

# Lecture 1. Bivariate Dependent Risks

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# Learning objectives

- Introduction to bivariate df's, pdf's, survival functions
- Introduction of copulas
- Calculation of moments for vectors of bivariate risks

# Bivariate random vectors and their joint df

Let  $X$  and  $Y$  be two random variables (rvs) with distribution functions (df's)  $F_1$  and  $F_2$ , respectively.

**Definition 1 (Bivariate random vector and its joint df).**

- The pair  $(X, Y)$  is referred to as a **bivariate random vector (RV)**.
- The **joint df<sup>1</sup>**  $F$  of  $(X, Y)$  is a function  $F : \mathbb{R}^2 \rightarrow [0, 1]$  defined by

$$F(x, y) = \mathbb{P}\{X \leq x, Y \leq y\}.$$

- We denote this by  $(X, Y) \sim F$ .
- Functions  $F_1(x) = \mathbb{P}\{X \leq x\}$  and  $F_2(y) = \mathbb{P}\{Y \leq y\}$  are called the **marginal dfs**.

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<sup>1</sup>df = distribution function

## Survival function

Let  $A = \{X \leq x\}$  and  $B = \{Y \leq y\}$ . Then

$$\begin{aligned}\mathbb{P}\{X \leq x \text{ or } Y \leq y\} &= \mathbb{P}\{A \cup B\} = \mathbb{P}\{A\} + \mathbb{P}\{B\} - \mathbb{P}\{A \cap B\} \\ &= F_1(x) + F_2(y) - F(x, y).\end{aligned}$$

Therefore,

$$\mathbb{P}\{X > x, Y > y\} = 1 - F_1(x) - F_2(y) + F(x, y).$$

**Definition 2 (Survival function).**

The function  $\bar{F} : \mathbb{R}^2 \rightarrow [0, 1]$  defined by

$$\bar{F}(x, y) = \mathbb{P}\{X > x, Y > y\}$$

is called the **joint survival function** of  $(X, Y)$ .

## Alternative forms of the same formula

By replacing  $F_i \rightsquigarrow 1 - \bar{F}_i$ , we can easily derive from

$$\bar{F}(x, y) = 1 - F_1(x) - F_2(y) + F(x, y)$$

another equivalent formula

$$\bar{F}(x, y) = \bar{F}_1(x) + \bar{F}_2(y) - 1 + F(x, y).$$

Both forms are occasionally useful.

# Product, upper and lower df's

If  $X \sim F_1$  is independent of  $Y \sim F_2$ , then the joint df of  $(X, Y)$  is given by

$$F(x, y) = F_1(x)F_2(y).$$

Define further the **upper df**

$$H(x, y) = \min(F_1(x), F_2(y))$$

and the **lower df**

$$G(x, y) = (F_1(x) + F_2(y) - 1)_+,$$

where  $a_+ = \max(0, a)$ .

## Not all functions are dfs

**Question:** A **df** is *by definition* a function such that  $F(x, y) = \mathbb{P}\{X \leq x, Y \leq y\}$  for *some* random vector  $(X, Y)$ . But if we are *given* a function  $F$ , how can we check whether it is a df of *some* random vector  $(X, Y)$ ?

Clearly,  $F$  must satisfy the following properties:

- $F$  is increasing (non-decreasing) in each argument
- $F$  is right-continuous
- $F(x, -\infty) = \mathbb{P}\{X \leq x, Y \leq -\infty\} = 0$
- $F(-\infty, y) = \mathbb{P}\{X \leq -\infty, Y \leq y\} = 0$

Are these conditions **sufficient**? **Answer:** No! There is one more condition: probabilities of *all rectangles* must be non-negative, i.e.

$$\mathbb{P}\{a < X \leq b, c < Y \leq d\} = F(b, d) - F(a, d) - F(b, c) + F(a, c) \geq 0$$

## Exercise

**Exercise.** Check that the functions  $G$  and  $H$  defined earlier are indeed dfs.

$$G(x, y) = (F_1(x) + F_2(y) - 1)_+, \quad H(x, y) = \min(F_1(x), F_2(y)).$$

## Quick checks if something is not a df

- If  $F$  assumes negative values, then it is not a df.
- If  $F$  assumes values greater than 1, then it is not a df.
- If  $F(x, y)$  is not increasing in  $x$  or  $y$ , then it is not a df.

## Joint df $\rightarrow$ marginal dfs

If  $(X, Y) \sim F$ , then the marginal dfs  $F_1$  and  $F_2$  can be obtained from  $F$  by

$$F_1(x) = F(x, \infty), \quad F_2(y) = F(\infty, y).$$

Indeed, as  $y \rightarrow \infty$ , the event  $\{Y \leq y\}$  becomes certain.

- **Question:** Can we determine the joint df  $F$  from the marginal dfs  $F_1$  and  $F_2$ ?
- **Answer:** In general, no!
- There are infinitely many joint dfs with the same marginals, each corresponding to a different **dependence structure** between  $X$  and  $Y$ .
- These dependence structures are encoded by **copulas** and will be the main subject of this course.

## Exercise

**Exercise.** Given marginal dfs  $F_1$  and  $F_2$ , show that the function

$$F(x, y) = F_1(x) F_2(y) (1 + a \bar{F}_1(x) \bar{F}_2(y)), \quad a \in [-1, 1]$$

is a joint df with marginals  $F_1$  and  $F_2$ .

This family of dfs is known as the **FGM distribution/family of distributions**.

## Joint df → joint pdf/pmf

### Definition 3 (Joint pdf).

We say that a function  $f \geq 0$  is the **joint pdf**<sup>2</sup> of a given df  $F$  if  $F$  can be represented as

$$F(x, y) = \int_{-\infty}^x \int_{-\infty}^y f(z, w) dz dw.$$

### Definition 4 (Joint pmf).

We say that a function  $f \geq 0$  is the **joint pmf**<sup>3</sup> of a given df  $F$  if  $F$  can be represented as

$$F(x, y) = \sum_{z \leq x, w \leq y} f(z, w).$$

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<sup>2</sup>pdf = probability density function

<sup>3</sup>pmf = probability mass function

## Examples of a joint pdf/pmf

Let  $f(x, y) = 1$  for all  $x, y \in [0, 1]^2$ . Then the corresponding df is

$$F(x, y) = \int_0^x \int_0^y f(s, t) ds dt = \int_0^x \int_0^y 1 ds dt = xy = F_1(x)F_2(y),$$

where

$$F_1(x) = x \quad \text{and} \quad F_2(y) = y \quad \text{for } x, y \in [0, 1].$$

Thus,  $F$  is the joint df of two independent  $\text{Unif}(0, 1)$  random variables.

Similarly, let  $f(x, y) = \frac{1}{4}$  for all  $x, y \in \{0, 1\}^2$ . Then the corresponding df is

$$F(x, y) = F_1(x)F_2(y),$$

where  $F_1$  and  $F_2$  are the dfs of two independent  $\text{Ber}(1/2)$  random variables.

## pdf (pmf) $\rightarrow$ joint df

If  $f \geq 0$  is an integrable (summable) function such that

$$\int_{\mathbb{R}^2} f(x, y) dx dy = 1, \quad \left( \sum_{i=1, j=1}^{\infty} f(x_i, x_j) = 1 \right),$$

then the function  $F$  **defined** by

$$F(x, y) = \int_{-\infty}^x \int_{-\infty}^y f(z, w) dz dw, \quad \left( F(x, y) = \sum_{z \leq x, w \leq y} f(z, w) \right)$$

is a df.

# Differentiable joint df $\rightarrow$ joint pdf/pmf

Given an joint df  $F$ , such that the following mixed derivative

$$f(x, y) = \frac{\partial^2 F}{\partial x \partial y}(x, y)$$

exists for almost all  $x, y \in \mathbb{R}$ , can we conclude that  $f$  is the joint pdf (pmf) of  $F$ ?

- If  $F$  is a df and the mixed partial derivative  $f$  exists, then  $f \geq 0$  automatically (follows from the rectangle property), so we don't need to check positivity.
- However, even if  $f \geq 0$ , it may not be a pdf due to a **loss of mass**<sup>4</sup>: it is possible to have  $\int_{\mathbb{R}^2} f(x, y) dx dy < 1$ .
- If  $f$  is continuous, then loss of mass cannot happen, so  $f$  is indeed the joint pdf of  $F$ .
- If  $f$  is discontinuous, we have to check that  $\int_{\mathbb{R}^2} f(x, y) dx dy = 1$ .

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<sup>4</sup>Where does mass go?

## Conditional pdf/pmf and marginal pdf/pmf

If  $(X, Y)$  with joint df  $F$  has a joint pdf (pmf)  $f$ , then the conditional pdf (pmf) of  $X \mid Y = y$  satisfies

$$f(x, y) = f_2(y) f_{1|2}(x \mid y), \quad x, y \in \mathbb{R},$$

where  $f_2$  is the marginal pdf (pmf) of  $Y$ .

Moreover, from  $f$  we can calculate the marginal pdf's (pmf's)  $f_i$ 's, namely

$$f_1(x) = \int_{\mathbb{R}} f(x, z) dz, \quad f_2(y) = \int_{\mathbb{R}} f(z, y) dz, \quad x, y \in \mathbb{R}.$$

These are pdfs of  $F_1$  and  $F_2$ .

# Expectations

Let  $(X, Y) \sim F$  and  $J : \mathbb{R}^2 \rightarrow \mathbb{R}$  be some function. Then, the expectation of  $J(X, Y)$  is defined by

$$\mathbb{E}\{J(X, Y)\} = \int_{\mathbb{R}^2} J(x, y) dF(x, y).$$

If  $F$  has a joint pdf  $f$ , then

$$\mathbb{E}\{J(X, Y)\} = \int_{\mathbb{R}^2} J(x, y) f(x, y) dx dy.$$

If  $F$  has a joint pmf  $f$ , then

$$\mathbb{E}\{J(X, Y)\} = \sum_{i,j} J(x_i, x_j) f(x_i, x_j).$$

# Smirnov transform/Inverse sampling method

## Theorem 5.

- Let  $X$  be any random variable with continuous df  $F$ .
- Apply the df  $F$  to  $X$ :  $Y = F(X)$ .
- **Claim:**  $Y \sim \text{Unif}(0, 1)$ .

**Proof** in the case when  $F$  is invertible:

$$\mathbb{P}\{Y \leq y\} = \mathbb{P}\{F(x) \leq y\} = \mathbb{P}\{X \leq F^{-1}(y)\} = F(F^{-1}(y)) = y,$$

which is the df of  $\text{Unif}(0, 1)$ .

# Copulas

## Definition 6 (Copula of a continuous bivariate df).

- Let  $(X, Y) \sim F$  be a bivariate random vector with continuous marginal dfs  $F_1$  and  $F_2$ .
- Then the **copula**  $C$  of  $F$  is the joint df of the random vector  $(F_1(X), F_2(Y))$ .

Note that the marginals of  $(F_1(X), F_2(Y))$  are  $\text{Unif}(0, 1)$  by the Smirnov transform theorem. This motivates the following alternative definition of a copula:

## Definition 7 (Copula).

A **copula** is a bivariate df  $C$  whose marginals are  $\text{Unif}(0, 1)$ .

*The two definitions are equivalent in the sense that every copula is the copula of some bivariate df and vice versa.*

# Idea of copulas

- A copula  $C$  is a compact way to encode the **dependence structure** between  $X$  and  $Y$ .
- By passing from  $(X, Y)$  to  $(F_1(X), F_2(Y))$ , we **throw away** the information about the marginal distributions of  $X$  and  $Y$ . The resulting vector does not know anything about the laws of  $X$  and  $Y$ , but knows everything about how  $X$  and  $Y$  depend on each other.
- If we know the copula  $C$  of  $F$  and the marginal dfs  $F_1$  and  $F_2$ , then we can reconstruct the joint df  $F$ . This is done by **Sklar's theorem**, which will be discussed later.

# Product, upper and lower copulas

Here are the most basic examples of copulas:

- The **product copula**  $C_I(u_1, u_2) = u_1 u_2$  encodes *independence*. This is the copula of two independent  $\text{Unif}(0, 1)$  random variables.
- The **upper copula**  $C_U(u_1, u_2) = \min(u_1, u_2)$  encodes *perfect positive dependence*. This is the copula of  $(U, U)$  where  $U \sim \text{Unif}(0, 1)$ .
- The **lower copula**  $C_L(u_1, u_2) = (u_1 + u_2 - 1)_+$  encodes *perfect negative dependence*. This is the copula of  $(U, 1 - U)$  where  $U \sim \text{Unif}(0, 1)$ .

## Not every function is a copula

**Question:** How can we check whether a given function  $C$  is a copula?

Clearly,  $C$  must satisfy the properties of a bivariate df. In addition, the marginals of  $C$  must be  $\text{Unif}(0, 1)$ , i.e.

$$C(u, 1) = u, \quad C(1, u) = u, \quad u \in [0, 1].$$

Are these conditions sufficient?

**Answer:** Yes! These conditions are necessary and sufficient for  $C$  to be a copula.

## Exercise

**Exercise.** Check that  $C_L$  is the copula of  $(U, 1 - U)$  where  $U \sim \text{Unif}(0, 1)$  by directly calculating its joint df.

# Upper and lower copulas do not have pdfs

Note that the functions

$$C_U(u_1, u_2) = \min(u_1, u_2) \quad \text{and} \quad C_L(u_1, u_2) = (u_1 + u_2 - 1)_+$$

are **not** differentiable on the diagonal  $u_1 = u_2$ , which is a set of Lebesgue measure zero. However, their mixed partial derivatives *away from the diagonal* are equal to zero<sup>5</sup>. Therefore,

$$\int_{[0,1]^2 \setminus \{u_1 = u_2\}} \frac{\partial^2 C_U}{\partial u_1 \partial u_2}(u_1, u_2) du_1 du_2 = 0,$$

and similarly for  $C_L$ . Therefore,  $C_U$  and  $C_L$  do not have joint pdfs.

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<sup>5</sup>Check this!