



UNIVERSITY OF
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Statistical Sciences

DoSS Summer Bootcamp Probability Module 1

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Roadmap

A bridge connecting undergraduate probability and graduate probability

Undergraduate-level probability

- Concrete;
- Examples and scenarios;
- Rely on computation...

Roadmap

A bridge connecting undergraduate probability and graduate probability

Undergraduate-level probability

- Concrete;
- Examples and scenarios;
- Rely on computation...

Graduate-level probability

- Abstract (measure theory);
- Laws and properties;
- Rely on construction and inference...

Roadmap

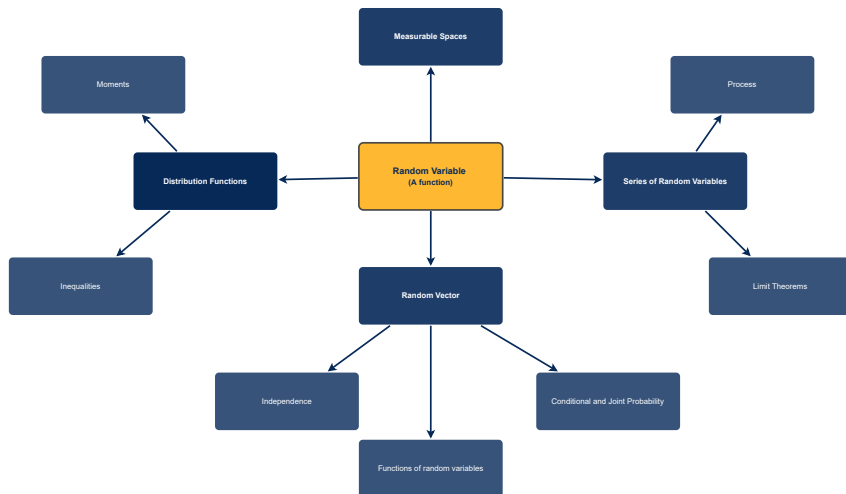


Figure: Roadmap

Outline

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

Today

→ Module 2.

Measurable spaces

Sample Space

The sample space Ω is the set of all possible outcomes of an experiment.

Examples:

- Toss a coin: $\{H, T\} = \Omega$
- Roll a die: $\{1, 2, 3, 4, 5, 6\} = \Omega$

Measurable spaces

Sample Space

The sample space Ω is the set of all possible outcomes of an experiment.

Examples:

- Toss a coin: $\{H, T\}$
- Roll a die: $\{1, 2, 3, 4, 5, 6\}$

Event

An event is a collection of possible outcomes (subset of the sample space).

Examples:

- Get head when tossing a coin: $\{H\} \subset \{H, T\} = \Omega$
- Get an even number when rolling a die: $\{2, 4, 6\} \subset \{1, 2, 3, 4, 5, 6\} = \Omega$

ex1) Tossing a coin twice

$$\Omega = \{HH, HT, TH, TT\} \rightarrow \text{discrete.}$$

$$P(HH) = P(HT) = P(TH) = P(TT) = \frac{1}{4}$$

Let X = the number of H

$$P(X=0) = P(X=2) = \frac{1}{4}$$

$$P(X=1) = \frac{1}{2}$$

$$P(X=0) + P(X=1) + P(X=2) = 1$$

$$\mathbb{E} X = \frac{1}{4} \cdot 0 + \frac{1}{2} \cdot 1 + \frac{1}{4} \cdot 2 = 1$$

ex2) Let $X \sim N(\mu, \sigma^2)$ gaussian

continuous

Density

$$p(x) = \frac{1}{\sqrt{2\pi} \sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

$$\int_{-\infty}^{\infty} p(x) dx = 1$$

$$\mathbb{E} X = \int_{-\infty}^{\infty} x p(x) dx = \mu$$

Discrete case.

$$P(X \leq k) = \sum_{l \leq k} P(X=l)$$

← assuming X only takes integer values for simplicity

$$E X = \sum_{k=-\infty}^{\infty} k P(X=k)$$

Continuity case

$$P(X \leq x) = \int_{-\infty}^x p(z) dz$$

$$E X = \int_{-\infty}^{\infty} x p(x) dx$$

Question

Is there any way to explain them
in a unified way?

Observation

If $A \cap B = \emptyset$, then $P(A \cup B) = P(A) + P(B)$.

For a discrete case, $\{X = k\}$ are disjoint.

$$1 = \sum_{k=-\infty}^{\infty} P(X = k) \quad \text{countable sum}$$

But for continuous case,

$$P(X = x) = 0 \quad \text{for any } x$$

Therefore,

$$1 = \sum_{x \in \mathbb{R}} P(X = x) = \sum_{x \in \mathbb{R}} 0 = 0$$

contradiction?

\Rightarrow uncountable sum is problematic.

\Rightarrow let's focus on countable sum

Measurable spaces

σ -algebra

A σ -algebra (σ -field) \mathcal{F} on Ω is a non-empty collection of subsets of Ω such that

- (i) • If $A \in \mathcal{F}$, then $A^c \in \mathcal{F}$, \rightarrow complement is also in \mathcal{F}
- (ii) • If $A_1, A_2, \dots \in \mathcal{F}$, then $\bigcup_{i=1}^{\infty} A_i \in \mathcal{F}$. \rightarrow countable union of subsets of \mathcal{F} is also in \mathcal{F} .

Remark: $\emptyset, \Omega \in \mathcal{F}$

(pf) Let $A \in \mathcal{F}$.

By (i), $A^c \in \mathcal{F}$.

By (ii) $\underbrace{A \cup A^c}_{= \Omega} \in \mathcal{F}$ so $\Omega \in \mathcal{F}$.

By (i) again, $\Omega^c \in \mathcal{F}$. So, $\emptyset \in \mathcal{F}$.

Construction of Probability Theory

Outline.

1) Define the collection of subsets of Ω , \mathcal{F} (σ -algebra) on which we can define "Probability measure".

2) Define probability measure as a function

$$P : \mathcal{F} \rightarrow [0, 1]$$

which has "countable additivity".

3) (Ω, \mathcal{F}, P) is called "Probability triple".

\uparrow \uparrow \uparrow
sample σ -algebra probability
space measure

Probability measures

Measures on σ -field

A function $\mu : \mathcal{F} \rightarrow \mathbb{R}^+ \cup \{+\infty\}$ is called a measure if

- $\mu(\emptyset) = 0$,
- If $A_1, A_2, \dots \in \mathcal{F}$ and $A_i \cap A_j = \emptyset$, then $\mu(\bigcup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} \mu(A_i)$.

If $\mu(\Omega) = 1$, then μ is called a probability measure.

countable additivity

Probability measures

Measures on σ -field

A function $\mu : \mathcal{F} \rightarrow \mathbb{R}^+ \cup \{+\infty\}$ is called a measure if

- $\mu(\emptyset) = 0$,
- If $A_1, A_2, \dots \in \mathcal{F}$ and $\underbrace{A_i \cap A_j = \emptyset}_{i \neq j}$, then $\mu(\cup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} \mu(A_i)$.

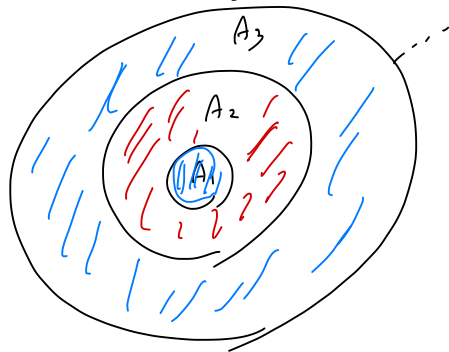
If $\mu(\Omega) = 1$, then μ is called a probability measure.

Properties:

- Monotonicity: $A \subseteq B \Rightarrow \mu(A) \leq \mu(B)$
- Subadditivity: $A \subseteq \cup_{i=1}^{\infty} A_i \Rightarrow \mu(A) \leq \sum_{i=1}^{\infty} \mu(A_i)$
- Continuity from below: $\underbrace{A_i \nearrow A}_{i \nearrow \infty} \Rightarrow \mu(A_i) \nearrow \mu(A)$
- Continuity from above: $\underbrace{A_i \searrow A}_{i \searrow \infty} \text{ and } \mu(A_i) < \infty \Rightarrow \mu(A_i) \searrow \mu(A)$

Probability measures

Proof of continuity from below:



Let $A_i \in \mathcal{F}$, $A_1 \subset A_2 \subset \dots$
 $\bigcup_{i=1}^{\infty} A_i = A$.

Let $B_i = A_i \setminus A_{i-1}$, $i \geq 2$.
 $B_1 = A_1$

Then B_i are disjoint.

$$\bigcup_{i=1}^{\infty} B_i = \bigcup_{i=1}^{\infty} A_i = A$$

By countable additivity $\mu(A) = \mu\left(\bigcup_{i=1}^{\infty} B_i\right) = \sum_{i=1}^{\infty} \mu(B_i)$

Note that

$$A_c = \underbrace{A_{c-1} \cup B_c}_{\text{disjoint union.}} \text{ implies}$$

$$\mu(A_c) = \mu(A_{c-1}) + \mu(B_c) \text{ by countable additivity.}$$

$$\text{Therefore } \mu(B_c) = \mu(A_c) - \mu(A_{c-1})$$

$$\begin{aligned} \text{Thus } \sum_{i=1}^n \mu(B_i) &= \mu(B_1) + \sum_{i=2}^n (\mu(A_i) - \mu(A_{i-1})) \\ &= \mu(A_1) + \mu(A_n) - \mu(A_1) \\ &= \mu(A_n) \end{aligned}$$

$$\text{So, } \sum_{i=1}^{\infty} \mu(B_i) = \lim_{n \rightarrow \infty} \mu(A_n)$$

$$\text{Thus, } \mu(A) = \lim_{n \rightarrow \infty} \mu(A_n)$$

Probability measures

$$A_i \supset A$$

Proof of continuity from above:

$$\mu(A_1) < \infty, \quad A_1 \supset A_2 \supset A_3 \supset \dots, \quad \bigcap_{i=1}^{\infty} A_i = A$$

$$B_i = A_1 - A_i$$

$$\text{Then } B_1 \subset B_2 \subset B_3 \subset \dots, \quad \bigcup_{i=1}^{\infty} B_i = A_1 \setminus A$$

By the continuity from below,

Remark: $\mu(A_i) < \infty$ is vital.

$$\lim_{n \rightarrow \infty} \mu(B_n) = \mu\left(\bigcup_{i=1}^{\infty} B_i\right) = \mu(A_1 \setminus A)$$

$$= \mu(A_1) - \mu(A)$$

Note that $\mu(B_n) = \mu(A_1 \setminus A_n) \overset{\text{red}}{=} \mu(A_1) - \mu(A_n)$

thus $\lim_{n \rightarrow \infty} (\mu(A_1) - \mu(A_n)) = \mu(A_1) - \mu(A) \quad \text{red } \mu(A_1) < \infty$

$\therefore \lim_{n \rightarrow \infty} \mu(A_n) = \mu(A)$

Summary $(\Omega, \mathcal{F}, \mathbb{P})$ probability triple.

"Countable additivity" is the key.

Question How can $(\Omega, \mathcal{F}, \mathbb{P})$
provide unified theory?

Observation

$X: \Omega \rightarrow \mathbb{R}$ random variable.

$$\Omega = \{x \in \mathbb{R}\}$$

$$= \bigcup_{i=-\infty}^{\infty} \{x \in [i, i+1)\}$$

By countable additivity

$$1 = P(\Omega) = \sum_{i=-\infty}^{\infty} P(x \in [i, i+1))$$

$$\Omega = \bigcup_{i=-\infty}^{\infty} \left\{x \in \left[\frac{i}{n}, \frac{i+1}{n}\right)\right\}$$

becomes finer as $n \uparrow \infty$

$$1 = P(\Omega) = \sum_{i=-\infty}^{\infty} P\left(x \in \left[\frac{i}{n}, \frac{i+1}{n}\right)\right)$$

Approximation of Expectation

$$\mathbb{E} X \approx \sum_{i=-\infty}^{\infty} \frac{c_i}{n} \cdot \mathbb{P}\left(X \in \left[\frac{c_i}{n}, \frac{c_{i+1}}{n}\right)\right)$$

should become more precise as $n \rightarrow \infty$

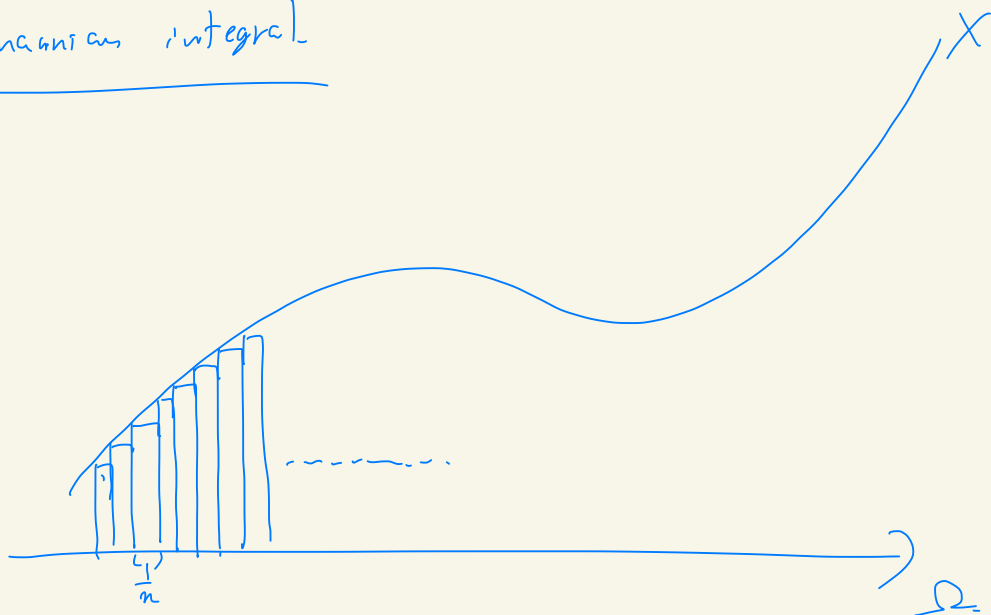
We can use this observation to define $\mathbb{E} X$

$$\mathbb{E} X = \lim_{n \rightarrow \infty} \sum_{i=-\infty}^{\infty} \frac{c_i}{n} \mathbb{P}\left(X \in \left[\frac{c_i}{n}, \frac{c_{i+1}}{n}\right)\right)$$

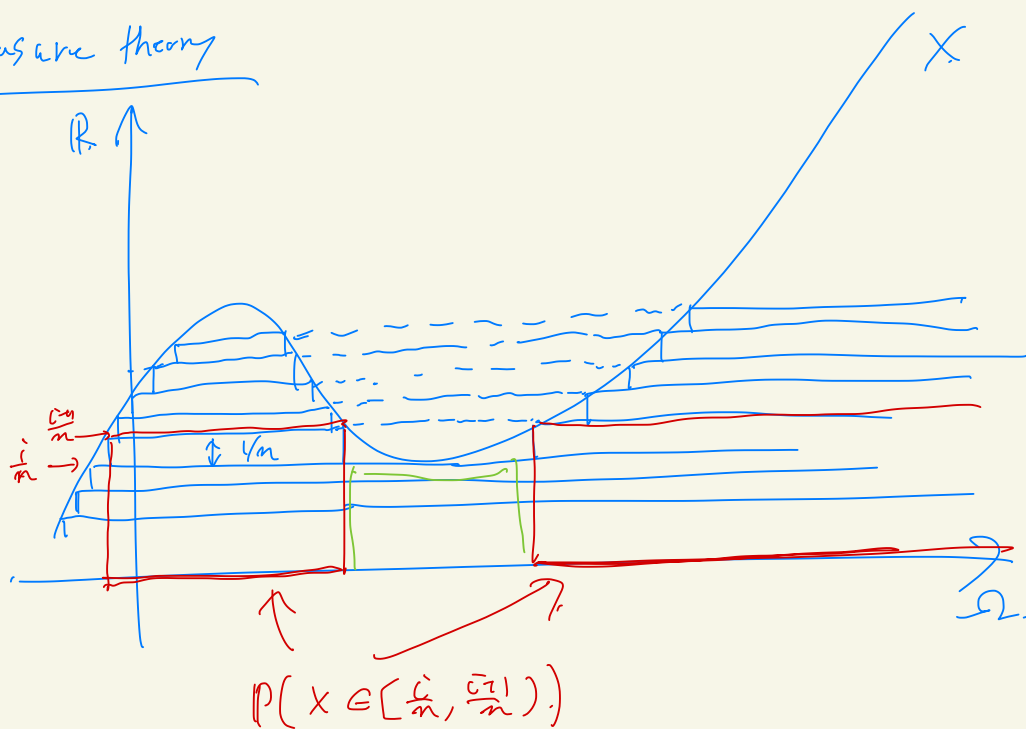
This looks similar to Riemannian integral

Difference between Riemannian integral

Riemannian integral



Measure theory



$$E X = \lim_{n \rightarrow \infty} \sum_{i=0}^{\infty} \frac{i}{n} P(X \in [\frac{i}{n}, \frac{i+1}{n})) = \int_{\Omega} x dP$$

We can show that

$$E X = \sum_{i=0}^{\infty} k_i P(X = k_i) \quad \text{discrete case.}$$

$$E X = \int_{-\infty}^{\infty} x p(x) dx \quad \text{continuous case.}$$

Probability measures

Examples:

$$\Omega = \{\omega_1, \omega_2, \dots\}, A = \{\omega_{a_1}, \dots, \omega_{a_i}, \dots\} \Rightarrow \mu(A) = \sum_{j=1}^{\infty} \mu(\omega_{a_j}).$$

Therefore, we only need to define $\mu(\omega_j) = p_j \geq 0$.

If further $\sum_{i=1}^{\infty} p_j = 1$, then μ is a probability measure.

- Toss a coin:
- Roll a die:

Conditional probability

Original problem:

- What is the probability of some event A ?
- $P(A)$ is determined by our probability measure.

New problem:

- Given that B happens, what is the probability of some event A ?
- $P(A \mid B)$ is the conditional probability of the event A given B .

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- What is the probability of some event A ?
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New problem:

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Example:

- Roll a die: $P(\{2\} \mid \text{even number})$

Conditional probability

Bayes' rule

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

Remark: Does conditional probability $P(\cdot \mid B)$ satisfy the axioms of a probability measure?

Conditional probability

Multiplication rule

$$P(A \cap B) = P(A | B)P(B) = P(B | A)P(A)$$

Generalization:

Law of total probability

Let A_1, A_2, \dots, A_n be a partition of ω , such that $P(A_i) > 0$, then

$$P(B) = \sum_{i=1}^n P(A_i)P(B | A_i)$$

Problem Set

Problem 1: Prove that for a σ -field \mathcal{F} , if $A_1, A_2, \dots \in \mathcal{F}$, then $\bigcap_{i=1}^{\infty} A_i \in \mathcal{F}$.

Problem 2: Prove monotonicity and subadditivity of measure μ on σ -field.

Problem 3: (Monty Hall problem) Suppose you're on a game show, and you're given the choice of three doors: Behind one door is a car; behind the others, goats. You pick a door, say No. 1, and the host, who knows what's behind the doors, opens another door, say No. 3, which has a goat. He then says to you, "Do you want to pick door No. 2?" Is it to your advantage to switch your choice?

(Assumptions: the host will not open the door we picked and the host will only open the door which has a goat.)