



Probability and Stochastic Processes

Lecture 15: Singular Random Variables, Multiple Random Variables,
Joint CDF, Joint PMF, Marginal CDFs from Joint CDF, Marginal PMFs
from Joint PMF, Conditional CDF

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Discrete Random Variable

Definition (Discrete Random Variable)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$. Let $X : \Omega \rightarrow \mathbb{R}$ be a random variable (RV).

Let \mathbb{P}_X denote the probability law of X .

The RV X is said to be **discrete** if there exists a **countable** set $E \subset \mathbb{R}$, say $E = \{e_1, e_2, \dots\}$, such that

$$\mathbb{P}_X(E) = 1.$$

PMF \longrightarrow CDF for a Discrete RV

The following implications are noteworthy:

$$p_X \begin{array}{c} \xleftarrow{\text{any } X} \\ \xrightarrow{\text{any } X} \end{array} \mathbb{P}_X \begin{array}{c} \xleftarrow{\text{any } X} \\ \xrightarrow{\text{any } X} \end{array} F_X.$$

PMF = complete probabilistic description for discrete RV.

Continuous Random Variable

Definition (Continuous Random Variable)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$. Let $X : \Omega \rightarrow \mathbb{R}$ be a random variable (RV).

Let \mathbb{P}_X denote the probability law of X .

The RV X is said to be **continuous** if $\mathbb{P}_X \ll \lambda$, i.e.,

$$\lambda(B) = 0 \implies \mathbb{P}_X(B) = 0.$$

PDF \longrightarrow CDF for a Continuous RV

The following implications are noteworthy:

$$f_X \begin{array}{c} \xrightarrow{X \text{ continuous}} \\ \xleftarrow{X \text{ continuous}} \end{array} F_X \begin{array}{c} \xrightarrow{\text{any } X} \\ \xleftarrow{\text{any } X} \end{array} \mathbb{P}_X.$$

PDF = complete probabilistic description for continuous RV.

Singular Random Variables

Singular Random Variable

Definition (Singular Random Variable)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$. Let $X : \Omega \rightarrow \mathbb{R}$ be a random variable (RV).

Let \mathbb{P}_X denote the probability law of X .

The RV X is said to be **singular** if:

- $\mathbb{P}_X(\{x\}) = 0$ for every $x \in \mathbb{R}$.
- There exists an **uncountable** set $U \subseteq \mathbb{R}$ such that

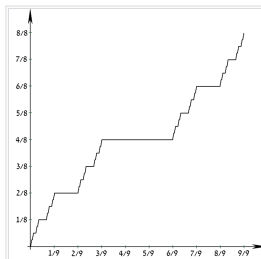
$$\lambda(U) = 0, \quad \text{whereas} \quad \mathbb{P}_X(U) = 1.$$

As usual, λ denotes the Lebesgue measure on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$.

- \mathbb{P}_X and λ act in opposing ways on U !
- If X is singular, then $\mathbb{P}_X(B) = 0$ for every countable $B \in \mathcal{B}(\mathbb{R})$

The Cantor Function

An Example of a Singular Random Variable's CDF



- If X is a random variable having the above CDF, then

$$\mathbb{P}_X(K^c) = 0 \quad \implies \quad \mathbb{P}_X(K) = 1, \quad \lambda(K) = 0, \quad \mathbb{P}_X(K) = 1$$

Multiple Random Variables

Understanding $\mathcal{B}(\mathbb{R}^2)$

- Consider the special class of semi-infinite rectangles in \mathbb{R}^2 , given by

$$\mathcal{P} = \left\{ (-\infty, x] \times (-\infty, y] : x, y \in \mathbb{R} \right\}.$$

- $\mathcal{B}(\mathbb{R}^2) = \sigma(\mathcal{P})$
- Other example sets in $\mathcal{B}(\mathbb{R}^2)$:
 - $(-\infty, x] \times \mathbb{R}, \quad (-\infty, x) \times \mathbb{R}, \quad [x, \infty) \times \mathbb{R}, \quad (x, \infty) \times \mathbb{R}, \quad x \in \mathbb{R}$
 - $\mathbb{R} \times (-\infty, y], \quad \mathbb{R} \times (-\infty, y), \quad \mathbb{R} \times [y, \infty), \quad \mathbb{R} \times (y, \infty), \quad y \in \mathbb{R}$
 - $\mathbb{R} \times (a, b), \quad (a, b) \times \mathbb{R}, \quad a, b \in \mathbb{R}$
 - $(a, b) \times (c, d), \quad a, b, c, d \in \mathbb{R}$
 - Circle of radius r centered at the origin, $r > 0$

Important

$$\mathcal{B}(\mathbb{R}^2) \neq \mathcal{B}(\mathbb{R}) \otimes \mathcal{B}(\mathbb{R}) = \left\{ B_1 \times B_2 : B_1, B_2 \in \mathcal{B}(\mathbb{R}) \right\}.$$

Two Random Variables (Bivariate Random Vector)

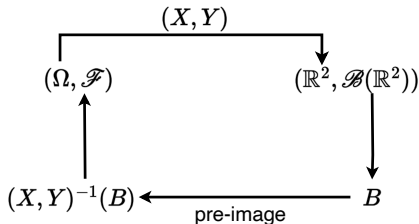
Definition (Bivariate Random Vector)

Fix a measurable space (Ω, \mathcal{F}) .

Let $X : \Omega \rightarrow \mathbb{R}$ and $Y : \Omega \rightarrow \mathbb{R}$ be random variables (with respect to \mathcal{F}).

We say $(X, Y) : \Omega \rightarrow \mathbb{R}^2$ is a **bivariate random vector** with respect to \mathcal{F} if

$$\forall B \in \mathcal{B}(\mathbb{R}^2), \quad (X, Y)^{-1}(B) = \underbrace{\{\omega \in \Omega : (X(\omega), Y(\omega)) \in B\}}_{\text{pre-image of } B} = \{(X, Y) \in B\} \in \mathcal{F}.$$



Bivariate Random Vector

Theorem (Equivalent Characterization of Bivariate Random Vector)

Fix a measurable space (Ω, \mathcal{F}) .

Let $X : \Omega \rightarrow \mathbb{R}$ and $Y : \Omega \rightarrow \mathbb{R}$ be random variables (with respect to \mathcal{F}).

Then,

$$(X, Y) \text{ random vector} \iff (X, Y)^{-1}(B) \in \mathcal{F} \quad \forall B \in \mathcal{P},$$

where \mathcal{P} is the collection $\mathcal{P} = \left\{ (-\infty, x] \times (-\infty, y] : x, y \in \mathbb{R} \right\}$.

Bivariate Random Vector Simplified

Fix a measurable space (Ω, \mathcal{F}) , and let X, Y be random variables.

$(X, Y) : \Omega \rightarrow \mathbb{R}^2$ is a bivariate random vector **if and only if** for all $x, y \in \mathbb{R}$,

$$(X, Y)^{-1}((-\infty, x] \times (-\infty, y]) = \underbrace{\{\omega \in \Omega : X(\omega) \leq x\} \cap \{\omega \in \Omega : Y(\omega) \leq y\}}_{\text{pre-image of } (-\infty, x] \times (-\infty, y]} \in \mathcal{F}.$$

Joint Probability Law

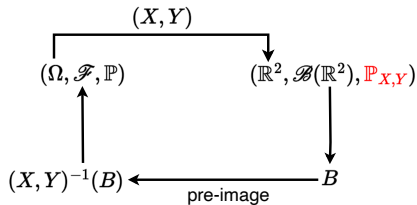
Definition (Joint Probability Law)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let $(X, Y) : \Omega \rightarrow \mathbb{R}^2$ be a bivariate random vector.

The **joint probability law of X and Y** is a function $\mathbb{P}_{X,Y} : \mathcal{B}(\mathbb{R}^2) \rightarrow [0, 1]$, defined as

$$\forall B \in \mathcal{B}(\mathbb{R}^2), \quad \mathbb{P}_{X,Y}(B) = \mathbb{P}((X, Y)^{-1}(B)) = \mathbb{P}(\{(X, Y) \in B\}).$$

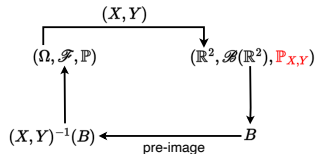


$$\mathbb{P}_{X,Y}(B) = \mathbb{P}((X, Y)^{-1}(B)) \quad \forall B \in \mathcal{B}(\mathbb{R}^2)$$

On $\mathbb{P}_{X,Y}$

$\mathbb{P}_{X,Y}$ is a **probability measure** on $(\mathbb{R}^2, \mathcal{B}(\mathbb{R}^2))$.

Joint CDF



$$\mathbb{P}_{X,Y}(B) = \mathbb{P}((X,Y)^{-1}(B)) \quad \forall B \in \mathcal{B}(\mathbb{R}^2)$$

- $\mathbb{P}_{X,Y}(B) \in [0, 1]$ for every $B \in \mathcal{B}(\mathbb{R}^2)$
- In particular, $\mathbb{P}_{X,Y}((-\infty, x] \times (-\infty, y]) \in [0, 1]$ for all $x, y \in \mathbb{R}$
- We thus have a mapping

$$(x, y) \mapsto \mathbb{P}_{X,Y}((-\infty, x] \times (-\infty, y])$$

- The above mapping (or function) is called the **joint CDF** of X and Y , denoted by $F_{X,Y}$

Joint CDF

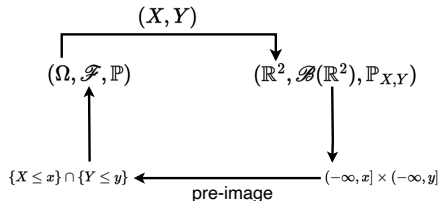
Definition (Joint CDF)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let $(X, Y) : \Omega \rightarrow \mathbb{R}^2$ be a random vector.

The **joint CDF of X and Y (or CDF of the vector (X, Y))** is a function $F_{X,Y} : \mathbb{R}^2 \rightarrow [0, 1]$ defined as

$$\forall x, y \in \mathbb{R}, \quad F_{X,Y}(x, y) = \mathbb{P}_{X,Y} \left((-\infty, x] \times (-\infty, y] \right) = \mathbb{P} \left(\{X \leq x\} \cap \{Y \leq y\} \right).$$



$$F_{X,Y}(x, y) = \mathbb{P}_{X,Y}((-\infty, x] \times (-\infty, y]) = \mathbb{P}(\{X \leq x\} \cap \{Y \leq y\}), \quad x, y \in \mathbb{R}$$

Properties of Joint CDF

Lemma (Properties of Joint CDF)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$. Let $(X, Y) : \Omega \rightarrow \mathbb{R}^2$ be a random vector with CDF $F_{X,Y}$. Then, $F_{X,Y}$ satisfies the following properties.

1. **(Monotonicity)** If $x_1 \leq x_2$ and $y_1 \leq y_2$, then $F_{X,Y}(x_1, y_1) \leq F_{X,Y}(x_2, y_2)$.
2. If $\{x_n\}_{n \in \mathbb{N}}$ and $\{y_n\}_{n \in \mathbb{N}}$ are any two sequences such that $\lim_{n \rightarrow \infty} x_n = -\infty$ and $\lim_{n \rightarrow \infty} y_n = -\infty$, then $\lim_{n \rightarrow \infty} F_{X,Y}(x_n, y_n) = 0$.
3. If $\{x_n\}_{n \in \mathbb{N}}$ and $\{y_n\}_{n \in \mathbb{N}}$ are any two sequences such that $\lim_{n \rightarrow \infty} x_n = +\infty$ and $\lim_{n \rightarrow \infty} y_n = +\infty$, then $\lim_{n \rightarrow \infty} F_{X,Y}(x_n, y_n) = 1$.

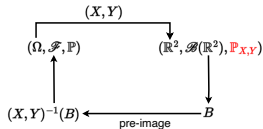
4. **(Continuity from Top-Right Quadrant)**

$F_{X,Y}$ is continuous from the top-right quadrant at each point in its domain.

More formally, for each $(x, y) \in \mathbb{R}^2$,

$$x_n > x \ \forall n \in \mathbb{N}, \quad y_n > y \ \forall n \in \mathbb{N}, \quad \lim_{n \rightarrow \infty} x_n = x, \quad \lim_{n \rightarrow \infty} y_n = y \implies \lim_{n \rightarrow \infty} F_{X,Y}(x_n, y_n) = F_{X,Y}(x, y).$$

Another Important Function

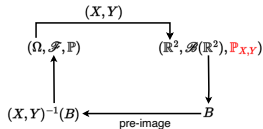


$$\mathbb{P}_{X,Y}(B) = \mathbb{P}((X, Y)^{-1}(B)) \quad \forall B \in \mathcal{B}(\mathbb{R}^2)$$

- Taking $B = (-\infty, x] \times (-\infty, y]$, and varying x, y , we get a mapping

$$(x, y) \mapsto \mathbb{P}_{X,Y}((-\infty, x] \times (-\infty, y])$$

Another Important Function



$$\mathbb{P}_{X,Y}(B) = \mathbb{P}((X, Y)^{-1}(B)) \quad \forall B \in \mathcal{B}(\mathbb{R}^2)$$

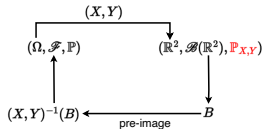
- Taking $B = (-\infty, x] \times (-\infty, y]$, and varying x, y , we get a mapping

$$(x, y) \mapsto \mathbb{P}_{X,Y}((-\infty, x] \times (-\infty, y])$$

- Taking $B = \{x\} \times \{y\}$, and varying x, y , we get a mapping

$$(x, y) \mapsto \mathbb{P}_{X,Y}(\{x\} \times \{y\})$$

Another Important Function



$$\mathbb{P}_{X,Y}(B) = \mathbb{P}((X, Y)^{-1}(B)) \quad \forall B \in \mathcal{B}(\mathbb{R}^2)$$

- Taking $B = (-\infty, x] \times (-\infty, y]$, and varying x, y , we get a mapping

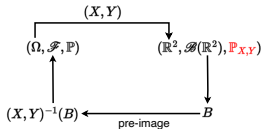
$$(x, y) \mapsto \mathbb{P}_{X,Y}((-\infty, x] \times (-\infty, y])$$

- Taking $B = \{x\} \times \{y\}$, and varying x, y , we get a mapping

$$(x, y) \mapsto \mathbb{P}_{X,Y}(\{x\} \times \{y\})$$

- The above map is called the **joint CDF**, denoted $F_{X,Y}$

Another Important Function



$$P_{X,Y}(B) = \mathbb{P}((X,Y)^{-1}(B)) \quad \forall B \in \mathcal{B}(\mathbb{R}^2)$$

- Taking $B = (-\infty, x] \times (-\infty, y]$, and varying x, y , we get a mapping

$$(x, y) \mapsto \mathbb{P}_{X,Y}((-\infty, x] \times (-\infty, y])$$

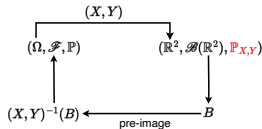
- The above map is called the **joint CDF**, denoted $F_{X,Y}$

- Taking $B = \{x\} \times \{y\}$, and varying x, y , we get a mapping

$$(x, y) \mapsto \mathbb{P}_{X,Y}(\{x\} \times \{y\})$$

- The above map is called the **joint PMF**, denoted $p_{X,Y}$

Another Important Function



$$\mathbb{P}_{X,Y}(B) = \mathbb{P}((X,Y)^{-1}(B)) \quad \forall B \in \mathcal{B}(\mathbb{R}^2)$$

- Taking $B = (-\infty, x] \times (-\infty, y]$, and varying x, y , we get a mapping

$$(x, y) \mapsto \mathbb{P}_{X,Y}((-\infty, x] \times (-\infty, y])$$

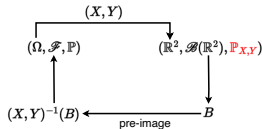
- The above map is called the **joint CDF**, denoted $F_{X,Y}$
- $F_{X,Y}(x, y) = \mathbb{P}(\{X \leq x\} \cap \{Y \leq y\})$

- Taking $B = \{x\} \times \{y\}$, and varying x, y , we get a mapping

$$(x, y) \mapsto \mathbb{P}_{X,Y}(\{x\} \times \{y\})$$

- The above map is called the **joint PMF**, denoted $p_{X,Y}$

Another Important Function



$$\mathbb{P}_{X,Y}(B) = \mathbb{P}((X,Y)^{-1}(B)) \quad \forall B \in \mathcal{B}(\mathbb{R}^2)$$

- Taking $B = (-\infty, x] \times (-\infty, y]$, and varying x, y , we get a mapping

$$(x, y) \mapsto \mathbb{P}_{X,Y}((-\infty, x] \times (-\infty, y])$$

- The above map is called the **joint CDF**, denoted $F_{X,Y}$
- $F_{X,Y}(x, y) = \mathbb{P}(\{X \leq x\} \cap \{Y \leq y\})$

- Taking $B = \{x\} \times \{y\}$, and varying x, y , we get a mapping

$$(x, y) \mapsto \mathbb{P}_{X,Y}(\{x\} \times \{y\})$$

- The above map is called the **joint PMF**, denoted $p_{X,Y}$
- $p_{X,Y}(x, y) = \mathbb{P}(\{X = x\} \cap \{Y = y\})$

Joint PMF

Definition (Joint PMF)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$. Let $(X, Y) : \Omega \rightarrow \mathbb{R}^2$ be a random vector.

Let $\mathbb{P}_{X,Y}$ denote the joint probability law of X and Y .

The **joint PMF of X and Y (or PMF of the vector (X, Y))** is a function $p_{X,Y} : \mathbb{R}^2 \rightarrow [0, 1]$ defined as

$$\forall x, y \in \mathbb{R}, \quad p_{X,Y}(x, y) = \mathbb{P}_{X,Y}(\{x\} \times \{y\}) = \mathbb{P}(\{X = x\} \cap \{Y = y\}).$$

- **Joint CDF ($F_{X,Y}$) and joint PMF ($p_{X,Y}$) are always defined for any two RVs X and Y**

Marginal CDFs from Joint CDF

Theorem (Marginal CDFs from Joint CDF)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let $(X, Y) : \Omega \rightarrow \mathbb{R}^2$ be a random vector. Let $F_{X,Y}$ denote the joint CDF of X and Y . Then, the following properties hold.

1. (Marginalization of Y)

If y_1, y_2, \dots is any sequence of real numbers such that $\lim_{n \rightarrow \infty} y_n = +\infty$, then

$$\forall x \in \mathbb{R}, \quad \lim_{n \rightarrow \infty} F_{X,Y}(x, y_n) = F_X(x).$$

2. (Marginalization of X)

If x_1, x_2, \dots is any sequence of real numbers such that $\lim_{n \rightarrow \infty} x_n = +\infty$, then

$$\forall y \in \mathbb{R}, \quad \lim_{n \rightarrow \infty} F_{X,Y}(x_n, y) = F_Y(y).$$

Conditional CDF

Definition (Conditional CDF)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let $(X, Y) : \Omega \rightarrow \mathbb{R}^2$ be a random vector.

1. Fix $A \in \mathcal{F}$ with $\mathbb{P}(A) > 0$.

The **conditional CDF of X , conditioned on A** , is defined as

$$F_{X|A} : \mathbb{R} \rightarrow [0, 1], \quad F_{X|A}(x) := \frac{\mathbb{P}(\{X \leq x\} \cap A)}{\mathbb{P}(A)}, \quad x \in \mathbb{R}.$$

2. The **conditional CDF of X , conditioned on Y** , is defined as

$$\forall x \in \mathbb{R}, \quad F_{X|Y}(x|y) := \frac{F_{X,Y}(x, y)}{F_Y(y)} = \frac{\mathbb{P}(\{X \leq x\} \cap \{Y \leq y\})}{\mathbb{P}(\{Y \leq y\})},$$

whenever denominator is non-zero.