

# Rappels de probabilités

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# Outline

- 1 What is probability exactly?
- 2 Espace de probabilités
- 3 Indépendance
- 4 Probabilités conditionnelles
- 5 Variables aléatoires
- 6 Lois discrètes ultra-classiques
- 7 Expectation

# Understanding probability

Probability terminology may often be mistaken with common language: “fairly sure”, “likely”, “almost certain”, “low chances” ...

Everyone has a personal view of what is a probability. Somehow it involves assigning a **number** to characterize the outcome of some uncertain experiment (e.g., games of chance).

Most common perceptions:

- intuitive view (above)
- **classical** [Laplace 1814]
- **frequentist** [Bernoulli 1713]
- **subjective** (information)
- logical [Keynes 1921 and Carnap 1950]
- **axiomatic** [Kolmogorov 1933]

# Understanding probability

## Classical view

1654, Pascal, Fermat and the Chevalier de Méré.

How to divide the stakes if a game of chance is interrupted before the end?  
 Compute favorable cases to possible outcomes and divide accordingly.

1663, Cardano:

compute

$$\frac{\text{\#favorable cases}}{\text{\#possible cases}}$$

to make a fair bet

The above formula is used by De Moivre and Laplace as a **definition of probability**.

However this definition relies implicitly on the *equiprobability assumption*.

# Understanding probability

## Classical view

### De Méré's problem:

It seems equally likely to :

- event  $A$ : get a 6 after throwing 1 die 4 times
- event  $B$ : get a double-6 after throwing two dice 24 times

Argument #1 (Antoine Gombaud):  $\mathbb{P}[A] = \frac{4 \text{ chances to get a 6}}{6 \text{ possibilities}} = \frac{2}{3}$

$\mathbb{P}[B] = \frac{24 \text{ chances to get a double 6}}{36 \text{ possibilities}}$

Here, probability was confused with **expectation**.

Argument #2 (Fermat)  $\mathbb{P}[A] = 0.518$  and  $\mathbb{P}[B] = 0.491$  (correct answer).

# Understanding probability

## Frequentist view

Your company has 30 license tokens for a popular mathematical software. 10 license tokens are in use today, 12 yesterday and 8 the day before. What is the probability that a given token is used?

## Bernoulli, 1713 (Law of large numbers)

Relative frequency of a given even in a large number of trials should be close to the theoretical probability of that event .

Probability can then be redefined as the **limit** of the relative frequency if the experiment were repeated infinitely many times.

## Limitations

- infinitely many is a lot :-)
- estimation of probability may vary, depending on samples
- sometimes, repetition is not possible

# Understanding probability

Information view (from the introduction)

## Information

What is the probability that the network went down yesterday?

It is a **past** event: there's **no randomness** after it happened. Still, we can model our **uncertainty** by using probabilities.

Examples:

- probability of finding survivors after earthquake
- probability that a message was transmitted with no errors
- probability that a patient has the flu

Probability depends on the **available information** on the event.

# Understanding probability

## Subjective view

So, probability is not that objective after all.

### Bayes theorem, 1763

Suppose  $A_1, \dots, A_n$  are *incompatible events* such that the collection represents all possibilities :  $\bigcup_{j=1}^n A_j = \Omega$ . Then

$$\mathbb{P}[A_j|B] = \frac{\mathbb{P}[B|A_j] \mathbb{P}[A_j]}{\mathbb{P}[B]} = \frac{\mathbb{P}[B|A_j] \mathbb{P}[A_j]}{\sum_{j=1}^n \mathbb{P}[B|A_j] \mathbb{P}[A_j]}$$

If we “know” the prior (first estimation)  $\mathbb{P}[A_j]$  and the likelihood  $\mathbb{P}[B|A_j]$  then **the observed data  $B$  can change the perceived probabilities** of the events  $A_j$  :  $\mathbb{P}[B|A_j]$  (posterior probabilities)

- Repetition of the same is not necessary
- Arbitrary prior distribution



# Understanding probability

## Axiomatic view

XXth century : Need for a formal theory of probability.

- using Borel's work on measure theory
- and Lebesgue integral,
- Kolmogorov (1933) defined the axiomatic theory.

Events are viewed as subsets of possible outcomes.

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# Espace de probabilité

- $\Omega$  est l'ensemble des réalisations possibles  $\{\omega_i\}$  (résultats d'une expérience aléatoire)
- $\Omega$  peut être fini ou non, dénombrable ou non.
- un **événement** est une partie  $A$  de  $\Omega$
- $\mathcal{F}$  est l'ensemble des événements:
  - ▶  $\emptyset \in \mathcal{F}$  et  $\Omega \in \mathcal{F}$  ("*aucun événement*" et "*tous les événements*" sont dans  $\mathcal{F}$ )
  - ▶ si  $A \in \mathcal{F}$  alors  $\bar{A} \in \mathcal{F}$  (si un événement est dans  $\mathcal{F}$ , son contraire aussi)
  - ▶ l'union d'événements est un événement:

$$\forall A_1, A_2, \dots \in \mathcal{F}, \cup_{n=1}^{\infty} A_n \in \mathcal{F}$$

- $\mathbb{P}[\cdot]$  est une **mesure de probabilité** sur  $(\Omega, \mathcal{F})$ :
  - ▶  $\mathbb{P}[\Omega] = 1$
  - ▶ Pour tout ensemble **dénombrable** d'événements **incompatibles**  $A_1, A_2, \dots$  on a:

$$\mathbb{P}[\cup_i A_i] = \sum_i \mathbb{P}[A_i]$$

## Example of a probability space

Random experiment : throwing a die.

Give the corresponding probability space.

- $\Omega = \{1, 2, 3, 4, 5, 6\}$
- $\mathcal{F}$  is the power set of  $\Omega$  (set of all subsets)

For instance, event  $E$  = "the result is odd" is in  $\mathcal{F} : \{1, 3, 5\}$ .

Another event  $E'$  = "the result is smaller or equal to 3" is also in  $\mathcal{F}$ . As is  $E \cup E'$ , or  $E \cap E'$ .

- $\forall k \in \Omega, \mathbb{P}[k] = \frac{1}{6}$ .

Therefore  $\mathbb{P}[E \cup E'] = ?$

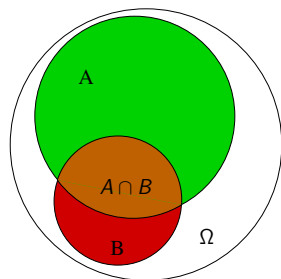
# Probability space for humans (not mathematicians)

- $\Omega$  is the universe of possible outcomes (if we really did the experiment)
- $\mathcal{F}$  is the set of **events**, that is, a group (set) of possible outcomes.
- The probability measure  $\mathbb{P}$  associates a positive **number**  $\mathbb{P}[A]$  to any possible *event*  $A \in \mathcal{F}$ , such that:
  - ▶  $\mathbb{P}[\Omega] = 1$  (probability of the universe)
  - ▶ if two events  $A$  and  $E$  are **incompatible** then  $\mathbb{P}[A \cup E] = \mathbb{P}[A] + \mathbb{P}[E]$  (union= OR)

In general  $\mathbb{P}[A \cup E] \neq \mathbb{P}[A] + \mathbb{P}[E]$  since it would count twice the case  $\{A \text{ and } E\}$  (noted  $A \cap E$ .)

# Propriétés

- $\mathbb{P}[\emptyset] = 0$
- $\mathbb{P}[\overline{A}] = 1 - \mathbb{P}[A]$
- $\mathbb{P}[A \cup B] = \mathbb{P}[A] + \mathbb{P}[B] - \mathbb{P}[A \cap B]$
- $P(A) \leq P(B)$  si  $A \subset B$



## Incompatibilité

Deux événements  $A$  et  $B$  sont **incompatibles** ssi  $\mathbb{P}[A \cap B] = \mathbb{P}[\emptyset] = 0$

## Remarque

$P(A) = 0 \not\Rightarrow A = \emptyset$ .

De même,  $P(A) = 1 \not\Rightarrow A = \Omega$ .

# Application to software testing [Mitzenmacher and Upfal]

## Polynomial computation testing

Given two polynoms  $F(x) = \sum_{i=1}^n a_i x^i$  and  $G(x) = \prod_{j=1}^n (b_j x + c_j)$ . Can you check that  $F=G$ ?

- compute  $G$  and  $F$  in canonical form and compare the coefficients
- Randomized algorithm : **pick** a number  $r$  uniformly in  $\{0, 1, \dots, 100n\}$ <sup>1</sup> and compare  $F(r)$  and  $G(r)$ .

The algorithm can only give a wrong answer if  $F \neq G$  and if  $F(r) = G(r) \Leftrightarrow r$  is a root of  $F - G$ . Let's call  $E$  this event.

There are at most  $n$  such roots ( $n$  is the max possible degree of  $F - G$ )

$$\mathbb{P}[E] \leq \frac{n}{100 \times n} = 10^{-2}$$

<sup>1</sup>where  $n$  is the degree of the polynoms

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## Independance

Let us improve the above method to get better confidence in the algorithm output.

Recall that the algorithm is always right when it outputs that  $F \neq G$ . If the output is  $F = G$ , we could **repeat** the experiment to increase the certainty.

Let us pick a second number  $r_2$  and check whether  $F(r_2) = G(r_2)$ . Let us call  $E_2$  the event  $F(r_2) = G(r_2)$  when  $F \neq G$ . Then as above,  $\mathbb{P}[E_2] \leq 10^{-2}$ .

If  $r_2$  is chosen *independently*<sup>2</sup> of  $r$ , then

$$\mathbb{P}[E \cap E_2] \leq (10^{-2})^2 = 10^{-4}$$

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<sup>2</sup>With replacement, so we need to treat properly the case  $r = r_2$

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# Probabilités conditionnelles

La probabilité qu'un événement  $A$  se produise **sachant qu'**un événement  $B$  s'est produit est notée  $\mathbb{P}[A|B]$ .

## Formule de Bayes

$$\mathbb{P}[A|B] = \frac{\mathbb{P}[A \cap B]}{\mathbb{P}[B]}$$

En généralisant (par récurrence) on a:

$$P\left(\bigcap_{k=0}^n A_k\right) = P(A_1|A_0)P(A_2|\dots A_1) \dots P(A_n|A_0 \cap A_1 \dots \cap A_{n-1})P(A_0)$$

# Causality and conditioning

$\mathbb{P}[A|B] \neq \mathbb{P}[A]$  does not mean that  $B$  has a causal effect on  $A$ .

## Example

- $A = \{\text{patient is infected by a virus}\}$
- $B = \{\text{disease test result is positive}\}$

Then  $\mathbb{P}[B|A]$  indicates a causal explanation (test is positive partly due to the fact that the patient is infected).

But  $\mathbb{P}[A|B]$  does not (the test has no effect on the presence of the virus in the patient).

## Loi des probabilités totales

Soit  $B_1, \dots, B_n$  une partition de  $\Omega$  ( $B_i \cap B_j = \emptyset$  et  $\cup_{1 \leq i \leq n} B_i = \Omega$ ) telle que  $\forall 1 \leq i \leq n, \mathbb{P}[B_i] > 0$ . Alors pour tout événement  $A$ :

$$\mathbb{P}[A] = \sum_{i=1}^n \mathbb{P}[A|B_i] \mathbb{P}[B_i]$$

## Indépendance

Deux événements  $A$  et  $B$  sont **indépendants** ssi  $P(A \cap B) = P(A) \times P(B)$ .

Remarque : si  $A$  et  $B$  sont indépendants alors  $\mathbb{P}[A|B] = \mathbb{P}[A]$ .

# Application of Bayes formula

## Rare illness paradox

<https://sciencetonante.wordpress.com/2012/10/08/les-probabilites-conditionnelles-bayes-level-1/>

## Yule-Simpson paradox

<https://sciencetonante.wordpress.com/2013/04/29/le-paradoxe-de-simpson/>

# Exercice

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# Variables aléatoires

Une **variable aléatoire**  $X$  est une **application**  $X : \Omega \rightarrow F$  ou  $F$  est un ensemble ordonné, t.q.

$$\forall x \in F, \{\omega \in \Omega : X(\omega) \leq x\} \in \mathcal{F}$$

## Human language translation

A random variable is a function  $X : \Omega \rightarrow \mathbb{R}$  (or  $\mathbb{N}$ ) characterizing the possible outcomes in  $\Omega$  such that intervals in  $\mathbb{R}$  have a probability.

- $X$  est une **v.a. discrète** si  $F$  est dénombrable (typ.  $\mathbb{N}$ )
- $X$  est une **v.a. continue** si  $F$  est indénombrable (typ.  $\mathbb{R}$ )

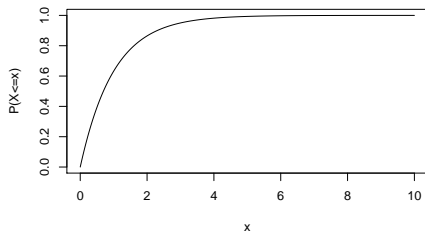
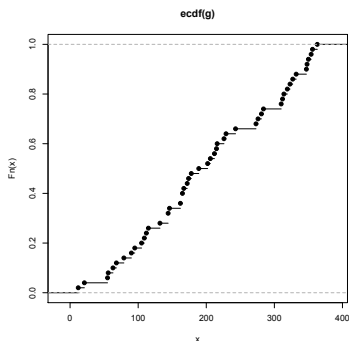
# Cumulative Distribution function (C.D.F)

Pour toute v.a.  $X$  on définit sa **fonction de répartition** (CDF en anglais):

$$\forall x, F(x) = \mathbb{P}[X \leq x]$$

$F$  donne les probabilités *cumulées*.

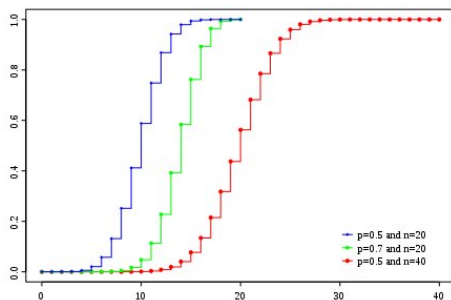
$F$  décrit la **loi** ou **distribution de probabilité de  $X$** .



- $0 \leq F(x) \leq 1$
- $F$  is nondecreasing

# Cas particulier d'une variable aléatoire discrète

La fonction de répartition (C.D.F) d'une variable aléatoire discrète est une fonction en escalier (sommes cumulées).



# Probability density function (P.D.F)

La distribution d'une variable aléatoire peut également être définie de façon plus "élémentaire" par :

## Cas d'une variable discrète

Fonction de distribution :

$$f(k) = \mathbb{P}[X = k]$$

pour toute valeur k possible.

## Cas d'une variable continue (réelle)

Densité de probabilité (PDF en anglais)  $f(x)$

$$\mathbb{P}[x \leq X \leq y] = \int_x^y f(u) du$$

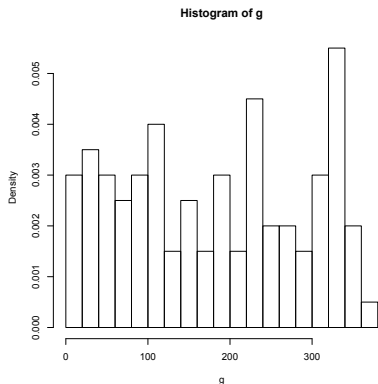
attention aux bornes  
d'intégration...

## Variables aléatoires discrètes

Pour une v.a. discrète (à valeurs entières par exemple) on définit la **fonction de distribution** (ou **loi**) par

$$f(k) = \mathbb{P}[X = k]$$

. C'est la fonction qui donne la probabilité de chaque valeur.



- $0 \leq f(k) \leq 1$
- $F(k) = \sum_{m=-\infty}^k f(m)$
- $f$  peut être approchée par l'histogramme d'un échantillon

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# Bernoulli trials

## Bernoulli

A **binary** random variable  $X \in \{0, 1\}$  such that  $\mathbb{P}[X = 1] = p$  is a Bernoulli random variable  $\mathcal{B}(p)$ .

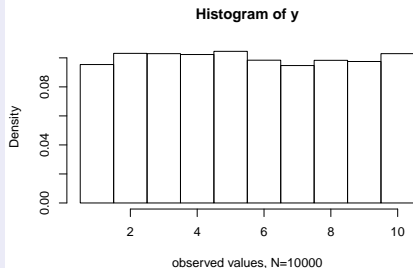
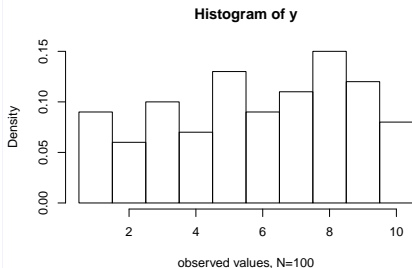
Typical example : coin tossing, test result (pass/fail)...

## Uniform distribution

Une variable  $X \in \{n_1, n_2, n_3, \dots, n_k\}$  pouvant prendre  $k$  valeurs est uniforme si chacune de ces valeurs a la même probabilité de se réaliser :

$$\mathbb{P}[X = n_i] = \frac{1}{k}$$

```
y=sample.int(10,size=N,replace=TRUE)
hist(y,breaks=br,freq=FALSE)
```





# Binomial distribution

Repeating bernoulli trials...

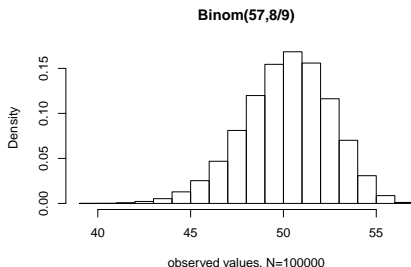
## Binomial

La somme de  $n$  v.a. de Bernoulli **indépendantes** de même paramètre  $p$  est une v.a. **binomiale**  $\text{Binom}(n, p)$ . Sa distribution est:

$$\mathbb{P}[X_1 + \dots + X_n = k] = C_n^k p^k (1 - p)^{n-k}$$

Exercice :

- 1 Preuve de la distribution?
- 2 Montrer que  $\sum_{i=0}^n \mathbb{P}[X = k] = 1$
- 3 Montrer que l'espérance est  $\mathbb{E}[X] = np$



## Geometric distribution (1)

Sequence of independent Bernoulli trials  $\mathcal{B}(p)$  **until** first success:

$$\mathbb{P}[X = k] = p \times (1 - p)^{k-1}$$

### Warning

The geometric distribution in the R language (`rgeom`) is slightly different (number of failures before first success)

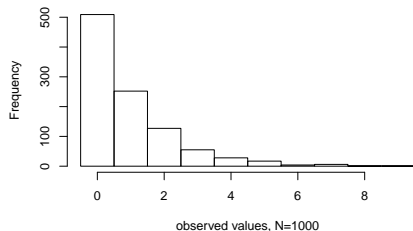
Exercice:

- Prove that  $\sum_{i=0}^{\infty} \mathbb{P}[X = k] = 1$
- Prove that  $\mathbb{E}[X] = \frac{1}{p}$

## Geometric distribution (2)

Note that the geometric r.v. has **infinite support**, i.e. can take an infinite number of values.

Geom(0.5)



```

y=rgeom(1000,prob=0.5)
br=seq(from=min(y)-0.5,to=max(y)+0.5,by=1)
hist(y,xlab="observed values, N=1000",main='Geom(0.5)',breaks=br)

```

# Poisson distribution

Limite de la binomiale pour de grandes valeurs de  $n$  (et petites valeurs de  $p$ )

Paramètre:  $\lambda$

$$\mathbb{P}[X = k] = \frac{\lambda^k}{k!} e^{-\lambda}$$

- Prove that  $\mathbb{E}[X] = \lambda$
- Link with binomial ? (hint: use  $\lambda = np$ )

`rpois(n,lambda)`

# Other classical distributions that you should know about

- Hypergeometric
- Negative binomial distribution
- Multinomial distribution

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# Expectation

## Espérance

La **moyenne** (mean) ou **espérance** (expectation en anglais) d'une v.a. discrète  $X$  à valeurs dans  $I$  (dénombrable) est:

$$\mathbb{E}[X] = \sum_{x \in I} x \mathbb{P}[X = x]$$

## Example

Soit  $0 < p < 1$ . Une variable aléatoire  $X$  à valeurs dans  $\{0, 1\}$  suit une loi de **Bernoulli**  $\mathcal{B}(p)$  ssi  $\mathbb{P}[X = 1] = p$  et  $\mathbb{P}[X = 0] = 1 - p$ .

Son espérance est  $\mathbb{E}[X] = 0 \times (1 - p) + 1 \times p = p$ .

## Exercise

What is the expected value of the sum of two fair dice?

# Expectation

## Linearity

Given two random variables  $X$  and  $Y$  we have:

$$\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

even if  $X$  and  $Y$  are dependent variables.

Also for any constant  $c$  we have:

$$\mathbb{E}[cX] = c\mathbb{E}[X]$$



# Expectation

- Compute the expectation of a binomial random variable  $Z$ .
- Let  $Y = X - \mathbb{E}[X]$ . Compute  $\mathbb{E}[Y]$  as a function of the moments of  $X$ .

# Conditional expectation

$$\mathbb{E}[Y|Z = z] = \sum_y y \mathbb{P}[Y = y|Z = z]$$

Law of total probability:

$$\mathbb{E}[Y] = \mathbb{E}[\mathbb{E}[Y|Z]]$$

where  $\mathbb{E}[Y|Z]$  is a random variable ( $f(Z)$ ).