



UNIVERSITY OF
TORONTO

Statistical Sciences

DoSS Summer Bootcamp Probability Module 2

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Recap

Learnt in last module:

- Measurable spaces
 - ▷ Sample Space
 - ▷ σ -algebra
- Probability measures
 - ▷ Measures on σ -field
 - ▷ Basic results
- Conditional probability
 - ▷ Bayes' rule
 - ▷ Law of total probability

Outline

- Independence of events
 - ▷ Pairwise independence, mutual independence
 - ▷ Conditional independence
- Random variables
- Distribution functions
- Density functions and mass functions
- Independence of random variables

Independence of events

Recall the Bayes rule:

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}, \quad P(B) > 0$$

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Independence of two events

Two events A and B are independent if $P(A \cap B) = P(A)P(B)$.

Remark:

Independence of events

Consider more than 2 events:

Pairwise independence

We say that events A_1, A_2, \dots, A_n are pairwise independent if

$$P(A_i \cap A_j) = P(A_i) \cdot P(A_j), \quad \forall i \neq j$$

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Example:

- Toss two fair coins.;
- $A = \{ \text{First toss is head} \}$, $B = \{ \text{Second toss is head} \}$, $C = \{ \text{Outcomes are the same} \}$;
- $A = \{HH, HT\}$, $B = \{HH, TH\}$, $C = \{HH, TT\}$;

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- $P(A \cap B) = P(A)P(B)$, $P(A \cap C) = P(A)P(C)$, $P(B \cap C) = P(B)P(C)$;
- $P(A \cap B \cap C) \neq P(A)P(B)P(C)$.

Independence of events

Conditional independence

Two events A and B are conditionally independent given an event C if

$$P(A \cap B \mid C) = P(A \mid C)P(B \mid C).$$

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Remark:

Equivalent definition:

$$\mathbb{P}(A \mid B, C) = \mathbb{P}(A \mid C).$$

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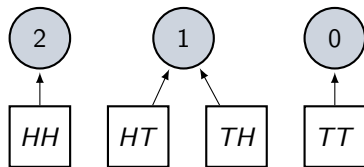


Figure: Mapping from the sample space to the numbers of heads

Random Variables

Example:

- Select twice from red and black ball with replacement: $\{RR, RB, BR, BB\}$
- Care about the number of red balls: $\{2, 1, 0\}$

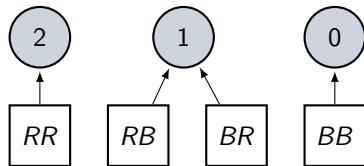


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Random Variables

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Random Variables

Consider sample space Ω and the corresponding σ -field \mathcal{F} , for $X : \Omega \rightarrow \mathbb{R}$, if

$$A \in \mathcal{R} \quad (\text{Borel sets on } \mathbb{R}) \Rightarrow X^{-1}(A) \in \mathcal{F},$$

then we call X as a random variable.

Here $X^{-1}(A) = \{\omega : X(\omega) \in A\}$.

We can also say X is \mathcal{F} -measurable.

Distribution functions

Probability measure $P(\cdot)$ on \mathcal{F} can induce a measure $\mu(\cdot)$ on \mathcal{R} :

Probability measure on \mathcal{R}

We can define a probability μ on (R, \mathcal{R}) as follows:

$$\forall A \in \mathcal{R}, \quad \mu(A) := P(X^{-1}(A)) = P(X \in A).$$

Then μ is a probability measure and it is called the distribution of X .

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Remark:

Verify that μ is a probability measure.

- $\mu(\mathbb{R}) = 1$.
- If $A_1, A_2, \dots \in \mathcal{R}$ are disjoint, then $\mu(\cup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} \mu(A_i)$.

Distribution functions

Consider the special set that belongs to \mathcal{R} , $(-\infty, x]$:

Cumulative Distribution Function

The cumulative distribution function of random variable X is defined as follows:

$$F(x) := P(X \leq x) = P(X^{-1}((-\infty, x])), \quad \forall x \in \mathbb{R}.$$

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Properties of CDF:

- $\lim_{x \rightarrow \infty} F(x) = 1$, $\lim_{x \rightarrow -\infty} F(x) = 0$
- $F(\cdot)$ is non-decreasing
- $F(\cdot)$ is right-continuous
- Let $F(x^-) = \lim_{y \nearrow x} F(y)$, then $F(x^-) = P(X < x)$
- $P(X = x) = F(x) - F(x^-)$

Distribution functions

Proofs of properties of CDF (first 2 properties):

Density functions and mass functions

Classification of the random variables:

- Discrete random variable: X takes either a finite or countable number of possible numbers.
- Continuous random variable: The CDF is continuous everywhere.

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Another perspective (function):

- Discrete random variable: focus on the probability assigned on each possible values
- Continuous random variable: consider the derivative of the CDF (The continuous monotone CDF is differentiable almost everywhere)

Density functions and mass functions

Probability mass function

The probability mass function of X at some possible value x is defined by

$$p_X(x) = P(X = x).$$

Relationship between PMF and CDF:

$$F(x) = P(X \leq x) = \sum_{y \leq x} p_X(y)$$

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Example:

Toss a coin

Density functions and mass functions

Probability density function

The probability density function of X at some possible value x is defined by

$$f_X(x) = \frac{d}{dx}F(x).$$

Relationship between PDF and CDF:

$$F(x) = P(X \leq x) = \int_{y \leq x} f_X(y) dy = \int_{-\infty}^x f_X(y) dy$$

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Example:

Independence of random variables

Define independence of random variables based on independence of events:

Independence of random variables

Suppose X_1, X_2, \dots, X_n are random variables on (Ω, \mathcal{F}, P) , then

X_1, X_2, \dots, X_n are independent

$\Leftrightarrow \{X_1 \in A_1\}, \{X_2 \in A_2\}, \dots, \{X_n \in A_n\}$ are independent, $\forall A_i \in \mathcal{R}$

$\Leftrightarrow P(\cap_{i=1}^n \{X_i \in A_i\}) = \prod_{i=1}^n P(\{X_i \in A_i\})$

Independence of random variables

Example:

Toss a fair coin twice, denote the number of heads of the i -th toss as X_i , then X_1 and X_2 are independent.

- A_i can be $\{0\}$ or $\{1\}$
- $\{(0, 0), (0, 1), (1, 0), (1, 1)\}$
- $P(\{X_1 \in A_1\} \cap \{X_2 \in A_2\}) = \frac{1}{4}$
- $P(\{X_1 \in A_1\}) = P(\{X_2 \in A_2\}) = \frac{1}{2}$

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Remark:

How to check independence in practice?

Independence of random variables

Corollary of independence

If X_1, \dots, X_n are random variables, then X_1, X_2, \dots, X_n are independent if

$$P(X_1 \leq x_1, \dots, X_n \leq x_n) = \prod_{i=1}^n P(X_i \leq x_i)$$

Independence of random variables

Corollary of independence

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Remark:

Independence of discrete random variables

Suppose X_1, \dots, X_n can only take values from $\{a_1, \dots\}$, then X_i 's are independent if

$$P(\cap\{X_i = a_i\}) = \prod_{i=1}^n P(X_i = a_i)$$

Problem Set

Problem 1: Give an example where the events are pairwise independent but not mutually independent.

Problem 2: Verify that the measure $\mu(\cdot)$ induced by $P(\cdot)$ is a probability measure on \mathcal{R} .

Problem 3: Prove properties 3 - 5 of CDF $F(\cdot)$.

Problem 4: Bob and Alice are playing a game. They alternatively keep tossing a fair coin and the first one to get a H wins. Does the person who plays first have a better chance at winning?