P(X = 0, Y = 0) = 0.1 \neq 0.3 \cdot 0.3 = P(X = 0) \cdot P(Y = 0)$$

# Independent vs Uncorrelated

Two random variables  $X$  and  $Y$  are called **uncorrelated** if

$$\text{Cov}(X, Y) = 0.$$

- ▶ independent  $\implies$  uncorrelated
- ▶ uncorrelated  $\not\implies$  independent

## Proposition

Let  $a, b, c \in \mathbb{R}$  be constants and  $X, Y$  be random variables. Then,

$$\text{Var}(aX + bY + c) = a^2\text{Var}(X) + b^2\text{Var}(Y) + 2ab\text{Cov}(X, Y).$$

In particular, if  $\text{Cov}(X, Y) = 0$  (for example if  $X$  and  $Y$  are independent),

$$\text{Var}(aX + bY + c) = a^2\text{Var}(X) + b^2\text{Var}(Y).$$

Taking  $a = b = 1, c = 0$ :

$$\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y).$$

## Proposition

More generally, if  $X_1, X_2, \dots, X_n$  are random variables such that

$$\text{Cov}(X_i, X_j) = 0$$

for all  $i, j$ , then

$$\text{Var}(X_1 + X_2 + \dots + X_n) = \text{Var}(X_1) + \text{Var}(X_2) + \dots + \text{Var}(X_n).$$

Therefore, if  $X_1, X_2, \dots, X_n$  are pairwise independent random variables

$$\text{Var}(X_1 + X_2 + \dots + X_n) = \text{Var}(X_1) + \text{Var}(X_2) + \dots + \text{Var}(X_n).$$