



Probability and Stochastic Processes

Lecture 19: Multiple Random Variables, Transformations (Part 1)

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Multiple Random Variables

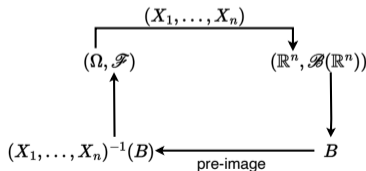
Definition (Multivariate Random Vector)

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

Let $X_1 : \Omega \rightarrow \mathbb{R}, X_2 : \Omega \rightarrow \mathbb{R}, \dots, X_n : \Omega \rightarrow \mathbb{R}$ be random variables with respect to \mathcal{F} .

We say $(X_1, \dots, X_n) : \Omega \rightarrow \mathbb{R}^n$ is a **multivariate random vector** if

$$\forall B \in \mathcal{B}(\mathbb{R}^n), \quad (X_1, \dots, X_n)^{-1}(B) = \underbrace{\{\omega \in \Omega : (X_1(\omega), \dots, X_n(\omega)) \in B\}}_{\text{pre-image of } B} = \{(X_1, \dots, X_n) \in B\} \in \mathcal{F}.$$



$$\forall B \in \mathcal{B}(\mathbb{R}^n), \quad (X_1, \dots, X_n)^{-1}(B) \in \mathcal{F}$$

Joint Probability Law

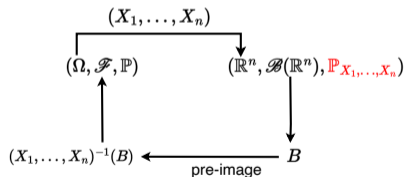
Definition (Joint Probability Law)

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

Let $(X_1, \dots, X_n) : \Omega \rightarrow \mathbb{R}^n$ be a multivariate random vector.

The **joint probability law of X_1, \dots, X_n** is a function $\mathbb{P}_{X_1, \dots, X_n} : \mathcal{B}(\mathbb{R}^n) \rightarrow [0, 1]$, defined as

$$\forall B \in \mathcal{B}(\mathbb{R}^n), \quad \mathbb{P}_{X_1, \dots, X_n}(B) = \mathbb{P}((X_1, \dots, X_n)^{-1}(B)) = \mathbb{P}(\{(X_1, \dots, X_n) \in B\}).$$



$$\mathbb{P}_{X_1, \dots, X_n}(B) = \mathbb{P}((X_1, \dots, X_n)^{-1}(B)) \quad \forall B \in \mathcal{B}(\mathbb{R}^n)$$

On $\mathbb{P}_{X_1, \dots, X_n}$

$\mathbb{P}_{X_1, \dots, X_n}$ is a **probability measure** on $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$.

Marginals from Joint

CDF	Probability Law
$F_{X_1, \dots, X_n}(x_1, \dots, x_n), \quad (x_1, \dots, x_n) \in \mathbb{R}^n$	$\mathbb{P}_{X_1, \dots, X_n}(B), \quad B \in \mathcal{B}(\mathbb{R}^n)$
$F_{X_1}(x_1) = \lim_{\substack{x_2 \rightarrow +\infty \\ x_3 \rightarrow +\infty \\ \vdots \\ x_n \rightarrow +\infty}} F_{X_1, \dots, X_n}(x_1, x_2, \dots, x_n)$	$\mathbb{P}_{X_1}(A) = \mathbb{P}_{X_1, \dots, X_n}(A \times \mathbb{R} \times \dots \times \mathbb{R})$
$F_{X_2}(x_2) = \lim_{\substack{x_1 \rightarrow +\infty \\ x_3 \rightarrow +\infty \\ \vdots \\ x_n \rightarrow +\infty}} F_{X_1, \dots, X_n}(x_1, x_2, \dots, x_n)$	$\mathbb{P}_{X_2}(A) = \mathbb{P}_{X_1, \dots, X_n}(\mathbb{R} \times A \times \mathbb{R} \times \dots \times \mathbb{R})$

Remark

Given joint CDF/law, we may extract the marginal CDFs/laws.
The converse is not possible in general.

Independence of Multiple Random Variables

Proposition (Independence and Joint CDFs)

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

Let $(X_1, \dots, X_n) : \Omega \rightarrow \mathbb{R}^n$ be a multivariate random vector.

We say that X_1, \dots, X_n are **mutually independent** if any one of the following equivalent conditions holds.

1. $\mathbb{P}_{X_1, \dots, X_n}(B_1 \times \dots \times B_n) = \prod_{i=1}^n \mathbb{P}_{X_i}(B_i)$ for all $B_1, \dots, B_n \in \mathcal{B}(\mathbb{R})$.
2. $F_{X_1, \dots, X_n}(x_1, \dots, x_n) = \prod_{i=1}^n F_{X_i}(x_i)$ for all $x_1, \dots, x_n \in \mathbb{R}$.
3. $\sigma(X_1), \dots, \sigma(X_n)$ are independent.

Independent and Identically Distributed (IID) Random Variables

We say that X_1, \dots, X_n are **independent and identically distributed (IID)** if:

- X_1, \dots, X_n are **mutually independent**.
- X_1, \dots, X_n **have the same CDF**, i.e., $F_{X_1} = \dots = F_{X_n}$.

Transformations of Random Variables

Transformations of Random Variables

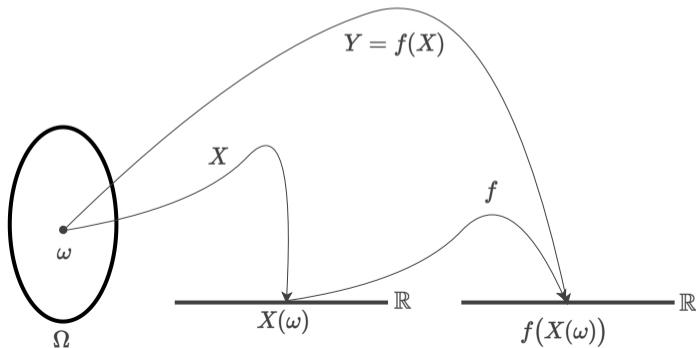
Fix $(\Omega, \mathcal{F}, \mathbb{P})$.

Let $X : \Omega \rightarrow \mathbb{R}$ be a **random variable** defined with respect to \mathcal{F} .

Let $f : \mathbb{R} \rightarrow \mathbb{R}$ be **measurable**.

Define $Y : \Omega \rightarrow \mathbb{R}$ as

$$Y = f(X), \quad Y(\omega) = f(X(\omega)) = f \circ X(\omega), \quad \omega \in \Omega.$$



Measurable Functions and Random Variables

- Y is a random variable with respect to \mathcal{F}
- Indeed, note that

$$\forall B \in \mathcal{B}(\mathbb{R}), \quad Y^{-1}(B) = X^{-1}\left(f^{-1}(B)\right)$$

- $f^{-1}(B) \in \mathcal{B}(\mathbb{R})$ because f is measurable
- $X^{-1}\left(f^{-1}(B)\right) \in \mathcal{F}$ because X is a random variable

The Key Question

Given the CDF/PMF/PDF of X , what is the CDF/PMF/PDF of $Y = f(X)$?

Measurable Functions – 1

Definition (Measurable Function)

A function $f : \mathbb{R} \rightarrow \mathbb{R}$ is said to be **measurable** if

$$f^{-1}(B) = \{x \in \mathbb{R} : f(x) \in B\} \in \mathcal{B}(\mathbb{R}) \quad \forall B \in \mathcal{B}(\mathbb{R}).$$

Remarks:

- **Every continuous function is measurable.** Thus,

$$f(x) = |x|, \quad f(x) = x^2, \quad f(x) = e^x, \quad f(x) = \log x,$$

are measurable

- $X : \Omega \rightarrow \mathbb{R}$ **random variable** $f : \mathbb{R} \rightarrow \mathbb{R}$ **measurable**
 $\implies f(X) : \Omega \rightarrow \mathbb{R}$ random variable

Measurable Functions – 2

Definition (Measurable Function)

A function $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is said to be **measurable** if

$$f^{-1}(B) = \{x \in \mathbb{R}^n : f(x) \in B\} \in \mathcal{B}(\mathbb{R}^n) \quad \forall B \in \mathcal{B}(\mathbb{R}^m).$$

Implication for $m = 1$:

- X_1, \dots, X_n **random variables**, $f : \mathbb{R}^n \rightarrow \mathbb{R}$ **measurable**
 $\implies f(X_1, \dots, X_n) : \Omega \rightarrow \mathbb{R}$ random variable with respect to \mathcal{F}
- Every continuous function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is measurable. Thus, for instance,

$$f(x_1, \dots, x_n) = \sum_{i=1}^n x_i$$

is measurable. Hence, $\sum_{i=1}^n X_i$ is a random variable.

Maximum of Random Variables

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

Let X_1, \dots, X_n be random variables defined with respect to \mathcal{F} , with joint CDF F_{X_1, \dots, X_n} .

- Show that $Y_n = \max\{X_1, \dots, X_n\}$ is a random variable with respect to \mathcal{F} .
- Derive the CDF of Y_n .
- Simplify the CDF of Y_n when X_1, \dots, X_n are IID.

Minimum of Random Variables

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

Let X_1, \dots, X_n be random variables defined with respect to \mathcal{F} , with joint CDF F_{X_1, \dots, X_n} .

- Show that $Z_n = \min\{X_1, \dots, X_n\}$ is a random variable with respect to \mathcal{F} .
- Derive the CDF of Z_n .
- Simplify the CDF of Z_n when X_1, \dots, X_n are IID.

Minimum of i.i.d. Exponential Random Variables

Fix $(\Omega, \mathcal{F}, \mathbb{P})$. Let $\lambda_1, \dots, \lambda_n > 0$ be fixed constants.

Let X_1, \dots, X_n be independent, with $X_i \sim \text{Exponential}(\lambda_i)$ for each $i \in \{1, \dots, n\}$.

Find the distribution of $Z = \min\{X_1, \dots, X_n\}$.

Sums of Random Variables

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

Let X and Y be random variables with respect to \mathcal{F} .

- Show that $X + Y$ is a random variable with respect to \mathcal{F} .
- In the cases when X and Y are jointly discrete/continuous, derive the PMF/PDF of $X + Y$.
- Simplify the PMF/PDF when X and Y are independent.

Sum of Two Independent Poissons

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

Let $X \sim \text{Poisson}(\lambda_1)$ and $Y \sim \text{Poisson}(\lambda_2)$. Assume $X \perp\!\!\!\perp Y$.

Determine the distribution of $Z = X + Y$.



Sum of Two Independent Exponentials

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

Let $X \sim \text{Exponential}(\mu_1)$ and $Y \sim \text{Exponential}(\mu_2)$. Assume $X \perp\!\!\!\perp Y$.

Determine the distribution of $Z = X + Y$.

Functions of Independent Random Variables are Independent Random Variables

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

Let X and Y be random variables with respect to \mathcal{F} . Assume $X \perp\!\!\!\perp Y$.

Let $g : \mathbb{R} \rightarrow \mathbb{R}$ and $h : \mathbb{R} \rightarrow \mathbb{R}$ be Borel-measurable.

Prove that $g(X) \perp\!\!\!\perp h(Y)$.

Sum of Random Number of Random Variables

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

Let $\{X_i : i \in \mathbb{N}\}$ be a collection of **i.i.d.** random variables defined with respect to \mathcal{F} and having a common CDF F .

Let N be a positive integer-valued random variable defined with respect to \mathcal{F} and having the PMF p_N .

Let N be independent of $\{X_i : i \in \mathbb{N}\}$.

Consider the sum

$$S_N := \sum_{i=1}^N X_i; \quad S_N(\omega) = \sum_{i=1}^{N(\omega)} X_i(\omega), \quad \omega \in \Omega.$$

- Show that $S_N : \Omega \rightarrow \mathbb{R}$ is a random variable with respect to \mathcal{F} .
- Determine the CDF of S_N .

Sum of Geometric Number of Exponential Random Variables

In the previous example, let $X_1, X_2, \dots \stackrel{\text{i.i.d.}}{\sim} \text{Exp}(\lambda)$. Let $N \sim \text{Geom}(p)$. Determine the distribution of S_N .