

# Lecture 2. Tractable dependence models

Enkelejd Hashorva & Pavel Ievlev  
Université de Lausanne

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# Learning objectives

- Understand uniform bivariate distributions on different domains;
- Introduce the concept of **conditional independence**;
- Introduce important classes of dependent risks such as **common monotonic**, **countermonotonic**, **implicit** and **explicit** risks;

# Uniform distribution on a rectangle

Consider the rectangle

$$D = [a, b] \times [c, d] \subset \mathbb{R}^2.$$

Consider the following pdf<sup>1</sup>:

$$f_D(x, y) = \frac{1}{(b-a)(d-c)} \mathbb{1}\{(x, y) \in D\}.$$

Let  $F$  be the corresponding df.

## Definition 1.

A random vector  $(X, Y)$  with df  $F$  is said to be **uniformly distributed** on the rectangle  $D$ . We denote this by  $(X, Y) \sim \text{Unif}(D)$ .

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<sup>1</sup>Why is this a valid pdf?

# Independent risks

Let  $F$  be some df and  $(X, Y) \sim F$ .

## Theorem 2.

*X and Y are independent if and only if F may be written as product of any<sup>2</sup> two functions G and H, i.e.*

$$F(x, y) = G(x)H(y).$$

## Theorem 3.

*Assume F has pdf/pmf f. Then (X, Y) is independent if and only if f may be written as product of any<sup>3</sup> two functions g and h, i.e.*

$$f(x, y) = g(x)h(y).$$

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<sup>2</sup>Check that  $G(x) = cF_1(x)$  and  $H(y) = F_2(y)/c$  for some  $c > 0$ . In other words, G and H are the marginal dfs *up to a constant*.

<sup>3</sup>Check that  $g(x) = cf_1(x)$  and  $h(y) = f_2(y)/c$  for some  $c > 0$ .

## Example: independence of uniform risks on a rectangle

Recall that the pdf of  $\text{Unif}(D)$  with  $D = [a, b] \times [c, d]$  is

$$f_D(x, y) = \frac{1}{(b-a)(d-c)} \mathbb{1}\{(x, y) \in D\}.$$

Note that

$$f_D(x, y) = \underbrace{\frac{1}{b-a} \mathbb{1}\{x \in [a, b]\}}_{g(x)} \cdot \underbrace{\frac{1}{d-c} \mathbb{1}\{y \in [c, d]\}}_{h(y)}.$$

Hence,  $X$  and  $Y$  are independent.

# Uniform distribution on a set $D$

Let  $D \subset \mathbb{R}^2$  be a set with **positive and finite area**

$$|D| = \iint_D dx dy \in (0, \infty).$$

Define the following pdf<sup>4</sup>:

$$f_D(x, y) = \frac{1}{|D|} \mathbb{1}\{(x, y) \in D\}.$$

Let  $F$  be the corresponding df.

## Definition 4.

A random vector  $(X, Y)$  with df  $F$  is said to be **uniformly distributed** on the set  $D$ . We denote this by  $(X, Y) \sim \text{Unif}(D)$ .

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<sup>4</sup>Why is this a valid pdf?

# Uniform distribution on $D$ is typically not independent

## Theorem 5.

Let  $(X, Y) \sim \text{Unif}(D)$ . If  $X$  and  $Y$  are independent, then  $D$  is of the form

$$D = A \times B \quad \text{for some} \quad A, B \subset \mathbb{R}$$

up to a set of zero area.

**Proof.** Assume that  $X$  and  $Y$  are independent:

$$f_D(x, y) = g(x)h(y) = \frac{1}{|D|} \mathbb{1}\{(x, y) \in D\}.$$

Take any point  $(x_0, y_0) \in D$  with  $f_D(x_0, y_0) \neq 0$ .

# Uniform distribution on $D$ is typically not independent

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up to a set of zero area.

**Proof.** We have:  $f_D(x, y) = g(x) h(y)$ ,  $g(x_0), h(y_0) \neq 0$ .

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## Theorem 5.

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up to a set of zero area.

**Proof.** We have:  $f_D(x, y) = g(x) h(y)$ ,  $g(x_0), h(y_0) \neq 0$ . Then,

$$f_D(x_0, y) = g(x_0) h(y) = \frac{1}{|D|} \mathbb{1}\{(x_0, y) \in D\} \implies h(y) = c \mathbb{1}\{(x_0, y) \in D\}$$

$$f_D(x, y_0) = g(x) h(y_0) = \frac{1}{|D|} \mathbb{1}\{(x, y_0) \in D\} \implies g(x) = c' \mathbb{1}\{(x, y_0) \in D\}$$

# Uniform distribution on $D$ is typically not independent

## Theorem 5.

Let  $(X, Y) \sim \text{Unif}(D)$ . If  $X$  and  $Y$  are independent, then  $D$  is of the form

$$D = A \times B \quad \text{for some} \quad A, B \subset \mathbb{R}$$

up to a set of zero area.

**Proof.** We have:  $f_D(x, y) = g(x) h(y)$ ,  $g(x_0), h(y_0) \neq 0$ . Then,

$$h(y) = c \mathbb{1}\{(x_0, y) \in D\} = c \mathbb{1}\{y \in B\} \quad \text{with} \quad B = \{y : (x_0, y) \in D\}$$

$$g(x) = c' \mathbb{1}\{(x, y_0) \in D\} = c' \mathbb{1}\{x \in A\} \quad \text{with} \quad A = \{x : (x, y_0) \in D\}$$

# Uniform distribution on $D$ is typically not independent

## Theorem 5.

*Let  $(X, Y) \sim \text{Unif}(D)$ . If  $X$  and  $Y$  are independent, then  $D$  is of the form*

$$D = A \times B \quad \text{for some} \quad A, B \subset \mathbb{R}$$

*up to a set of zero area.*

**Proof.** We have:  $f_D(x, y) = g(x) h(y)$ ,  $g(x_0), h(y_0) \neq 0$ . Then,

$$f_D(x, y) = cc' \mathbb{1}\{x \in A\} \mathbb{1}\{y \in B\} \implies D = A \times B$$

*up to a set of zero area.* □

# Conditional independence

**Definition 6 (Conditional independence).**

$X_1, \dots, X_d$  are **conditionally independent** given  $W = w$  if for all real numbers  $x_1, \dots, x_d$  holds

$$\mathbb{P} \{X_1 \leq x_1, \dots, X_d \leq x_d \mid W = w\} = \prod_{i=1}^d \mathbb{P} \{X_i \leq x_i \mid W = w\}.$$

*If  $W$  is independent of  $X_1, \dots, X_d$ , then conditional independence implies independence.*

## “Common deflator/inflator” dependence structure

Let  $\Theta, Z_1, Z_2, \dots, Z_d$  be **independent** exponentially distributed random variables. Define

$$X_1 = \frac{Z_1}{\Theta}, \quad X_2 = \frac{Z_2}{\Theta}, \quad \dots, \quad X_d = \frac{Z_d}{\Theta}.$$

Then, **conditionally on**  $\Theta = \theta$ ,  $X_1, \dots, X_d$  are **independent** exponentially distributed random variables.

# Comonotonic risks

**Definition 7 (Comonotonic risks).**

Random variables  $X$  and  $Y$  are said to be **comonotonic** if there exists **one** random variable  $U \sim \text{Unif}(1)$  (common risk) such that  $X = F_1^{-1}(U)$  and  $Y = F_2^{-1}(U)$ . We say that  $(X, Y)$  is a **comonotonic vector**.

**Example.** Let  $X = c_1 U$  and  $Y = c_2 U$ , where  $c_1, c_2 > 0$ . Then  $(X, Y)$  is a comonotonic vector with  $\text{Unif}(0, c_i)$  marginals.

**Theorem 8 (Comonotonicity conditions).**

*The following conditions are equivalent:*

- $(X, Y)$  is comonotonic
- $F(x, y) = \min(F_1(x), F_2(y))$  ( $F$  is the **upper df**)
- There exists a random variable  $Z$  (common risk) and two non-decreasing functions  $h_1, h_2$  such that  $X = h_1(Z)$  and  $Y = h_2(Z)$ .

# Stop-loss transform

**Definition 9 (Stop-loss).**

Let  $X$  be a random variable with df  $F_1$ . Its **stop-loss transform** is defined as

$$Y_s = \max\{0, X - s\}, \quad s \in \mathbb{R}.$$

Let  $F_2$  be the df of  $Y_s$ . Then

$$\mathbb{P}\{X \leq x, (X - s)_+ \leq y\} = \min\{F_1(x), F_2(y)\}.$$

Hence,  $(X, Y_s)$  is a comonotonic vector.

# Countermonotonic risks

## Definition 10 (Countermonotonic risks).

Random variables  $X$  and  $Y$  are said to be **countermonotonic** if there exists **one** random variable  $U \sim \text{Unif}(1)$  such that  $X = F_1^{-1}(U)$  and  $Y = F_2^{-1}(\mathbf{1} - U)$ . We say that  $(X, Y)$  is a **countermonotonic vector**.

## Theorem 11 (Countermonotonicity conditions).

*The following conditions are equivalent:*

- $(X, Y)$  is countermonotonic
- $F(x, y) = \max(F_1(x) + F_2(y) - 1, 0)$  ( $F$  is the **lower df**)
- There exists a random variable  $Z$  and two non-increasing functions  $h_1, h_2$  such that  $X = h_1(Z)$  and  $Y = h_2(-Z)$ .

# Explicit functional dependence with independent generators

## Definition 12.

Let  $Z_1, \dots, Z_d$  be **independent** random variables and  $q : \mathbb{R}^d \rightarrow \mathbb{R}^k$  some function. Define

$$(X_1, \dots, X_k) = q(Z_1, \dots, Z_d).$$

Then  $(X_1, \dots, X_k)$  is said to be an **explicit functional dependence model** with **independent generators**  $Z_1, \dots, Z_d$ .

**Example.** The path  $(X_1, \dots, X_n)$  of a **random walk**

$$X_n = \sum_{i=1}^n Z_i.$$

# Implicit functional dependence

**Idea:** given independent generators<sup>5</sup>  $Z_1, \dots, Z_d$ , we can define a model **implicitly via a system of equations**. For example, **recursively**.

**Example.** The path  $(X_1, \dots, X_n)$  of a **moving average time series**

$$X_{n+1} = a_n X_n + a_{n-1} X_{n-1}$$

with  $X_1 = V_1$  and  $X_2 = V_2$ .

**Example.** Define  $X_{n+1}$  recursively as the **solution** of the following equation:

$$X_{n+1} + \sum_{i=1}^n q_i(X_i) = 0,$$

where  $q_i$  are some known functions.

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<sup>5</sup>Think of them as *sources of randomness* in the model.

## Exercises/questions

- Is the df  $F$  corresponding to the following pdf

$$f(x, y) = \frac{4xy + 2x + 2y + 1}{4}, \quad (x, y) \in [0, 1]^2$$

a **product** df?

- Is the df  $F$  corresponding to the pdf  $f(x, y) = x + y$  a product df?
- If  $X$  and  $Y$  have correlation  $\rho = \pm 1$ , then  $(X, Y)$  does not possess a pdf. Why? How is this related to functional dependence?