

Statistical Methods for Data Science

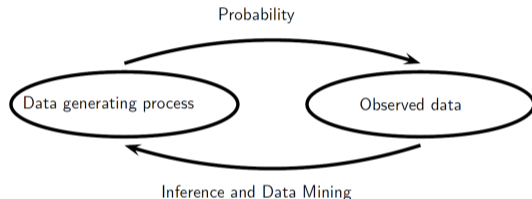
Lesson 01 - Introduction

Salvatore Ruggieri

Department of Computer Science
University of Pisa
salvatore.ruggieri@unipi.it

Why Statistics

We need grounded means for reasoning about data science mechanisms.



What will I learn?

- Probability: properties of data generated according to a known randomness model
- Statistics: properties of a randomness model that could have generated given data
- Simulation and R

Sample spaces and events

- An **experiment** is a measurement of a random process
- The **outcome** of a measurement takes values in some set Ω , called the **sample space**.

Examples:

- ▶ Tossing a coin: $\Omega = \{H, T\}$ *[Finite]*
- ▶ Month of birthdays $\Omega = \{\text{Jan}, \dots, \text{Dec}\}$ *[Finite]*
- ▶ Population of a city $\Omega = \mathbb{N} = \{0, 1, 2, \dots, \}$ *[Countably infinite]*
- ▶ Length of a street $\Omega = \mathbb{R}^+ = (0, \infty)$. *[Uncountably infinite]*
- ▶ Tossing a coin twice: what is Ω ?

Look at seeing-theory.brown.edu

- An **event** is some subset of $A \subseteq \Omega$ of possible outcomes of an experiment.
 - ▶ $L = \{ \text{Jan}, \text{March}, \text{May}, \text{July}, \text{August}, \text{October}, \text{December} \}$ *a long month with 31 days*
- We say that an event A **occurs** if the outcome of the experiment lies in the set A .
 - ▶ If the outcome is Jan then L occurs

Probability functions

A **probability function** is a mapping from events to **real numbers** that satisfies certain axioms. *Intuition: how likely is an event to occur.*

DEFINITION. A *probability function* P on a finite sample space Ω assigns to each event A in Ω a number $P(A)$ in $[0,1]$ such that

- (i) $P(\Omega) = 1$, and
- (ii) $P(A \cup B) = P(A) + P(B)$ if A and B are disjoint.

The number $P(A)$ is called the probability that A occurs.

- Fact: $P(\{a_1, \dots, a_n\}) = P(\{a_1\}) + \dots + P(\{a_n\})$

[Generalized additivity]

- Examples:

- ▶ $P(\{H\}) = P(\{T\}) = 1/2$

- ▶ $P(\text{Jan}) = 31/365, P(\text{Feb}) = 28/365, \dots P(\text{Dec}) = 31/365$

- ▶ $P(L) = 7/12$ or $31 \cdot 7/365$?

Properties of probability functions

- Assigning probability is **NOT** an easy task.
 - ▶ **Frequentist** interpretation: probability measures a “*proportion of outcomes*”.
 - ▶ **Bayesian** (or epistemological) interpretation: probability measures a “*degree of belief*”.
- $P(A^c) = 1 - P(A)$
- $P(\emptyset) = 0$
- $A \subseteq B \Rightarrow P(A) \leq P(B)$
- $P(A \cup B) = P(A) + P(B) - P(A \cap B)$ [*Inclusion-exclusion principle*]
- probability that at least one coin toss over two lands head?

Products of sample spaces

An experiment made of multiple sub-experiments

- Eg., $\Omega = \{ H, T \} \times \{ H, T \} = \{(H, H), (H, T), (T, H), (T, T)\}$
- $P((H, H)) = 1/4$

In general:

- $\Omega = \Omega_1 \times \Omega_2 = \{(\omega_1, \omega_2) \mid \omega_1 \in \Omega_1, \omega_2 \in \Omega_2\}$
- $P((a_1, a_2)) = 1/|\Omega_1| \cdot 1/|\Omega_2|$ *[Uniform function over independent experiments]*

The Monty Hall problem

<https://math.andyou.com/tools/montyhallsimulator/montysim.htm>

(See also Exercise 2.14 of textbook [T])

	Car location:	Host opens:	Total probability:	Stay:	Switch:
1/3	Door 1	1/2 Door 2	1/6	Car	Goat
		1/2 Door 3	1/6	Car	Goat
1/3	Door 2	1 Door 3	1/3	Goat	Car
1/3	Door 3	1 Door 2	1/3	Goat	Car

Exercise at home: generalize to n doors where host opens $n - 2$ doors with goats.

A (countably) infinite sample space

DEFINITION. A *probability function* on an infinite (or finite) sample space Ω assigns to each event A in Ω a number $P(A)$ in $[0, 1]$ such that

- (i) $P(\Omega) = 1$, and
- (ii) $P(A_1 \cup A_2 \cup A_3 \cup \dots) = P(A_1) + P(A_2) + P(A_3) + \dots$
if A_1, A_2, A_3, \dots are disjoint events.

- Example

- ▶ Experiment: we toss a coin repeatedly until H turns up.
- ▶ Outcome: the number of tosses needed.
- ▶ $\Omega = \{1, 2, \dots\} = \mathbb{N}^+$
- ▶ Suppose: $P(H) = p$. Then: $P(n) = (1 - p)^{n-1}p$
- ▶ Is it a probability function? $P(\Omega) = \dots$

Conditional probability

- Long months and months with 'r'

- ▶ $L = \{ \text{Jan, Mar, May, July, Aug, Oct, Dec} \}$

a long month with 31 days

- ▶ $R = \{ \text{Jan, Feb, Mar, Apr, Sep, Oct, Nov, Dec} \}$

a month with 'r'

- ▶ $P(L) = 7/12$ $P(R) = 8/12$

- Anna is born in a long month. What is the probability she is born in a month with 'r'?

$$\frac{P(L \cap R)}{P(L)} = \frac{P(\{ \text{Jan, Mar, Oct, Dec} \})}{P(L)} = \frac{4/12}{7/12} = \frac{4}{7}$$

- **Intuition:** probability of an event in the restricted sample space $\Omega \cap L$

Another example at seeing-theory.brown.edu

Conditional probability

DEFINITION. The **conditional probability** of A given C is given by:

$$P(A|C) = \frac{P(A \cap C)}{P(C)},$$

provided $P(C) > 0$.

Properties:

- $P(A|C) \neq P(C|A)$, in general
- $P(\Omega|C) = 1$
- if $A \cap B = \emptyset$ then $P(A \cup B|C) = P(A|C) + P(B|C)$

THE MULTIPLICATION RULE. For any events A and C :

$$P(A \cap C) = P(A|C) \cdot P(C).$$

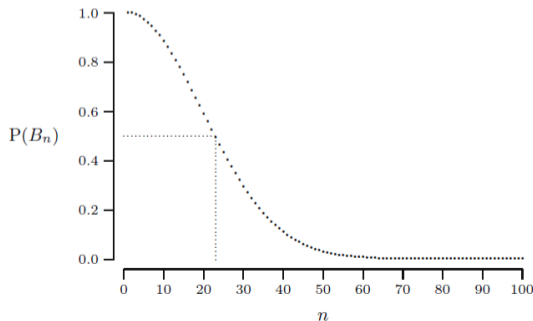
More generally, the **Chain Rule**:

$$P(A_1 \cap A_2 \cap A_3 \dots \cap A_n) = P(A_1) \cdot P(A_2|A_1) \cdot P(A_3|A_2, A_1) \cdot \dots \cdot P(A_n|A_{n-1}, \dots, A_1)$$

Example: no coincident birthdays

- $B_n = \{n \text{ different birthdays}\}$
- For $n = 1$, $P(B_1) = 1$
- For $n > 1$,

$$\begin{aligned} P(B_n) &= P(B_{n-1}) \cdot P(\{\text{the } n\text{-th person's birthday differs from the other } n-1\} | B_{n-1}) \\ &= P(B_{n-1}) \cdot \left(1 - \frac{n-1}{365}\right) = \dots = \prod_{i=1}^{n-1} \left(1 - \frac{i}{365}\right) \end{aligned}$$



Example: case-based reasoning

Factory 1's light bulbs work for over 5000 hours in 99% of cases.

Factory 2's bulbs work for over 5000 hours in 95% of cases.

Factory 1 supplies 60% of the total bulbs on the market and Factory 2 supplies 40% of it.

What is the chance that a purchased bulb will work for longer than 5000 hours?

- $A = \{\text{bulbs working for longer than 5000 hours}\}$
- $C = \{\text{bulbs made by Factory 1}\}$, hence $C^c = \{\text{bulbs made by Factory 2}\}$
- Since $A = (A \cap C) \cup (A \cap C^c)$ with $(A \cap C)$ and $(A \cap C^c)$ disjoint:

$$P(A) = P(A \cap C) + P(A \cap C^c)$$

- and then by the multiplication rule:

$$P(A) = P(A|C) \cdot P(C) + P(A|C^c) \cdot P(C^c)$$

Answer: $P(A) = 0.99 \cdot 0.6 + 0.95 \cdot 0.4 = 0.974$

The law of total probability

THE **LAW OF TOTAL PROBABILITY**. Suppose C_1, C_2, \dots, C_m are disjoint events such that $C_1 \cup C_2 \cup \dots \cup C_m = \Omega$. The probability of an arbitrary event A can be expressed as:

$$P(A) = P(A | C_1)P(C_1) + P(A | C_2)P(C_2) + \dots + P(A | C_m)P(C_m).$$

- **Intuition:** case-based reasoning

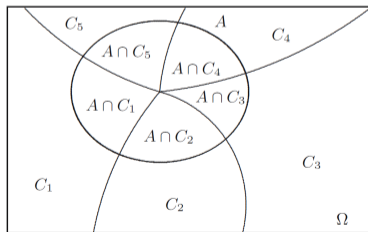


Fig. 3.2. The law of total probability (illustration for $m = 5$).

Testing for Covid-19

A new test for Covid-19 (or Mad-Cow disease, or drug use) has been developed.

- $+$ = { people tested positive } $-$ = { people tested negative } = $+^c$
- C = { people with Covid-19 } C^c = { people without Covid-19 }

In lab experiments, people with and without Covid-19 tested

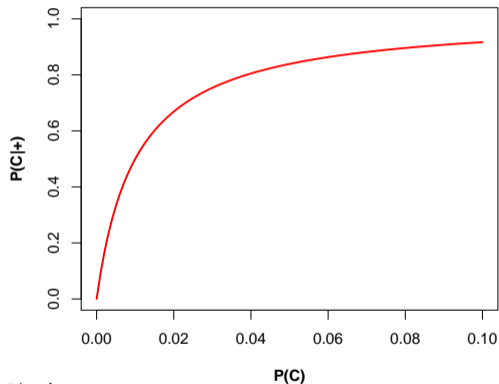
- $P(+|C) = 0.99$ *[Sensitivity/Recall/True Positive Rate]*
- $P(-|C^c) = 0.99$ *[Specificity/True Negative Rate]*

What is the probability I really have Covid-19 given that I tested positive? *[Precision]*

$$P(C|+) = \frac{P(C \cap +)}{P(+)} = \frac{P(+|C) \cdot P(C)}{P(+)} = \frac{P(+|C) \cdot P(C)}{P(+|C) \cdot P(C) + P(+|C^c) \cdot P(C^c)}$$
$$P(C|+) = \frac{0.99 \cdot P(C)}{0.99 \cdot P(C) + 0.01 \cdot (1 - P(C))}$$

Testing for Covid-19

$P(C)$, the probability of having Covid-19, is **unknown**. Let's plot $P(C|+)$ over $P(C)$:



- For $P(C) = 0.02$, $P(C|+) = .67$
- For $P(C) = 0.06$, $P(C|+) = .86$
- For $P(C) = 0.10$, $P(C|+) = .92$

Bayes' Rule

BAYES' RULE. Suppose the events C_1, C_2, \dots, C_m are disjoint and $C_1 \cup C_2 \cup \dots \cup C_m = \Omega$. The conditional probability of C_i , given an arbitrary event A , can be expressed as:

$$P(C_i | A) = \frac{P(A | C_i) \cdot P(C_i)}{P(A | C_1)P(C_1) + P(A | C_2)P(C_2) + \dots + P(A | C_m)P(C_m)}.$$

- It follows from $P(C_i | A) = \frac{P(A | C_i) \cdot P(C_i)}{P(A)}$ and the law of total probability
- Useful when:
 - ▶ $P(C_i | A)$ not easy to calculate
 - ▶ while $P(A | C_j)$ and $P(C_j)$ are known for $j = 1, \dots, m$
 - ▶ E.g., in classification problems (see Bayesian classifiers from Data Mining)
- $P(C_i)$ is called the *prior* probability
- $P(C_i | A)$ is called the *posterior* probability (after seeing event A)

Independence of events

Intuition: whether one event provides any information about another.

DEFINITION. An event A is called *independent* of B if

$$P(A|B) = P(A).$$

- For $P(C) = 0.10$, $P(C|+) = .92$ - knowing test result changes prob. of being infected!
- Tossing 2 coins:
 - ▶ A_1 is "H on toss 1" and A_2 is "H on toss 2"
 - ▶ $P(A_1) = P(A_2) = 1/2$
 - ▶ $P(A_2|A_1) = P(A_2 \cap A_1)/P(A_1) = 1/4/1/2 = 1/2 = P(A_2)$
- Properties:
 - ▶ A independent of B iff $P(A \cap B) = P(A) \cdot P(B)$
 - ▶ A independent of B iff B independent of A

[Symmetry]

Independence of two or more events

INDEPENDENCE OF TWO OR MORE EVENTS. Events A_1, A_2, \dots, A_m are called independent if

$$P(A_1 \cap A_2 \cap \dots \cap A_m) = P(A_1)P(A_2) \dots P(A_m)$$

and this statement *also* holds when any number of the events A_1, \dots, A_m are replaced by their complements throughout the formula.

- It is **stronger** than **pairwise independence**

$$P(A_i \cap A_j) = P(A_i) \cdot P(A_j) \text{ for } i \neq j \in \{1, \dots, m\}$$

Independence of two or more events

Alternative definition

Events A_1, A_2, \dots, A_m are called independent if

$$P\left(\bigcap_{i \in J} A_i\right) = \prod_{i \in J} P(A_i)$$

for every $J \subseteq \{1, \dots, m\}$

- **Exercise at home:** show the two definitions are equivalent
- Example: what is the probability of at least one head in the first 10 tosses of a coin?
 $A_i = \{\text{head in } i\text{-th toss}\}$

$$P\left(\bigcup_{i=1}^{10} A_i\right) = 1 - P\left(\bigcap_{i=1}^{10} A_i^c\right) = 1 - \prod_{i=1}^{10} P(A_i^c) = 1 - \prod_{i=1}^{10} (1 - P(A_i))$$