PROBA

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Table des matières

List of Theorems

Lecture 1: Introduction

Wed 22 Sep

1 Some historical models

1.1 Laplace Model

Definition 1 (Laplace Model)
Ω finite set, $|\Omega| = n$ is the set of outcomes.
We can observe whether $E \subset \Omega$ happens, and we define it's probability

$$\mathbb{P}(E) = \frac{|E|}{|\Omega|}$$

Question

Why should this have any meaning/content ?

Proposition 1
Consider laplace model for n coint tosses $\Rightarrow$ every sequence has probability 2^{-n}
Denote by H_n the number of heads in n tosses

$$\mathbb{P}(|\frac{H_n}{n} - \frac{1}{2}| > \epsilon) \to 0$$

More generally

Proposition 2
If you have a laplace modelfor some event E, and look at n repetitions, then

$$\forall \epsilon > 0 \mathbb{P}(|\frac{E_n}{n} - \mathbb{P}(E)| > \epsilon) \to 0$$

Limitations of Laplace Model

- All outcomes have equal probability ?
- Need $|\Omega| < \infty$, so what about infinite sets ?

What next ?

Definition 2 (Intermediate model)
Let Ω to be any set and $P : \Omega \to [0, 1]$, s.t. $\sum_{\omega \in \Omega} p(\omega) = 1$

Event : $E \subset \Omega$ and

$$\mathbb{P}(E) := \sum_{\omega \in E} p(\omega)$$

- More freedom
- If you take Ω finite, $p(\omega) = \frac{1}{|\Omega|} \Rightarrow$ Laplace model
- Price ? How to choose $p : \Omega \to [0, 1] \to$ collect data, do statistics
- keeps many nice properties

— For contable sets, this is equivalent to the standard model.
— For uncountable Ω ?
— Problem 1 : There is no function s.t.

$$p(\omega) > 0 \forall \omega \in \Omega \text{ and } \sum p(\omega) = 1$$

This intermediate model is in essence only for countable sets.

What about uncountable sets ?

— What about a random point int $[0,1]$ or $[0,1]^n$?

Intuitively, consider $[0,1]$, then we can set

$$\mathbb{P}(A) = \text{length}(A)$$

Definition 3 (Geometric probability)
Take $f : \mathbb{R} \to (0,\infty)$ to be a riemann-integrable function with total mass 1.
For any $A \subset \mathbb{R}$,s.t. 1_A riemann-integrable, we set $\mathbb{P}(A) = \int_A f(x)dx$

— In general quite ok
BUT

— You would expect there is one framework for uncountable and countable sets.
— What about more complicated spaces (eg. space of continuous functions)
— $\mathbb{P}(\mathbb{Q})$ is undefined

2 Basic Formalism

2.1 Measure spaces : A notion of area

— Set + structure
— General setting to talk about area

Definition 4 (Measure space)
$(\Omega, \mathcal{F}, \mu)$ is called a measure space if :
— *Ω is some set*
— *$\mathcal{F} \subset P(\Omega)$ called a σ-algebra*
  — $\emptyset \in \mathcal{F}$
  — $F \in \mathcal{F} \Rightarrow F^c \in \mathcal{F}$
  — *$F_1, F_2, \ldots, \in \mathcal{F}$, then $\bigcup_{i\geq 1} F_i \in \mathcal{F}$ each F is called a measurable set.*
— *$\mu : \mathcal{F} \to [0,\infty)$ called the measure*
  — $\mu(\emptyset) = 0$

— *If $F_1, \dots,$ are disjoints sets of the σ-algebra, then*

$$\mu(\bigcup_{i\geq 1} F_i) = \sum_{i\geq 1} \mu(F_i)$$

— *Defined by Borel 1898 and Lebesgue 1901-1903*

2.2 Probability spaces

Given by Kolmogorov in 1933

Definition 5 (Probability space)
A triple $(\Omega, \mathcal{F}, \mathbb{P})$ is called a probability space if it is a measure space and $\mathbb{P}(\Omega) = 1$

Interpretation

— Ω state space/universe
— $\mathcal{F}$ is the set of events you can observe/have access to
— $\mathbb{P}(E)$ is the probability of E

Lemme 3
Let $(\Omega, \mathcal{F}, \mu)$ be a measure space
— $\Omega \in \mathcal{F}$
— $F_1, F_2 \in \mathcal{F} \Rightarrow F_1 \setminus F_2 \in \mathcal{F}$
— $F_1, \ldots \in \mathcal{F} \Rightarrow \bigcap F_i \in \mathcal{F}$
— $F_1, F_2, \ldots \in \mathcal{F} \Rightarrow \bigcap_{i\geq 1} F_i$

Let us compare this definition with the prior ones
— Ω finite set, $\mathcal{F} = \mathcal{P}(\Omega), \mathbb{P}(F) = \frac{|F|}{|\Omega|}$ this is a probability space and a laplace model.
— For Ω countable, $\mathcal{F} = \mathcal{P}(\Omega), \mathbb{P}(E) = \sum_{\omega \in E} \mathbb{P}(\omega)$
— The really new part is $\mathcal{F}$ which restricts the sets we can measure

Lecture 2: ...

Wed 29 Sep

2.3 Basic properties

— $F_1, F_2, \ldots, \in \mathcal{F}$ disjoint

$$\mu(\bigcup F_i) = \sum \mu(F_i)$$

— $F_1 \subset F_2 \in \mathcal{F}$ $\mu(F_1) \leq \mu(F_2)$
— $F_1 \subset F_2 \ldots \in \mathcal{F}$

$$\mu(F_n) \to \mu(\bigcup F_i)$$

— $F_1, F_2, \ldots, \mathcal{F}$
$$\mu(\bigcup F_i) \leq \sum \mu(F_i)$$

In addition, in probability spaces

— $\mathcal{P}(F^c) = 1 - \mathcal{P}(F)$

— $F_1 \supset F_2 \supset \ldots \Rightarrow \mathcal{P}(F_n) \to \mathcal{P}(\bigcap F_i)$

2.4 Measurable and measure preserving maps

Definition 6

Let $(\Omega_1, \mathcal{F}_1, \mu_1), (\Omega_2, \mathcal{F}_2, \mu_2)$ *two measure spaces.*
$f : \Omega_1 \to \Omega_2$ *is called measurable if for every* $F \in \mathcal{F}_2$, $f^{-1}(F) \in \mathcal{F}_1$
A measurable function $f : (\Omega_1, \mathcal{F}_1) \to (\Omega_2, \mathcal{F}_2)$ *is called measure preserving if* $\forall F \in \mathcal{F}_2$ $\mu_1(f^{-1}(F)) = \mu_2(F)$.

Lemme 4 (Push-Forward measure)
Let $(\Omega_1, \mathcal{F}_1, \mathbb{P}_1), (\Omega_2, \mathcal{F}_2)$ *be two measure spaces, and* f *measurable, then* $\mathbb{P}_2(F) = \mathbb{P}_1(f^{-1}(F))$ *is a probability measure.*

3 Probability spaces

— Discrete probability spaces : Ω countable

— Continuous probability spaces : Ω uncountable.

3.1 Discrete probability spaces

Does introducing a σ-algebra $\mathcal{F}$ enlargen the generality ?

Proposition 5
If $(\Omega, \mathcal{F}, \mathbb{P})$ *is a discret probability space,* $\exists \Omega_2$ *countable,* $\mathbb{P}_2 : \mathcal{P}(\Omega_2) \to [0, 1]$ *s.t.* $(\Omega_2, P(\Omega_2), \mathbb{P}_2)$ *is a probability space and* $\exists f : (\Omega_1, \mathcal{F}_1) \to (\Omega_2, \mathcal{F}_2)$ *is measure preserving*

Still $\mathcal{F}$ is useful :

— can sequentially study a model/situation by taking $\mathcal{F}_1 \subset \mathcal{F}_2 \ldots$

Lemme 6
There is no shift-invariant probability measure on $(\mathbb{Z}, P(\mathbb{Z}))$

Preuve

$$\mathbb{P}(\mathbb{Z}) = \mathbb{P}(\bigcup_n \{n\}) = \sum \mathbb{P}(\{n\}) = \infty$$

$\Rightarrow$ *cannot treat everyone on an equal ground !* $\square$

3.1.1 Symmetric simple random walk

A simple walk of length n s.t. $|s_n - s_{n-1}| = 1$.
Let Ω be the set of all walks of length n, and consider $(\Omega, P(\Omega), \mathbb{P})$.
What is the probability that S hits 0 ?
What does it look like, what is it's max ?

3.2 Continuous probability spaces

Can we define a probability measure on S^1 s.t. $(S^1, P(S^1))$ that is rotation invariant ?
Similarly to the countable case, but not the same as Ω is uncountable and setting $P(\{\omega\}) = 0$ gives no contradiction.

Proposition 7
You can not.

Preuve
Idea : decompose S^1 into countable many sets A_n st $\bigcup A_n = S^1$, they are disjoint and rotations of each other.
$\forall x \in S^1$, define S_x as $\{\dots, T^{-2}x, T^{-1}x, x, Tx, \dots\}$.
Note that either $S_x = S_y$ or $S_x \bigcap S_y = \emptyset$.

Lecture 3: Measurable maps

Wed 06 Oct

3.3 Borel σ-algebra

- Cannot define shift-invariant probability measure on $([0,1], \mathcal{P}([0,1]))$.
- What σ-algebra to choose on (X, τ) ?
- Want to know the siize of all open-sets

Definition 7 (Borel sigma-algebra)
On (X, τ) the borel σ-algebra $\mathcal{F}_\tau$ is the smallest σ-algebra containing τ.

This is well defined because, given a collection of σ-algebras, their intersection is too.

Two nice properties

- Continuous functions on a Borel σ-algebra are also measurable.

  Preuve
  Suffices to check that $f^{-1}(U) \in \mathcal{F}_{\tau_1}$ for $U \in \tau_2$ but this is immediate since f is continuous.

In $(\mathbb{R}^n, \tau_E)$*, the Borel* σ*-algebra* $\mathcal{F}_E$ *is generated by* $(a_1, b_1) \times ... \times (a_n, b_n)$*.*
$\mathcal{F}_E$ *is the smallest* σ*-algebra containing open intervalls.* □

3.4 Probability Measures on $\mathbb{R}^n$

Theorème 8 (Existence of Lebesgue-measure)
There exists a unique measure λ *on* $(\mathbb{R}^n, \mathcal{F}_E)$ *s.t.* $\lambda((a_1 \times b_1) \times \ldots \times (a_n, b_n)) = \prod_i |b_i - a_i|$

Theorème 9 (Uniforme Measure)
There exists a unique $\mathbb{P}$ *measure on* $([0,1]^n, \mathcal{F}_E)$ *with the same property.*

Both λ and $\mathbb{P}$ are shift-invariant in fact only shift invariant measures on $\mathbb{R}$ (up to a constant)

Preuve
Consider the case of $(\mathbb{R}^n, \mathcal{F}_E)$ *and* $f_r : x \to x + \tau, \tau \in \mathbb{R}^n$*.*
- f_r *continuous* $\Rightarrow$ *measurable*
- $\tilde{\mathbb{P}}(A) = \mathbb{P}(f^{-1}(A))$ *is a probability measure*
- *All boxes have the same measure* □

3.5 Probability measures on $(\mathbb{R}, \mathcal{F}_E)$

We saw that we can put a uniform measure on $[0, 1]$.
All probability measures on $(\mathbb{R}, \mathcal{F}_E)$

1. $\mathbb{P} : \mathcal{F}_E \to [0, 1]$
2. These are actually only characterized by $\mathbb{P}((-\infty, x))$

Definition 8 (Cumulative distribution function)
$F : \mathbb{R} \to [0, 1]$ *is called a c.d.f if*
- F *is non-decreasing*
- $F(x_n) \to 0$ *then* $x_n \to -\infty$
- $F(x_n) \to 1$ *if* $x_n \to 1$
- F *is right-continuous.*

Theorème 10
Given a probability measure $\mathbb{P}$ *on* $(\mathbb{R}, \mathcal{F}_E)$ *, then* $f(x) := \mathbb{P}((-\infty, x))$ *is a c.d.f*
Given a c.d.f, there exists a unique probability measure s.t. $\mathbb{P}(-\infty, x) = F(x)$

Preuve
Given $\mathbb{P}$ *on* $(\mathbb{R}, \mathcal{F}_E)$*.*
Let's show that $F(x) = \mathbb{P}((-\infty, x))$ *is a c.d.f.*

— $x < y \quad F(x) = \mathbb{P}((-\infty, x)) \leq \mathbb{P}(-\infty, y) = F(y)$

— $x_n \to -\infty \quad F(x_n) = \mathbb{P}(-\infty, x_n) \to \mathbb{P}(\bigcap_n (-\infty, x_n)) = 0$

— $x_n \to \infty \Rightarrow F(x_n) \to 1$ *is similar*

— *Also for right continuous* $x_n \to x$ *, we have that* $[x_n, \infty) \subset [x_{n+1}, \infty)$

How do we construct $\mathbb{P}$ *given* F *?*

Trick using push-forward measure.

Define $f : (0,1) \to \mathbb{R}$*, define*

$$f(x) = \inf_{y \in \mathbb{R}} \{F(y) \geq x\}$$

□

Define $\mathbb{P}(A) := \mathbb{P}_U(f^{-1}(A)) \forall A \in \mathcal{F}_E$ *Why is* f *measurable ?*

If f *is increasing* $\Rightarrow$ f *is measurable*

Lecture 4: ...

Wed 13 Oct

Each c.d.f gives rise to a unique $\mathbb{P}$.

A priori $\mathbb{P}_1 = \mathbb{P}_2$ means $\forall F \in \mathcal{F}_E \mathbb{P}_1(F) = \mathbb{P}_2(F)$.

We show that it suffices to show that $\mathbb{P}_1((-\infty, x]) = \mathbb{P}_2((-\infty, x]) \forall x \in \mathbb{R}$.

Lemme 11

Given $(\mathbb{R}, \mathcal{F}_E, \mathbb{P})$ *then* $\forall B \in \mathcal{F}_E, \forall \epsilon > 0$ *one can find disjoint intervals* $I_1, \ldots, I_n$ *s.t.* $\mathbb{P}(B \Delta (I_1 \cup \ldots \cup I_n)) < \epsilon$

Preuve

Consider the collection H *of all subsets* $H \in \mathcal{F}_E$ *s.t. the property above holds.*

We know that H *contains all intervalls, hence* $\sigma(H) = \mathcal{F}_E$.

So we only need to show that H *is a* $\sigma-$*algebra*

1. $\emptyset \in H$ *: Know that* $\forall x (-\infty, x] \in H$
2. *If* $B \in H \Rightarrow B^C \in H$.
   Given $\epsilon > 0$*, choose* $I_1, \ldots, I_n$ *s.t.* $\mathbb{P}(B \Delta (I_1 \cup \ldots)) < \epsilon$*, but* $(B \Delta A) = B^C \Delta A^C$ *, hence*
   $$\mathbb{P}(B^C \Delta (I_1 \cup \ldots)) < \epsilon$$
3. $H_1, \ldots \in H$*, we want* $\bigcup_i H_i \in H$ $\exists n \in \mathbb{N}$
   $$\mathbb{P}((\bigcup_{i=0}^{m} H_i) \Delta (\bigcup_i H_i)) < \frac{\epsilon}{2}$$
   $\forall i = 1, \ldots, m$ *, we have disjoint* $I_{i,1}, \ldots, I_{i,m_i}$ *s.t.*
   $$\mathbb{P}(H_i \Delta (I_{i,1} \cup \ldots)) < \frac{\epsilon}{2m}$$
   Now use that
   $$(\bigcup_{i=1}^{m} H_i) \Delta (\bigcup_{i=1}^{m} \bigcup_{j=1}^{m_i} I_{i,j}) \subseteq \bigcup_{i=1}^{m} (H_i \Delta \bigcup_{j=1}^{m_i} I_{i,j})$$
   Finally, we can write a finite union of disjoint intervals

□

Corollaire 12
$\mathbb{P}_1, \mathbb{P}_2$ probability measure on $(\mathbb{R}, \mathcal{F}_E)$, then $\mathbb{P}_1 = \mathbb{P}_2$ as soon as

$$\mathbb{P}_1((-\infty, x]) = \mathbb{P}_2((-\infty, x])$$

or

$$\mathbb{P}_1(x, y) = \mathbb{P}_2(x, y)$$

Preuve
Notice $(-\infty, x)$ can be written as

$$(-\infty, x) = (\bigcup_n (x, x+n))^C$$

So it suffices to prove the first point.
Observe, for all intervalls $\mathbb{P}_1(I) = \mathbb{P}_2(I)$ since

$$\mathbb{P}_i(y, x) = \mathbb{P}_i(-\infty, x) - \mathbb{P}_i(-\infty, y)$$

The condition holds for B if $\forall \epsilon > 0$, we can pick $I_1, \ldots, I_n$ s.t.

$$\mathbb{P}_1(B \Delta (I_1 \cup \ldots)) < \epsilon$$

and

$$\mathbb{P}_2(B \Delta (I_1 \cup \ldots)) < \epsilon$$

So we need to check again that this is a $\sigma-$ algebra and we are done.
Now we can conclude that

$$|\mathbb{P}_1(B) - \mathbb{P}_1(I_1 \cup \ldots)| = |\mathbb{P}_1(B) - \mathbb{P}_2(I_1 \cup \ldots)| < \epsilon$$

and

$$|\mathbb{P}_2(B) - \mathbb{P}_1(I_1 \cup \ldots)| = |\mathbb{P}_2(B) - \mathbb{P}_2(I_1 \cup \ldots)| < \epsilon \qquad \square$$

An abstract uniqueness result follows from a similar strategy.

Theorème 13 (Dynkin)
$\mathbb{P}_1$ and $\mathbb{P}_2$ two probability measures on $(\Omega, \mathcal{F})$, suppose $\mathbb{P}_1(H) = \mathbb{P}_2(H)$ for all $H \in \mathcal{H} \subset \mathcal{F}$ and
- $\sigma(H) = \mathcal{F}$
- $H_1 \in \mathcal{H}, H_2 \in \mathcal{H} \Rightarrow H_1 \cap H_2 \in \mathcal{H}$

Then $\mathbb{P}_1 = \mathbb{P}_2$

3.6 Probability measures on $\mathbb{R}^n$

Definition 9 (Joint c.d.f.)
$F : \mathbb{R}^n \to [0, 1]$

— *F non-decreasing in each coordinate*
— *$F(x_1, \ldots, x_n) \to 1$ if all $x_i \to -\infty$*
— *right-continuous*

Theorème 14
Joint c.d.f $\iff$ $\mathbb{P}$ on $(\mathbb{R}^n, \mathcal{F}_E)$

3.7 Product probability measures on $\mathbb{R}^n, \mathbb{R}^{\mathbb{N}}$

— Related to independence
— Natural mathematically

2 steps

— product σ-algebra
— product measure

3.7.1 Product σ-algebra

Definition 10 (Product algebra)
Let $(\Omega_i, \mathcal{F}_i)_{i \geq 1}$ measurable spaces, then the product σ-algebra $\mathcal{F}_\pi$ on $\prod_i \Omega_i$ is the σ-algebra generated by sets $F = E_1 \times \ldots \times E_n \times \Omega_{n+1} \times \ldots$, $E_i \in \mathcal{F}_i$

Remarque
— *Projections are measurable*
— *In fact, product σ-algebra s.t. all projections are measurable*

Notice on $\mathbb{R}^n$, we now have two ways to define a $\sigma-$algebra.
— Take $(\mathbb{R}^n, \tau_E)$ and induce a Borel σ-algebra
— Take n copies of $(\mathbb{R}, \mathcal{F}_E)$ and consider $\mathcal{F}_\pi$ on $\mathbb{R}^n$

3.8 Product measures

Definition 11
Given $(\Omega_i, \mathcal{F}_i, \mathbb{P}_i)_{i \geq 1}$ probability spaces $\mathbb{P}_\pi$ on $(\prod_i \Omega_i, \mathcal{F}_\pi)$ is called the product measure of $\mathbb{P}_i$.
If $\forall n \geq 1$, all sets $E = E_1 \times E_2 \times \ldots \times E_n \times \Omega_{n+1} \times \ldots$

$$\mathbb{P}_\pi(E) = \prod_{i=1}^{n} \mathbb{P}_i(E_i)$$

Lecture 5: Conditional probability

Wed 20 Oct

3.9 Infinite product spaces

Case of $(\mathbb{R}, \mathcal{F}_E, \mathbb{P}_i)_{i \geq 1}$.

Space of infinite faire coin tosses

We want the infinite product of $(\{0,1\}, P(\{0,1\}), \mathbb{P})$.
We use the uniform measure $([0,1], \mathcal{F}_E, \mathbb{P})$, for $x \in [0,1)$, $x = 0.x_1x_2\ldots$, we send $f : x \to (x_1, x_2, \ldots)$

Lemme 16
f as defined above is measurable

Preuve
Note that

- $\mathcal{F}_\pi$ *generated by* $F_1 \times \ldots, F_n \times \{0,1\} \times \{0,1\}$ *with* $|F_i| = 1$
- $\mathcal{F}_E$ *is generated by sets of the forme* $(2^{-n}j, 2^{-n}(j+1))$. □

Moreover, $(j2^{-n}, (j+1)2^{-n})$ *is in correspondence with* $F_1 \times \ldots \times F_n \times \{0,1\} \times \ldots$.

Proposition 17
There existes a product probability measure on $(\{0,1\}^{\mathbb{N}}, \mathcal{F}_\pi)$

Preuve
Consider $f : ([0,1], \mathcal{F}_E) \mapsto (\{0,1\}^{\mathbb{N}}, \mathcal{F}_\pi)$.
We define $\mathbb{P}_\pi$ *as the pushforward of* $\mathbb{P}_U$ *under* f □

Lecture 6: Random Variables

Wed 27 Oct

4 Random Variables

Definition 12 (Random Variables)
Let $(\Omega, \mathcal{F}, \mathbb{P})$ *be a probability space.*
Then $X : \Omega \mapsto t\mathbb{R}$ *measurable as a map* $(\Omega, \mathcal{F}) \to (\mathbb{R}, \mathcal{F}_E)$ *is called a (real) random variable.*

The pushforward measure $\mathbb{P}_X(F) = \mathbb{P}(X^{-1}(F)) \forall F \in \mathcal{F}_E$ is called the law of X

Remarque
There is a more general notion of $(\Omega_2, \mathcal{F}_2)$ *valued random variable.*

Definition 13 (Equality of RV)
X, Y two random variables are called equal in law if

$$\mathbb{P}_X(F) = \mathbb{P}_Y(F) \forall F \in \mathcal{F}_E$$

Definition 14
X is a R.V. we call the c.d.f. of $\mathbb{P}_X$ F_X

$$F_X(s) = \mathbb{P}_X(X \leq s)$$

Proposition 19
Each R.V. X gives rise to a unique c.d.f. $F_X(s) = \mathbb{P}_X(X \leq s)$ and conversely, each c.d.f. gives rise to a unique law of a probability measure

Preuve
Follows directly from the proposition relating probability measures and c.d.f. □

Lemme 20

1. $\mathbb{P}_X < s = F(S^-)$
2. $\mathbb{P}_X(X = s) = F(s) - F(s^-)$
3. $\mathbb{P}_X(X \in (a, b)) = F(b^-) - F(a)$

Definition 15
X a R.V., $s \in \mathbb{R}$.
If $F(s) - F(s^-) > 0 \iff \mathbb{P}_X(X = s) > 0$, then s is a atom of X

Lemme 21
A R.V. can have at most countably many atoms or in other words, a c.d.f. can have at most countably many jumps.

Definition 16
X a R.V.
If F_X increases by jumps, we call X a discrete R.V.
If F_X is cts, we call X a cts R.V.

Proposition 22
X a R.V. Then we can write $F(X) = aF_Y + bF_Z$ s.t. $a + b = 1$ and Y discrete, Z cts R.V.

Preuve
If F_X is discrete or cts, we are done.
$\exists S = \{s_1, s_2, \ldots\}$ s.t. $F_X(s_i) - F_X(s_i^-) > 0$ iff $s_i \in S$.
Consider

$$\hat{F}_Y(s) = \sum 1_{\{S \geq s_i\}}(F(s_i) - F(s_i^-))$$

and

$$\hat{F}_Z(s) = F_X(s) - \hat{F}_Y(s)$$

We now show that $\hat{F}_Z$ continuous.
Finally, define

$$F_Y(s) = \frac{\hat{F}_Y(s)}{\hat{F}_Y(\infty)}$$

and similarly

$$F_Z(s) = \frac{\hat{F}_Z(s)}{\hat{F}_Z(\infty)}$$

□

Lecture 7: Example of RV

Wed 03 Nov

Geometric R.V.

Let $S = \mathbb{N}$ and $0 < p \leq 1$.

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

Corresponds to first succes if success rate is p.

Definition 17
We call a rv with support $\mathbb{N}$ memoryless if

$$\mathbb{P}(X > k + l | X > k) = \mathbb{P}(X > l)$$

Proposition 23
Geo(p) is memoryless and every memoryless RV with suppport on $\mathbb{N}$ is a geometric rv.

Preuve

$$\mathbb{P}(X > k + l | X > k)\mathbb{P}(X > k) = \mathbb{P}(X > k + l) = (1 - p)^{k+l}$$

But also $\mathbb{P}(X > l) = (1 - p)^l$

$$\mathbb{P}(X > k + l | X > k) = (1 - p)^l$$

Now suppose X is a memoryless RV with $\mathbb{P}(X > 1) > 0$, then

$$\mathbb{P}(X > l + 1 | X > 1) = \frac{\mathbb{P}(X > l + 1)}{\mathbb{P}X > 1} = \mathbb{P}(X > l)$$

□

Inductively, it follows that $\mathbb{P}(X > l) = \mathbb{P}(X > 1)^l$

Poisson RV

Define

$$\mathbb{P}(Poi(\lambda) = k) = \frac{\lambda^k}{k!} e^{-\lambda}$$

Proposition 24

$$Ber(n, \frac{\lambda}{n}) \mapsto Poi(\lambda) \text{ as } n \to \infty$$

in the sense that $\forall k \in \mathbb{N}$

$$\mathbb{P}(Ber(n, \frac{\lambda}{n}) = k) \to \mathbb{P}(Poi(\lambda) = k)$$

Preuve

$$\mathbb{P}(Bin(n, \frac{\lambda}{n}) = k) = \binom{n}{k} (\frac{\lambda}{n})^k (1 - \frac{\lambda}{n})^{n-k} = \mathbb{P}(Bin(n, \frac{\lambda}{n}) = k) = \binom{n}{k} (\frac{\lambda}{n})^k (1 - \frac{\lambda}{n})^n (1 - \frac{\lambda}{n})^{-k}$$

$$= \frac{\lambda^k}{k!} e^{-\lambda} (\frac{n!}{(n-k!)n^k} (1 - \frac{\lambda}{n})^{-k}) \to \frac{\lambda^k}{k!} e^{-\lambda} \quad \square$$

4.1 Independence of RV

Definition 18 (Independence of RV)
$(X_i)_{i \geq 1}$ RV defined on $(\Omega, \mathcal{F}, \mathbb{P})$ are called mutually independent if $\forall J \subset \{1, 2, \ldots\}$ finite ad $\forall E_j \in \mathcal{F}_E \forall j \in J$.

$$\mathbb{P}(\bigcap_{j \in J} \{X_j \in E_j\}) = \prod \mathbb{P}(X_j \in E_j)$$

Proposition 25
$(X_i)_{i \geq 1}$ RV with laws $\mathbb{P}_{X_i}$ then we can find a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and RV $\tilde{X}_i$ s.t.
- *$X_i \simeq \tilde{X}_i$*
- *$(\tilde{X}_i)$ are mutually independent.h*

Preuve
Consider the product probability space of $(\mathbb{P}_{X_i})$ i.e. $(\mathbb{R}^n, \mathcal{F}_\pi, \mathbb{P}_\pi)$.
Let $\tilde{X}_i$ be the projection on the i-th coordinate.
Are $(\tilde{X}_i)$ independent ?

$$\mathbb{P}_\pi(\bigcap_{j \in J} \left\{\tilde{X}_j \in E_j\right\}) = \mathbb{P}_\pi(\bigcap_i F_i) \quad \square$$

With $F_i = \mathbb{R}$ if $i \notin J$ and $F_i = E_i$ if $i \in J$

4.2 Example of continuous random variables

We will mainly work with a subclass of continuous rv :

Definition 19 (Random variables with density)
We call a continuous rv X with c.d.f. F_x a r.v. with densite if $\exists f : R \to [0, \infty)$ which is integrable, $\int_{\mathbb{R}} f = 1$ st

$$\mathbb{P}(X \leq t) = F_X(t) = \int_{-\infty}^{t} f_X(s) ds$$

Lecture 8: rv with density

Wed 10 Nov

The gaussian random variable describes sums of independent errors

Theorème 26 (Version of central limit theorem)
Let $X_1, \dots$ be iid random variables s.t. $\mathbb{P}(|X_I| < C) = 1$ for some $C > 0$ and such that $-X_i$ and X_i have the same law.
Then $S_n = \frac{\sum_{i=1}^n X_i}{\sqrt{n}} \to \mathcal{N}(0, \sigma^2)$ in the sense that $\mathbb{P}(S_n \in (a,b)) \to \mathbb{P}(\mathcal{N}(0,\sigma^2) \in (a,b))$

4.3 Transformation of random variables

Lemme 27
If $\phi : \mathbb{R} \to \mathbb{R}$ continuous and r.v. on $(\omega, \mathcal{F}, \mathbb{P})$ then $\phi(X)$ is also r.v. on $(\Omega, \mathcal{F}, \mathbb{P})$

Preuve
Need to check that $\phi \circ X$ is measurable.
- *Continuous functions are measurable*
- *Composition of measurable functions is measurable* □

Proposition 28
Let X be a continuous random variable with density $f_X : \mathbb{R} \to [0, \infty)$.
Let $\phi : \mathbb{R} \to \mathbb{R}$ bijective, continuously differentiable with $\phi'(x) \neq 0 \forall x \in \mathbb{R}$.
Then $\phi(X)$ is a r.v. with density given by

$$f_{\phi(X)}(x) = \frac{1}{\phi' \circ \phi^{-1}(X)} f_X(\phi^{-1}(x))$$

5 Random Vectors

Definition 20 (Random Vector)
$(\Omega, \mathcal{F}, \mathbb{P})$ $X_1, \dots, X_n$ random variables then $\overline{X} = (X_1, \dots, X_n)$ is called a random vector.

Remarque
Marginal laws on their own do not describe the behavior of $\overline{X}$.

Lemme 30
If $X_1, \dots, X_n : (\Omega, \mathcal{F}) \to (\mathbb{R}, \mathcal{F}_E)$ measurable $\overline{X}$ is measurable from $(\Omega, \mathcal{F}) \to (\mathbb{R}^n, \mathcal{F}_E)$

Preuve
Suffices to check that $\overline{X}^{-1}$ *of each* $E = F_1 \times \ldots \times F_n$ *is in* $\mathcal{F}$

$$\overline{X}^{-1}(E) = \bigcap X_i^{-1}(F_i) \in \mathcal{F}$$

Hence we can define

$$\mathbb{P}_{\overline{X}}(E) \coloneqq \mathbb{P}(\overline{X}^{-1}(E)) \forall E \in \mathcal{F}_E$$

Which is a probability law on $(\mathbb{R}^n, \mathcal{F}_E)$ *called the joint law of* $\overline{X}$ $\square$

Proposition 31
The joint law of a random vector $\overline{X}$ *is uniquely characterised by the joint cdf*

Preuve
Restatement of probability measure on $\mathbb{R}^n$ *are in correspondence with joint cdf* $\square$

Lemme 32
$X_1, \ldots, X_n$ *random variables* $(\Omega, \mathcal{F})$ *are independent if and only if*

$$F_{\overline{X}}(x_1, \ldots, x_n) = \prod_i F_i(x_i)$$

Transformations of random vectors

Proposition 33
$\overline{X}$ *is a* $\mathbb{R}^n$ *valued random vector and* $\phi : \mathbb{R}^n \to \mathbb{R}^m$ *continuous then* $\phi(\overline{X})$ *is a* $\mathbb{R}^n$ *valued random vector with values in* $\mathbb{R}^n$

Corollaire 34
Let $X_1, \ldots, X_n$ *be random variables on* Ω *then* $\sum a_i X_i$ *is a random variable*

Definition 21 (Random vectors with density)
Let $\overline{X} = (X_1, \ldots, X_n)$ *random vector then*

$$f_{\overline{X}} : \mathbb{R}^n \to [0, \infty)$$

Riemann integrable with $\int_{\mathbb{R}^n} f_{\overline{X}}(y)dy = 1$ *if* $\forall [a_0, b_1) \times \ldots [a_n, b_n) = B$ *we have*

$$\mathbb{P}(\{X_1 \in [a_0, b_1)\} \cap \ldots) = \int_B f_{\overline{X}}(y)dy$$

Gaussian vectors

Let $\overline{\mu} \in \mathbb{R}^n$ and C positive definite $n \times n$ matrix called covariance matrix then the density

$$f_{\overline{\mu},C}(\overline{x}) = \frac{1}{(2\pi)^{\frac{n}{2}} \det C^{\frac{1}{2}}} \exp\left(-2(\overline{x} - \overline{\mu})^T C^{-1}(\overline{x} - \overline{\mu})\right)$$

Lecture 9: Expectation

Wed 17 Nov

Proposition 35
$\overline{X}$ random vector on $\mathbb{R}^n$, $\Phi : \mathbb{R}^n \to \mathbb{R}^n$ a C^1-diffeomorphism with $J = \det D\Phi \neq 0$, then $\Phi(\overline{X})$ is a random vector with density

$$f_{\Phi(\overline{X})}(\overline{y}) = \frac{1}{|J_\phi(\Phi^{-1}(\overline{y}))} f_{\overline{X}}(\Phi^{-1}(\overline{y}))$$

Corollaire 36
X, Y independent r.v. with density f_X, f_Y, the density of $X+Y$ is then equal to

$$f_{X+Y}(y) = \int_{\overline{R}} f_X(x) f_{Y(y-x)} dx$$

Preuve
$\Phi : \mathbb{R}^2 \to \mathbb{R}^2, (x_0, y_0) \to (x_0, x_0 + y_0)$.
Φ is a nice diffeo with $J = 1$, then

$$f_{X,X+Y}(x_0, y_0) = f_{X,Y}(x_0, y_0 - x_0) = f_X(x_0) f_Y(y_0 - x_0)$$ □

5.1 Conditional law

Definition 22
Let (X, Y) be a discrete random vector Let S_X be the support of X and S_Y the support of Y, then $\forall x \in S_X$ the conditional law of Y given $X = x$ defined as

$$\forall y \in S_Y : \mathbb{P}(Y = y | X = x) = \frac{\mathbb{P}\{X = x\} \cap \{Y = y\}}{\mathbb{P}(X = x)}$$

What about continuous r.v. ?
In general, no recipe, but all is good for r.v. with density

Definition 23 (Conditional law of rv with density)
Let (X, Y) be r.v. with density, suppose $f_X(x_0) > 0$, then the conditional density of Y given $X = x_0$

$$f_{Y|X}(y) = \frac{f_{X,Y}(x_0, y_0)}{f_X(x_0)}$$

defines a density of a random variable.

Lemme 37
$(X, Y) \sim N(\mu, C)$, then the conditional law of Y given $X = x_0$ is again a gaussian.

6 Mathematical Expectation

Definition 24 (Expectation for discrete r.v.)
Let X be a discrete r.v. with support S_X, we call X integrable if

$$\sum_{s \in S_X} |s| \mathbb{P}(X = s) < \infty$$

and if X is integrable, we define

$$\mathbb{E}[X] = \sum_{s \in S_X} s \mathbb{P}(X = s)$$

to be the expectation.

Remarque
$\mathbb{E}[X]$ *only depends on* $\mathbb{P}_X$, *does not determine* $\mathbb{P}_X$

Proposition 39
Let X, Y be integrable and discrete r.v.

- *Linearity*

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

-

$$|\mathbb{E} X| \leq \mathbb{E}|X|$$

Preuve

$$\mathbb{E}[X + Y] = \sum_{s \in S_{X+Y}} s \mathbb{P}[X + Y = s]$$

Notice

$$\mathbb{P}(X + Y = s) = \sum_{x \in S_X} \sum_{y \in S_Y} \mathbb{P}(\{X = x_0\} \cap \{Y = y_0\}) 1_{s = x_0 + y_0}$$

$$\mathbb{E}[X + Y] = \sum_{x_0} \sum_{y_0} \sum_{s} s 1_{x_0 + y_0 = s} \mathbb{P}(\{X = x_0\} \cap \{Y = y_0\}) = \mathbb{E} X + \mathbb{E} Y \quad \square$$

Corollaire 40
Let X, Y be integrable r.v. s.t.

$$\mathbb{P}(X \geq Y) = 1 \implies \mathbb{E} X \geq \mathbb{E} Y$$

Lecture 10: Expectation

Wed 24 Nov

6.1 Expected value for general random variables

Let X be a r.v.on $(\Omega, \mathcal{F}, \mathbb{P})$.
We discretize X , define

$$\forall n \geq 1 X_n(\omega) = 2^{-n} \lfloor 2^n X(\omega) \rfloor$$

X_n is a random variable.
Exo that

$$X_n(\omega) \leq X(\omega) \leq X_n(\omega) + 2^{-n}$$

Proposition 41
Let X be a random variable, we say that X is integrable if

$$\mathbb{E}|X_1| < \infty$$

and then, $\forall n \geq 1$, $\mathbb{E}|X_n| < \infty$.
In which case, the limite

$$\lim_{n \to +\infty} \mathbb{E}X_n$$

existsand we define $\mathbb{E}|X| = \lim \mathbb{E}|X_n|$

Preuve
The property above implies

$$X_n(\omega) - 1 \leq X_1(\omega) \leq X_n(\omega) + 1 \quad \forall \omega \in \Omega$$

To show that the limit exists, we show that the sequence $(\mathbb{E}X_n)$ is cauchy.
Take $n \in \mathbb{N}, m \geq n$

$$|\mathbb{E}X_n - \mathbb{E}X_m| = |\mathbb{E}(X_n - X_m)|$$

But now $X_n - X_m \leq 2^{-n+1}$, and hence $\mathbb{E}|X_n - X_m| \to 0$ □

Proposition 42
Properties of $\mathbb{E}$

- *linear*
- $\mathbb{E}X \leq \mathbb{E}|X|$
- $\mathbb{P}(X \leq Y) = 1 \Rightarrow \mathbb{E}X \leq \mathbb{E}Y$

Preuve
By discretization □

Proposition 43
X a r.v. with density, then X is integrable iff

$$\int_{\mathbb{R}} |y| f_X(y) dy < \infty$$

and then

$$\mathbb{E}X = \int_{\mathbb{R}} y f_X(y) dy$$

Preuve
Take X_n the discretization of X, we have

$$\mathbb{E}X_n = \sum_{k\in\mathbb{Z}} k2^{-n} \mathbb{P}(X_n = k2^{-n})$$

Then

$$\mathbb{P}(X_n = k2^{-n}) = \int_{k2^{-n}}^{(k+1)2^{-n}} f_X(y) dy$$

$$\mathbb{E}X_n = \sum_{k\geq 2} \int_{k2^{-n}}^{(k+1)2^{-n}} k_2^{-n} f_X(y)$$

$$\mathbb{E}X_n \leq \sum_{k\in\mathbb{Z}} \int_{k2^{-n}}^{(k+1)2^{-n}} y f_X(y) dy$$

and

$$\mathbb{E}X_n \geq \sum_{k\in\mathbb{Z}} \int_{k2^{-n}}^{(k+1)2^{-n}} (y - 2^{-n}) f_X(y) dy$$

and hence

$$\mathbb{E}X_n \to \int_{\mathbb{R}} y f_X(y) dy$$

□

Proposition 44
Take $\overline{X}$ some random vector in $\mathbb{R}^n$ and

$$\Phi : \mathbb{R}^n \to \mathbb{R}$$

measurable.

— *$\overline{X}$ is discrete, then $\Phi(\overline{X})$ is also discrete, so if*

$$\Phi(\overline{X})$$

integrable, then

$$\mathbb{E}\Phi(\overline{X}) = \sum_{s\in S_{\Phi(X)}} s\mathbb{P}(\Phi(\overline{X}) = s) = \sum_{x\in S_X} \Phi(x)\mathbb{P}(\overline{X} = x_0)$$

Similarly if $\overline{X}$ is a random vector with density, $\Phi(\overline{X})$ is integrable and "nice", then

$$\mathbb{E}\Phi(\overline{X}) = \int_{\mathbb{R}^n} \Phi(x) f_{\overline{X}}(x) dx$$

Preuve

Sketch for 2 :

Discretisize Φ and write

$$\mathbb{E}\Phi_n = \sum_{k \in \mathbb{Z}} k2^{-n} \mathbb{P}(\Phi_n = k2^{-n})$$

□

Proposition 45

$X \sim Y$ iff

$$\forall g : \mathbb{R} \to \mathbb{R} \text{ continuous and bounded}$$

$$\mathbb{E}g(X) = \mathbb{E}g(Y)$$

Preuve

One direction is obvious.

In the other direction, note that

$$X \sim Y \iff \forall t \in \mathbb{R} F_X(t) = F_Y(t)$$

but

$$F_X(t) = \mathbb{P}(X \leq t) = \mathbb{E}1_{X \leq t}$$

hence $X \sim Y$ iff

$$\forall t \in \mathbb{R} \mathbb{E}1_{X \leq t} = \mathbb{E}1_{X \leq t}$$

We approximate $1_{X \leq t}$ by a continuous function. □

Proposition 46

If X, Y independent, $g(X), h(Y)$ integrable, then

$$\mathbb{E}g(X)h(Y) = \mathbb{E}g(X)\mathbb{E}h(Y)$$

Furthermore, if $\forall h, g$ continuous and bounded

$$\mathbb{E}h(X)g(Y) = \mathbb{E}h(X)g(Y)$$

then X and Y independent.

Preuve

X, Y are independent iff $F_{X,Y}(t) = F_X(t)F_Y(t)$, hence

$$\mathbb{E}1_{X \leq t_1, Y \leq t_2} = \mathbb{E}1_{X \leq t_1} \mathbb{E}1_{Y \leq t_2}$$

We then approximate as in the last proof.
For the second part, using the exercise sheet shows that

$$X, Y \text{ independent } \implies g(X)h(Y) \text{ independent}$$

so it suffices to shwo that $\mathbb{E}XY = \mathbb{E}X\mathbb{E}Y$.
We have to prove in two steps
— X, Y *discrete*
— *via discretization* X_n, Y_n.
Note that

$$\mathbb{E}XY = \sum_{S_{XY}} s\mathbb{P}(XY = s)$$

and

$$\mathbb{E}X\mathbb{E}Y \sum_{S_X} \sum_{S_Y} x_0 y_0 \mathbb{P}(X = x_0)\mathbb{P}(Y = y_0)$$

$$\mathbb{E}XY = \sum_{S_X} \sum_{S_Y} xy\mathbb{P}(X = x, Y = y) \sum_{S_{X,Y}} 1_{s=xy}$$

$$= \sum_{S_{X,Y}} \sum_{S_X} \sum_{S_Y} s1_{s=xy}\mathbb{P}(X = x, Y = y) = \mathbb{P}(XY = s) \qquad \square$$

Lecture 11: Variance

Wed 01 Dec

6.2 Variance and covariance

Definition 25 (Variance)
Let X be an integrable random variable s.t. X^2 is also integrablee, then we define the variance of X as

$$var(X) = \mathbb{E}((X - \mathbb{E}X)^2)$$

and it is well defined

Then $\sigma(X) = \sqrt{var(X)}$ is called the standard deviation.

Remarque

$$(X - \mathbb{E}X)^2 \leq |X|^2 + 2|X|\mathbb{E}X + (\mathbb{E}X)^2 < 2(|X|^2 + \mathbb{E}|X|^2)$$

Note that if $Var(X) = 0$, then $X = \mathbb{E}X$ almost surely. Furthermore

$$\mathbb{E}(X - \mathbb{E}X)^2 = \mathbb{E}(X^2) - 2\mathbb{E}(X\mathbb{E}X) + (\mathbb{E}X)^2 = \mathbb{E}X^2 - (\mathbb{E}X)^2$$

Proposition 48 (Chebyshev inequality)
X integrable random variable with finite variance

$$\mathbb{P}(|X - \mathbb{E}X| > t) \leq \frac{VarX}{t^2}$$

Preuve
If Y is positive and integrable, we have

$$\mathbb{P}(Y > t) = \frac{\mathbb{E}y}{t}$$

and we apply this to $Y = (X - \mathbb{E}X^2)$. □

Definition 26 (Covariance)
Let X, Y be integrable, with finite variance, then the covariance of X and Y is defined as

$$Cov(X, Y) = \mathbb{E}((X - \mathbb{E}X)(Y - \mathbb{E}Y))$$

and we call

$$Cor(X, Y) = \frac{Cov(X, Y)}{\sqrt{VarXVarY}}$$

the correlation.
As long as the variances are different from 0.

6.3 Moments of a random variable

Definition 27 (Moment)
Let X be a random variable such that $|X|^n$ is integrable.
Then we say that X admits a n-th moment $\mathbb{E}X^n$.

Why is this useful ?
— We get control on the tails, if X admits a n-th moment, then $\mathbb{P}(|X|^n > t) \leq \frac{\mathbb{E}|X|^n}{t^n}$
— Sometions determines the law

Proposition 49
Let X, Y be random variable such that $\mathbb{P}(X)(X \in [-C, C]) = \mathbb{P}(Y \in [-C, C]) = 1$ for some $C \in \mathbb{R}$.
Then $X \sim Y$ if and only if $\forall n \mathbb{E}X^n = \mathbb{E}Y^n$

Preuve
Notice that X, Y admit n-th moments for all n as they are bounded by C.
Clearly if X, Y are equal in law, then X^n, Y^n are equal in law.

Theorème 50 (Stone- Weierstrass)
Let g be a continuous function on $[-c, c]$.
Then $\forall \epsilon > 0$, there exists a polynomial P_ϵ s.t. $\sup_{x\in[-c,c]} |g(x) - P_\epsilon(x)| < \epsilon$

We will use this theorem to prove the proposition.
It suffices to show that $\forall g$ continuous and bounded $\mathbb{E}g(X) = \mathbb{E}g(Y)$.
Observe that $\forall$ polynomial P, $\mathbb{E}P(X) = \mathbb{E}P(Y)$ by linearity of $\mathbb{E}$.
Given g continuous and bounded, notice that $\mathbb{E}g(X) = \mathbb{E}\tilde{g}(X)$.
This is because $\mathbb{P}(X \in [-C, C])$.
Now pick $\epsilon > 0$ and apply Stone-Weierstrass to $\tilde{g}$.
This gives P_ϵ s.t. $\sup_{x\in[-C,C]} |\tilde{g}(x) - P_\epsilon(x)| < \epsilon$.
Now

$$|\mathbb{E}g(X) - \mathbb{E}g(Y)| \leq |\mathbb{E}g(X) - \mathbb{E}P_\epsilon(X)| + |\mathbb{E}P_\epsilon(Y) - \mathbb{E}g(Y)|$$

□

Remarque

— *Holds more generally, but not always :*
Sometimes moments don't exist
Sometimes moments grow too fast and don't characterise uniquely

6.4 Moment Generating functions

Definition 28
Let X be a random variable s.t. $\exists c > 0$ s.t. $\forall t \in [-c, c]$, the function $\exp(tX)$ is integrable, then we define the moment generating function

$$M_x(t) = \mathbb{E}(\exp(tX))$$

Remarque
Might no exist even when all moments exist.

Theorème 53 (MGF determines the law)
If X, Y are random variables that admit MGF in some interval $[-c, c]$, then $X \sim Y \iff \forall(-t, t) M_X(t) = M_Y(t)$.

We can also define MGF for random vectors

Definition 29 (MGF for random vectors)
Let $(X_1, \ldots, X_N)$ be random vectors s.t. $\forall t$

$$\exp \langle t, \overline{X} \rangle$$

is integrable, then MGF of $\overline{X}$ is defined as

$$M_{\overline{X}}(t) = \mathbb{E}\exp(\langle t, X \rangle)$$

Theorème 54

If X, Y are random vectors admitting MGF in some $(-c, c)^n$, then $X \sim Y \iff M_X(t) = M_Y(t)$