

# Introduzione alla data science e al pensiero computazionale

## Lezione 8: Revisione dei fondamenti di statistica

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# Probability – History of the term

- Classical probability
- Frequency probability
- Axiomatic probability

Evolution: Classical  $\rightarrow$  Frequency  $\rightarrow$  Axiomatic



## Classical probability. Definition

**Definition** If a random experiment (process with an uncertain outcome) can result in  $n$  *mutually exclusive and equally likely* outcomes, and if  $n_A$  of these outcomes has an attribute  $A$ , then the probability of  $A$  is the fraction  $n_A/n$ .



## Classical probability. Definition

A basic assumption in the definition of classical probability is that  $n$  is a finite number; that is, there is only a finite number of possible outcomes. If there is an infinite number of possible outcomes, the probability of an outcome is not defined **in the classical sense**.



# Classical probability. Examples

- Roll of a dice
- Draw a card from a deck
- Toss of a coin



# Classical probability. Problems

- (Already mentioned) Infinite events
- Definition of equally likely (circular)
- Management of non physical problems for which there is no experiment



# Frequency probability

- We start from considering the case of the outcomes not being equally likely and  $n$  being potentially infinite.
- In such cases, how might we define the probability of an outcome that has attribute “a”?



# Frequency probability

**Definition** We might take a random (finite) sample from the population of interest and identify the proportion of the sample with attribute “a”.

$$Freq_a = \frac{n_a}{n}$$

We estimate  $Pr[a]$  with  $Freq_a$ .





## Problems with frequency probability

- We cannot run infinite trials, and our stopping point may induce ambiguities or errors in results, e.g., tossing the coin  
...
- What if we cannot run trials? This definition requires repeatable experiments.



## Axiomatic probability – Sample space

Definitions:

- The sample space  $\Omega$  is the set of possible outcomes of an experiment.

For example:

- Tossing a coin, the sample space is  $\{ H, T \}$
- Tossing a coin twice, the sample space is  $\{ HH, HT, TH, TT \}$
- Rolling a dice, the sample space is  $\{ 1, 2, 3, 4, 5, 6 \}$
- Football match, the sample space is  $\{ W, L, D \}$
- Selecting a point in the interval  $(0,1)$ , the sample space is  $S = (0,1)$
- Selecting a salary in the range  $[50K\text{€}, 200K\text{€}]$ , the sample space is  $S = [50K\text{€}, 200K\text{€}]$

*This and the following slides are inspired by:*

<https://faculty.math.illinois.edu/~kkirkpat/SampleSpace.pdf>



## Axiomatic probability – Events

Definitions:

- Subsets of  $\Omega$  are called events.

For example:

- Tossing a coin with the sample space  $\{ H, T \}$ , an event  $E$  is  $\{ H \}$
- Tossing a coin twice with sample space  $\{ HH, HT, TH, TT \}$ , an event  $E$  is  $\{ HH, TT \}$
- Rolling a dice with sample space  $\{1, 2, 3, 4, 5, 6\}$ , an event  $E$  is  $\{1, 3, 5\}$ , *the odd sides*
- Football match with sample space  $\{W, L, D\}$ , an event  $E$  is  $\{W, D\}$ , *not losing*
- Selecting a point in the interval  $(0,1)$  with the sample space  $S = (0,1)$ , an event  $E$  is  $(0,1/2)$ , *the first half*
- Selecting a salary in the range  $[50\text{K}\text{P}, 200\text{K}\text{P}]$ , an event  $E$  is  $(150\text{K}\text{P}, 200\text{K}\text{P}]$ , *top salary*



## Axiomatic probability – Probability measure

A probability measure is a function  $\mathbb{P}$  defined on the  $\sigma$ -algebra<sup>†</sup> of events  $\mathcal{E}$  such that:

- $\forall A \in \mathcal{E}, \mathbb{P}(A) \geq 0$ ,
- $\mathbb{P}(\Omega) = 1$ ,
- if  $A_1, A_2, \dots \in \mathcal{E}$  are disjoint then

$$\mathbb{P}\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} \mathbb{P}(A_i).$$

<sup>†</sup> *The definition of  $\sigma$ -algebra is omitted*



## Axiomatic probability – Probability space

The triple  $(\Omega, \mathcal{E}, \mathbb{P})$  is called a **probability space**.

For the example of rolling a dice:

- $\Omega$  - all possible outcomes: 1, 2, ... , 6
- $\mathcal{E}$  - subsets of  $\Omega$ :
  - $\{1\}$
  - the odd sides:  $\{1, 3, 5\}$
  - the small sides:  $\{1, 2\}$
  - any side:  $\{1, 2, 3, 4, 5, 6\}$
- $\mathbb{P}$  - the probability measure of events from  $\mathcal{E}$ :
  - $\mathbb{P}(\{1\}) = 1/6$
  - $\mathbb{P}(\text{the odd sides}) = 1/2$
  - $\mathbb{P}(\text{the small sides}) = 1/3$
  - $\mathbb{P}(\text{any side}) = 1$



## Axiomatic probability – Random variable

A **random variable** is a function  $X : \Omega \rightarrow \mathbb{A}$  such that:

- $\mathbb{A}$  is a measurable space,
- for every real  $a$ ,  $\{\omega \in \Omega : X(\omega) \leq a\} \in \mathcal{E}$ .

Note that:

- Usually  $\mathbb{A}$  is  $\mathbb{R}$  or a subset of it
- A random variable is NOT a variable but a function



## Example of random variable (1/2)

Tossing a dice three times:

- the sample space  $\Omega$  is  $\{ 111, 112, 113, 211, \dots \}$
- events  $E_i$  are:
  - $\{ 222 \}$
  - $\{ 111, 555 \}$
  - $\{ 123, 456, 531 \}$
  - $\dots$
- the probability measure is the function  $\mathbb{P}$ 
  - $\mathbb{P}(\{ 222 \}) = 1/216$
  - $\mathbb{P}(\{ 111, 555 \}) = 1/108$
  - $\mathbb{P}(\{ 123, 456, 531 \}) = 1/72$
  - $\mathbb{P}(\dots)$
  - $\dots$



## Example of random variable (2/2)

Tossing a dice three times:

- a random variable  $X$  is the sum of the three results
- the sample space  $\Omega_X$  is  $\{ 3, 4, 5, 6, 7, 8, 9, \dots, 18 \}$
- events  $E_{X,i}$  are:
  - $\{ 3 \}$
  - $\{ 4, 6 \}$
  - $\{ 16, 17, 18 \}$
  - $\dots$
- the probability measure is the function  $\mathbb{P}_X$ 
  - $\mathbb{P}_X(\{ 3 \}) = 1/216$
  - $\mathbb{P}_X(\{ 4, 6 \}) = 13/216$
  - $\mathbb{P}_X(\{ 16, 17, 18 \}) = 10 / 216 = 5/108$
  - $\dots$





## Axiomatic probability – Pdf

Given:

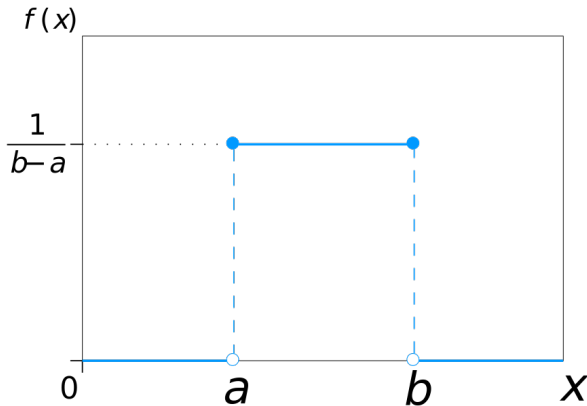
- A random variable  $X$
- A set in which it is defined  $S$  (called the support)
- A **probability density function** (pdf) is a function  $f(X) \geq 0, X \in S$
- defined for the continuous case as:

$$\mathbb{P}(S) = \int_S f(X) dX$$



## Axiomatic probability – Pdf – Example

Example: Uniform distribution:  
pdf:





## Axiomatic probability – Pmf

Given:

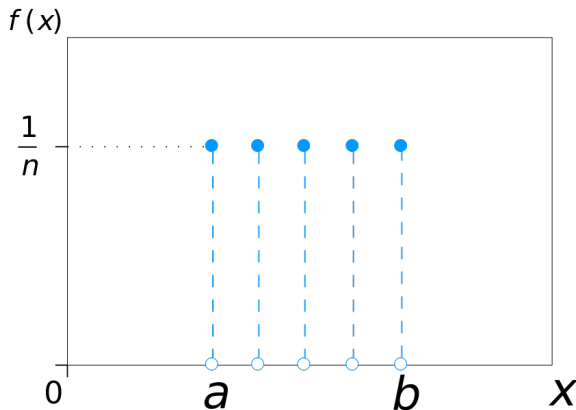
- A random variable  $X$
- A set in which it is defined  $S$  (called the support again)
- A **probability mass function** (pdf) is a function  $f(X) \geq 0, X \in S$
- defined for the discrete case as:

$$\mathbb{P}(S) = \sum_S f(X)$$



# Axiomatic probability – Pmf – Example 1

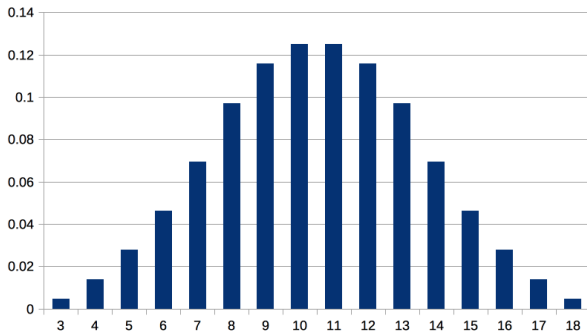
Example 1: Discrete Uniform distribution:  
pmf:





## Axiomatic probability – Pmf – Example 2

Example 2: Computing the score of rolling a dice three times:  
pmf:





## Axiomatic probability – Cdf (continuous)

Given:

- A random variable  $X$
- A set in which it is defined  $S$  (called the support)
- The probability density function of  $X$ ,  $f_X$
- We define the **(cumulative) distribution function** of  $X$  in the continuous case as:

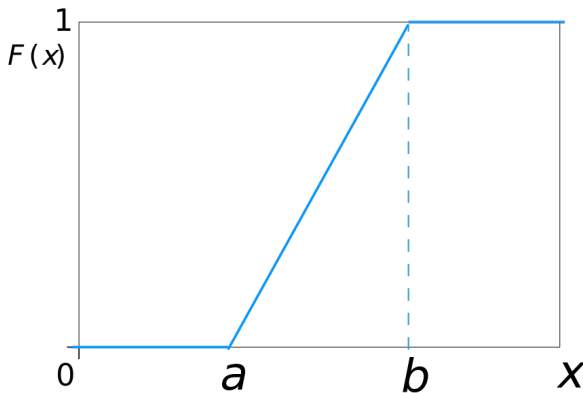
$$F_X(x) = \mathbb{P}(X \leq x) = \int_{-\infty}^x f_X(w)dw$$

*Note. The subscript  $X$  is sometimes omitted, so we often write  $F$  instead of  $F_X$ .*



## Axiomatic probability – Cdf – Example

Example: Uniform distribution:  
cdf:





## Axiomatic probability – Cdf (discrete)

Given:

- A random variable  $X$
- A set in which it is defined  $S$  (called the support)
- The probability mass function of  $X$ ,  $f_X$
- We define the **(cumulative) distribution function** of  $X$  in the discrete case as:

$$F_X(x) = \mathbb{P}(X \leq x) = \sum_{w \leq x} f_X(w)$$

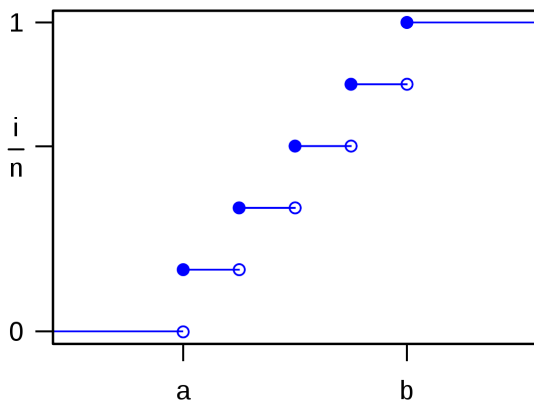
*Note. The subscript  $X$  is sometimes omitted, so we often write  $F$  instead of  $F_X$ .*





# Axiomatic probability – Cdf – Example 1

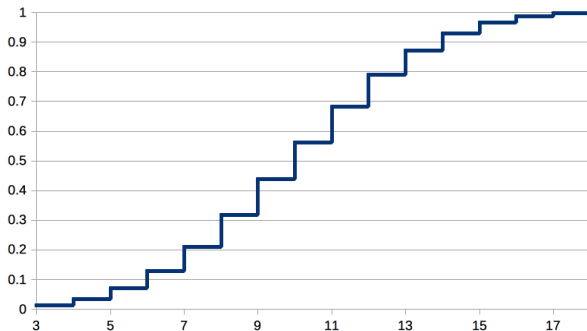
Example 1: Discrete uniform distribution:  
cdf:





## Axiomatic probability – Cdf – Example 2

Example 2: Computing the score of rolling a dice three times:  
cmf:





## Axiomatic probability – Expected value

Let:

- $x$  be a random variable
- $a(x)$  be a function of  $x$
- $F$  be its cdf
- $f$  be its pdf or pmf (if discrete)

The **expected value** of  $a(X)$  is:

- In continuous:

$$\mathbb{E}(a(X)) = \int_{x \in S} a(x) f(x) dx$$

- In discrete:

$$\mathbb{E}(a(X)) = \sum_j a(x_j) f(x_j)$$



## Basic definitions – Mean (continuous)

Let  $a(X) = X$ , then the mean of  $X$  is:

- in the continuous case:

$$\mu = \mathbb{E}(X) = \int_{x \in S} x f(x) dx$$

where  $S$  is the Support.



## Example of mean (continuous)

Example: Uniform distribution on an interval  $[a, b]$ .

pdf =  $\frac{1}{b-a}$  if  $x \in [a, b]$  and pdf=0 elsewhere

Mean:

$$\begin{aligned}\mu = \mathbb{E}(X) &= \int_{-\infty}^{+\infty} x \frac{1}{b-a} dx = \frac{1}{b-a} \left( \frac{x^2}{2} \right) \Big|_a^b = \\ &= \frac{1}{2} * \frac{1}{b-a} * (b^2 - a^2) = \frac{1}{2}(a+b)\end{aligned}$$



## Basic definitions – Mean (discrete)

Let  $a(X) = X$ , then the mean of  $X$  is:

- in discrete case:

$$\mu = \mathbb{E}(X) = \sum_j x_j f(x_j)$$



## Example of mean (discrete)

Example: a dice with 6 edges (6 outcomes:  $X = \{1, 2, 3, 4, 5, 6\}$ ).  
PMF equals  $1/6$  for each outcome.

Mean:

$$\begin{aligned}\mu &= \mathbb{E}(X) = \sum_{x \in X} x \frac{1}{6} = \\ &= 1 * \frac{1}{6} + 2 * \frac{1}{6} + 3 * \frac{1}{6} + 4 * \frac{1}{6} + 5 * \frac{1}{6} + 6 * \frac{1}{6} = \\ &= \frac{1}{6}(1 + 2 + 3 + 4 + 5 + 6) = 3.5\end{aligned}$$



## Basic definitions – Variance

**Variance** of random variable:

$$\mathbb{V}(X) = \mathbb{E}[(X - \mathbb{E}(X))^2]$$

- for discrete case:  $\mathbb{V}(X) = \sum_j (x_j - \mu)^2 f(x_j)$
- for continuous case:  $\mathbb{V}(X) = \int_S (x - \mu)^2 f(x) dx$





## Example of variance

Example: Uniform distribution on an interval  $[a,b]$ .  $\mu = \frac{1}{2}(a+b)$

$$\begin{aligned}\mathbb{V}(X) &= \int_{-\infty}^{+\infty} (x - \mu)^2 \frac{1}{b-a} dx = \\ &= \int_{-\infty}^{+\infty} \left(x - \frac{1}{2}(a+b)\right)^2 \frac{1}{b-a} dx = \frac{1}{b-a} \left( \frac{(x - \frac{1}{2}(a+b))^3}{3} \right) \Big|_a^b = \\ &= \frac{1}{3 \cdot 2^3(b-a)} ((b-a)^3 - (a-b)^3) = \frac{1}{12}(b-a)^2\end{aligned}$$



## Basic definitions – $\alpha$ -quantile

**$\alpha$ -quantile** ( $\alpha \in (0, 1)$ ):

$$X_\alpha : \mathbb{P}(X \leq X_\alpha) = \alpha;$$

$$\mathbb{P}(X > X_\alpha) = 1 - \alpha.$$



## Basic definitions – Median

Median (0.5-**quantile**):

$$X_{0.5} : \mathbb{P}(X \leq X_{0.5}) = 0.5;$$

$$\mathbb{P}(X > X_{0.5}) = 0.5$$



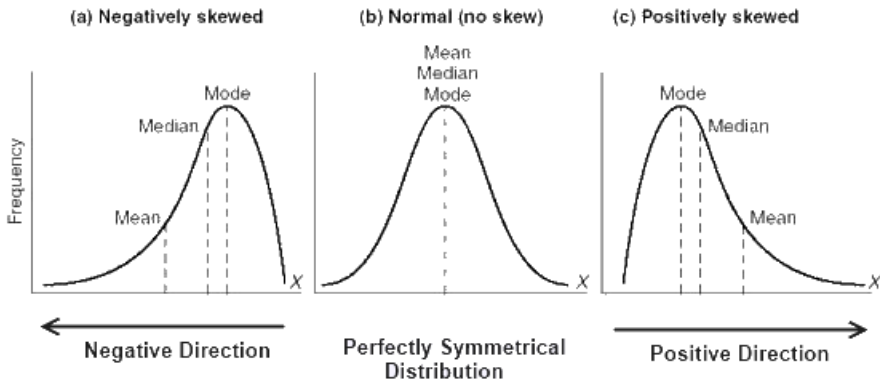
## Basic definitions – Mode

Mode (the most frequent element):

$$mode = \operatorname{argmax}(f(x))$$



# Mean. Median. Mode. Examples





# Normal distribution

The random variable  $X$  has a **normal distribution** with mean  $\mu$  and variance  $\sigma^2$  if it has density:

$$\phi(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}};$$

and CDF:

$$\Phi(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^x e^{-\frac{(t-\mu)^2}{2\sigma^2}} dt.$$

We write  $X \sim N(\mu, \sigma^2)$ .



# Standard Normal distribution

The random variable  $Z$  has a **standard normal distribution** if  $\mu = 0$  and  $\sigma = 1$ . Hence it has density:

$$\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2};$$

and CDF:

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-t^2/2} dt.$$

We write  $Z \sim N(0, 1)$ .

The  $\alpha$  upper quantile is denoted by  $z_\alpha$ . Thus, if  $Z \sim N(0, 1)$ , then we write  $\mathbb{P}(Z > z_\alpha) = \alpha$ .

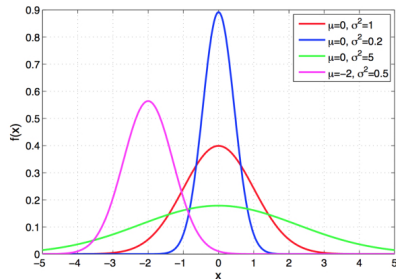
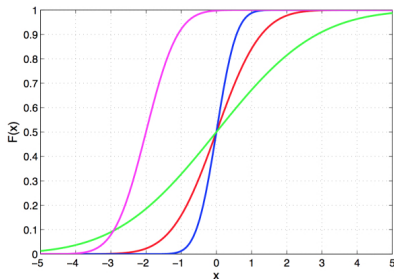


# Normal distribution

$$X \in \mathbb{R} \sim N(\mu, \sigma^2), \sigma^2 > 0$$

$$F(x) = \Phi\left(\frac{x - \mu}{\sigma}\right)$$

$$f(x) = \frac{1}{\sigma} \phi\left(\frac{x - \mu}{\sigma}\right)$$







## Exercise 1

- A discrete random variable has the following probability mass function defined as:

$x$	0	2	4	6
$P(X = x)$	$\frac{1}{7}$	$\frac{3}{7}$	$\frac{1}{7}$	$\frac{2}{7}$

- Compute:
  - mean
  - median
  - mode
  - variance
  - standard deviation



## Exercise 1 – solution

- A discrete random variable has the following probability mass function defined as:

$x$	0	2	4	6
$P(X = x)$	$\frac{1}{7}$	$\frac{3}{7}$	$\frac{1}{7}$	$\frac{2}{7}$
$x \times P(X = x)$	0	0,857	0,571	1,714
$x - \bar{x}$	-3,143	-1,143	0,857	2,857
$(x - \bar{x})^2$	9,878	1,306	0,735	8,163
$(x - \bar{x})^2 \times P(X = x)$	1,411	0,560	0,105	2,332

- So we get:
  - $\bar{x} = \sum (x \times P(X = x)) = 3,143$
  - $\mathbb{V}(x) = \sum ((x - \bar{x})^2 \times P(X = x)) = 4,408$



## Exercise 2

- A discrete random variable has the following probability mass function defined as:

$x$	1	2	3	4	5
$P(X = x)$	$\frac{2}{10}$	$\frac{2}{10}$	$k$	$\frac{3}{10}$	$\frac{1}{10}$

- Compute:
  - the value of  $k$
  - mean
  - median
  - mode
  - variance
  - standard deviation



## Exercise 3

- A continuous random variable  $X$  has probability density function defined as:

$$f(x) = \begin{cases} \frac{x^2}{9}, & \text{if } 0 < x < 3 \\ 0, & \text{elsewhere} \end{cases}$$

- Compute:
  - mean
  - median
  - mode
  - variance
  - standard deviation



## Exercise 3 – solution

- A continuous random variable  $X$  has probability density function defined as:

$$f(x) = \begin{cases} \frac{x^2}{9}, & \text{if } 0 < x < 3 \\ 0, & \text{elsewhere} \end{cases}$$

- Compute:
  - mean = 2,25
  - median  $\approx 2,38$
  - mode = 3
  - variance = 0,3375
  - standard deviation = 0,581



## Exercise 4

- A continuous random variable  $X$  has probability density function defined as:

$$f(x) = \begin{cases} \frac{\sin(x)}{2}, & \text{if } 0 \leq x \leq \pi \\ 0, & \text{elsewhere} \end{cases}$$

- Compute:
  - mean
  - median
  - mode
  - variance
  - standard deviation



## Exercise 4 - solution

- A continuous random variable  $X$  has probability density function defined as:

$$f(x) = \begin{cases} \frac{\sin(x)}{2}, & \text{if } 0 \leq x \leq \pi \\ 0, & \text{elsewhere} \end{cases}$$

- Compute:
  - mean  $= \frac{\pi}{2}$
  - median  $= \frac{\pi}{2}$
  - mode  $= \frac{\pi}{2}$
  - variance  $= \frac{\pi^2}{4} - 2 \approx 0,467$
  - standard deviation  $\approx 0,684$



# Domande?

Fine della lezione otto.