

## 2<sup>nd</sup> LECTURE - ADVANCED STOCHASTIC PROCESSES

Recall:  $(X_n)_{n \geq 0}$  MC with initial measure  $\mu \in \mathcal{P}(S)$  and transition matrix  $P = (P_{x,y})_{x,y \in S}$  (in short: MC  $(\mu, P)$ ) has law  $\mathbb{P}_\mu$  identified by the joint law  $(X_{n_1}, \dots, X_{n_k})$   $\forall k \geq 0$   
 $\forall n_1, \dots, n_k \geq 0$

Notation

*finite dimension distributions*

- The average with respect to  $\mathbb{P}_\mu$  is denoted by  $\mathbb{E}_\mu$   
 (to avoid confusion, if  $Y \sim \mu$ , then its average is denoted  $\mu(Y)$ )

- If  $\mu = \delta_x$ , with  $x \in S$ , we write  $\mathbb{P}_x$  instead of  $\mathbb{P}_{\delta_x}$

↳ Example: consider the random walk  $(S_n)_{n \geq 0}$  st.

$$S_0 = x, \quad S_n = x + \sum_{k=1}^n \xi_k, \quad \text{with } x \in S$$

From the Markov property, it is easy to prove:

$$\mathbb{P}_\mu(X_{m+n} = y | X_m = x) \stackrel{\text{homogeneity}}{=} \mathbb{P}_\mu(X_m = y | X_0 = x) = \mathbb{P}_x(X_m = y) = \sum_{x_1 \in S} \dots \sum_{x_{m-1} \in S} P_{x, x_1} \dots P_{x_{m-1}, y}$$

$$(B) \quad = (P^m)_{x,y} =: \underline{P_{x,y}^{(m)}} \Rightarrow P_{x,y}^{(m)} \text{ is the distribution of } X_m | X_0 = x$$

In particular,  $\forall m \in \mathbb{N}$ ,  $P^m$  is called m-steps transition matrix.

If we think of  $P^m$  as a linear operator acting on functions

$f: S \rightarrow \mathbb{R}$ , we are led to the following definition.

**Def** Given a MC  $(X_n)_{n \geq 0}$  with transition matrix  $P$ , the associated (Markovian) semigroup is the family of operators  $(P^m)_{m \in \mathbb{N}}$ , on the set of real functions on  $S$ , i.e.  $P: \mathbb{R}^S \rightarrow \mathbb{R}^S$   
 $f \mapsto P^m f$

$$\text{with } \boxed{P^m f(x) = \sum_{y \in S} P_{x,y}^{(m)} f(y)}$$

In particular, from (B)

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$$\bullet \quad \underline{P^n f(x)} = \sum_{y \in S} \mathbb{P}_x(X_n=y) f(y) = \underline{\mathbb{E}_x(f(X_n))}$$

$(P^n)_{n \geq 0}$  is indeed a semigroup:

$$P^0 = \text{Id} \quad \text{and} \quad P^{m+n} = P^n \cdot P^m$$

Check:  $P_{x,y}^{(m+n)} = \mathbb{P}_x(X_{m+n}=y) = \sum_{z \in S} \mathbb{P}_x(X_{m+n}=y | X_m=z) \mathbb{P}_x(X_m=z)$

$$= \sum_{z \in S} P_{z,y}^{(n)} \cdot P_{x,z}^{(m)} = (P^n \cdot P^m)_{x,y}$$

The transition matrices  $P^n$  can also be seen as acting on the space  $\mathcal{P}(S)$  by right multiplication.

Explicitly  $P^n: \mathcal{P}(S) \rightarrow \mathcal{P}(S)$ , with  $\mu \rightarrow \mu P^n$ ,

$$\mu P^n(y) = \sum_{x \in S} \mu(x) P_{x,y}^{(n)}$$

In particular, from (B)

$$\underline{\mu P^n(y)} = \sum \mu(x) \cdot \mathbb{P}_x(X_n=y) = \underline{\mathbb{P}_\mu(X_n=y)}$$

In other words, given that  $X_0 \sim \mu \Rightarrow X_n \sim \mu P^n$ ,  $\forall n \in \mathbb{N}$

In short:  $\text{Law}_\mu(X_n) = \mu P^n$

$\hookrightarrow$  special case:  $\mu = \delta_x \Rightarrow \delta_x P^n = P_{x,\cdot}^{(n)}$  (x-row of  $P^n$ )

$$\text{Law}_{\delta_x}(X_n) = \delta_x P^n$$

We give an equivalent formulation of the Markov property that can be reinforced to a **Strong Markov property**.

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Markov Property - equivalent formulation

Let  $(X_m)_{m \geq 0}$  be a given stochastic process from  $(\Omega, \mathcal{F}, \mathbb{P})$  to  $(S, \mathcal{J})$   
and let  $\mathcal{F}_m^x = \sigma(X_m, 1 \leq m \leq m)$ ,  $m \in \mathbb{N}_0$ , its natural filtration.

Then  $(X_m)_{m \geq 0}$  has the Markov property  $\iff \forall A \in \mathcal{J}, \forall m, m \in \mathbb{N}_0$

$$(a) \quad \boxed{\mathbb{P}_\mu(X_{m+m} \in A | \mathcal{F}_m^x) = \mathbb{P}_\mu(X_{m+m} \in A | X_m)} \quad \mathbb{P}_\mu \text{ a.s.}$$

In particular, if  $(X_m)_{m \geq 0}$  is a homogeneous MC

$$\mathbb{P}_\mu(X_{m+m} \in A | X_m) = \mathbb{P}_{X_m}(X_m \in A)$$

*should be understood as a component of a second MC which starts its dynamics at  $X_m$*

In other words, from (a), (b):  $\text{Law}_\mu((X_{m+m})_{m \geq 0} | \mathcal{F}_m^x) = \text{Law}_{X_m}((X_m)_{m \geq 0})$

Proof

$\implies$  is obvious since the cylinder events  $\{X_0 = x_0, \dots, X_m = x_m\}$  generate  $\mathcal{F}_m^x$ , and satisfy the equality.

$\impliedby$  Take  $A = \{y\}$  and  $E = \{X_1 = x_1, \dots, X_m = x\} \in \mathcal{F}_m^x$

From (a) we get

$$\mathbb{P}(X_{m+m} = y, E) = \mathbb{E}(\mathbb{E}(\mathbb{1}_{X_{m+m}=y} | \mathcal{F}_m^x) \cdot \mathbb{1}_E) =$$

$$\stackrel{(a)}{=} \mathbb{E}(\mathbb{P}(X_{m+m} = y | X_m) \mathbb{1}_E) = \mathbb{P}(X_{m+m} = y | X_m = x) \mathbb{P}(E)$$

$$\forall \omega \in E: \mathbb{P}(X_{m+m} = y | X_m)(\omega) = \mathbb{P}(X_{m+m} = y | X_m = x)$$

Thus  $\mathbb{P}(X_{m+m} = y | E) = \mathbb{P}(X_{m+m} = y | X_m = x) = \mathbb{P}_x(X_m = y) \neq$   
 $\downarrow$   
Markov property

Theorem (Strong Markov Property)

## Theorem (Strong Markov Property)

Let  $\tau$  be a stopping time for a MC  $(X_m)_{m \geq 0}$ , a.s. finite and let  $\mathcal{F}_\tau$  the corresponding  $\sigma$ -algebra. Then,  $\forall A \in \mathcal{J}$ :

$$\mathbb{P}_\mu(X_{m+\tau} \in A | \mathcal{F}_\tau) = \mathbb{P}_\mu(X_{m+\tau} \in A | X_\tau) = \mathbb{P}_{X_\tau}(X_m \in A)$$

Strong Markov property

$$\text{Equivalently: } \text{Law}_\mu((X_{\tau+m})_{m \geq 0} | \mathcal{F}_\tau) = \text{Law}_{X_\tau}((X_m)_{m \geq 0})$$

Proof: Recall that  $\mathcal{F}_\tau = \{E \in \mathcal{F} \text{ s.t. } E \cap \{\tau \leq m\} \in \mathcal{F}_m, \forall m \geq 0\}$

By the Tower property of conditional expectation, and the Markov property of  $(X_m)_{m \geq 0}$ , we get:

$$\begin{aligned} \mathbb{P}_\mu(X_{m+\tau} \in A | \mathcal{F}_\tau) &= \mathbb{E}_\mu(\mathbb{1}_{\{X_{m+\tau} \in A\}} | \mathcal{F}_\tau) \\ &= \sum_{m=0}^{\infty} \underbrace{\mathbb{E}_\mu(\mathbb{1}_{\{\tau=m\}} \mathbb{1}_{\{X_{m+\tau} \in A\}} | \mathcal{F}_\tau)}_{\in \mathcal{F}_m} \\ &= \sum_{m=0}^{\infty} \mathbb{E}_\mu(\mathbb{1}_{\{\tau=m\}} \cdot \underbrace{\mathbb{E}_\mu(\mathbb{1}_{\{X_{m+\tau} \in A\}} | \mathcal{F}_m)}_{\text{Markov Property}} | \mathcal{F}_\tau) \\ &= \sum_{m=0}^{\infty} \mathbb{E}_\mu(\mathbb{1}_{\{\tau=m\}} \cdot \mathbb{P}_{X_m}(X_m \in A) | \mathcal{F}_\tau) \\ &= \mathbb{P}_{X_\tau}(X_m \in A) \quad \neq \end{aligned}$$

## Construction of MC

A deterministic dynamics at discrete time is a function  $F: S \rightarrow S$  s.t., for every initial condition  $x \in S$ , the whole trajectory  $(x_m)_{m \geq 0}$  is recursively defined by  $x_{m+1} = F(x_m)$

A MC can be obtained similarly by adding some randomness at each step:

→ (1) ... (2) ... (3) ... (4) ... (5) ... (6) ... (7) ... (8) ... (9) ... (10) ...

at each step:

Take  $(U_m)_{m \geq 1}$  iid  $\sim U[0,1]$  and  $F: S \times [0,1] \rightarrow S$

$$\text{Set } (1) \left\{ \begin{array}{l} \cdot X_0 \sim \mu \text{ independent of } (U_m)_{m \geq 1} \\ \cdot X_{m+1} = F(X_m, U_m) \end{array} \right.$$

This is the content of the following result

**Theorem:** Let  $(X_n)$  be a MC with transition matrix  $P$  and initial measure  $\mu$ . Then,  $\exists F: S \times [0,1] \rightarrow S$  s.t.  $(X_n)$  is given by (1).

Proof: By definition  $X_0 \sim \mu$ .  $\checkmark$

We have to construct  $F$  from  $P$ .

1. For any  $x \in S$ , consider a partition  $I_x = (I_{x,y})_{y \in S}$  of  $[0,1]$  s.t.  $\lambda(I_{x,y}) = P_{x,y}$ , for example identifying  $S$  with  $\mathbb{N}$  (it is countable)  $\uparrow$  Lebesgue on  $\mathbb{R}$ .

and setting:  $I_{x,1} = [0, P_{x,1}]$ ,  $I_{x,2} = [P_{x,1}, P_{x,1} + P_{x,2}]$ ,  $\dots$



Hence, if  $(\Omega, \mathcal{F}, P)$  is the space describing  $X_0$  and  $(U_m)_{m \in \mathbb{N}}$ , we have  $P(U_m \in I_{x,y}) = P_{x,y}$

2. Define, for  $x \in S$  and  $u \in [0,1]$

$$F(x, u) := \sum_{y \in S} y \cdot \mathbb{1}_{I_{x,y}}(u) = \begin{cases} y & \text{if } u \in I_{x,y} \\ 0 & \text{otherwise} \end{cases}$$

Then, if  $X_{m+1} := F(X_m, U_m)$ , we have

$$P(X_{m+1} = y | X_m = x) = P(F(x, U_m) = y) = P(U_m \in I_{x,y}) = P_{x,y}$$

$\rightarrow$  The Markov property is verified

- The Markov property is verified
- $(X_m)$  is a MC with trans. matrix  $P \neq$

## EXAMPLES

a. Evolution models for the transmission of a genetic trait

General model assumptions

- The gene has 2 possible phenotypes, say A and B (called types)
- No type is favored
- Cells are haploid → type comes from only 1 ancestor
- the population has constant size  $N \in \mathbb{N}$

### Wright's model

- Consider a (stochastic) dynamics starting from a 0-generation where there are  $N$  individuals, each with type A or B.
- At each time  $m \in \mathbb{N}$ , a new generation born so that any new individual, independently from the others, choose an ancestor uniformly among the previous generation, and make a clone of the gene.

Let  $X_m = \#$  of individuals of type A in  $m$ -generation,  $m \in \mathbb{N}$

so that  $X_m \in \{0, 1, \dots, N\} = S$ ,  $\forall m \in \mathbb{N}$

Then  $(X_m)_{m \in \mathbb{N}_0}$  is a MC on  $S$ .

Indeed, for  $m \in \mathbb{N}_0$ ,  $j \in \{1, \dots, N\}$ , let

$$Y_j^m = \mathbb{1}_{\{j\text{-th individual in } m\text{-generation has type A}\}}$$

so that  $Y_j^m | X_{m-1} \sim \text{Be} \left( \frac{X_{m-1}}{N} \right)$  and  $X_m = \sum_{j=1}^N Y_j^m$

$\Rightarrow X_m | X_{m-1} \sim \text{Bin} \left( N; \frac{X_{m-1}}{N} \right)$  (only depends on the  $\dots$ )

$$\Rightarrow X_m | X_{m-1} \sim \text{Bin} \left( N; \frac{X_{m-1}}{N} \right) \quad (\text{only depends on the last visited state})$$

$\Rightarrow (X_m)_{m \in \mathbb{N}_0}$  is a MC with transition probabilities

$$P_{j,k} = \mathbb{P}(X_m = k | X_{m-1} = j) = \mathbb{P} \left( \text{Bin} \left( N, \frac{j}{N} \right) = k \right), \text{ for } j, k \in S$$

Remarks:

1.  $X$  is a MC on  $\{0, \dots, N\}$  s.t.  $P_{j,k} > 0 \quad \forall j \in \{1, \dots, N-1\}, k \in S$  while  $P_{0,0} = 1$  and  $P_{N,N} = 1$  (hence  $P_{0,j} = 0 \quad \forall j \neq 0$   
 $P_{N,i} = 0 \quad \forall i \neq N$ ).

When this happens, we call the state absorbing, as the MC that ends in it, stays there forever.

Notice that states 0 and  $N$  correspond to the situation in which a type has dominated the other  $\left( \begin{array}{l} 0 \rightarrow \text{only type B} \\ N \rightarrow \text{only type A} \end{array} \right)$   
 $\hookrightarrow$  called fixation

2. The Wright's model can be equivalently defined as the evolution of the frequency of type A among the generations (this is indeed the most common representation):

$$\forall m \in \mathbb{N}_0: Z_m := \frac{X_m}{N} \in \left\{ 0, \frac{1}{N}, \dots, \frac{N-1}{N}, 1 \right\} = S'$$

Then (easy check)  $(Z_m)_{m \geq 0}$  is a MC with trans. matrix

$$P_{x,y} = \mathbb{P}(\text{Bin}(N, x) = N \cdot y), \text{ for } x, y \in S'$$

This representation is convenient because it allows to consider large value of  $N$  (hence the limit  $N \rightarrow \infty$ ) keeping  $S'$  compact.

We state a general result of martingale theory, which is powerful and that will be applied in our context to compute some relevant quantities.

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### Theorem (Martingale convergence theorem)

Let  $(X_n)_{n \geq 0}$  be a  $(\mathcal{F}_n)_{n \geq 0}$ -martingale

▶ If  $(X_n)_{n \geq 0}$  is  $L^1$ -bounded (i.e.  $\mathbb{E}(|X_n|) \leq C, \forall n \geq 0$ )  
 $\Rightarrow \exists X_\infty$ , with  $\mathbb{E}(X_\infty) < \infty$  s.t.  $X_n \xrightarrow[n \rightarrow \infty]{a.s.} X_\infty$

▶ If  $(X_n)_{n \geq 0}$  is  $L^p$ -bounded for some  $p > 1$  ( $\mathbb{E}(|X_n|^p) \leq C, \forall n \geq 0$ )  
 $\Rightarrow \exists X_\infty$  s.t.  $X_n \xrightarrow[n \rightarrow \infty]{L^p, a.s.} X_\infty$

### • Probability of fixation

From the definition, it turns that  $(X_n)_{n \in \mathbb{N}_0}$  is a bounded martingale. Indeed,  $\forall j \in S$  initial state ( $X_0 \sim \delta_j$ ):

$$\mathbb{E}_j(X_{n+1} | X_n) = \mathbb{E}(\text{Bin}(N, \frac{X_n}{N}) | X_n) = X_n \quad \forall n \in \mathbb{N}_0$$

$$\text{so that } \mathbb{E}_j(X_n) = \mathbb{E}_j(X_0) = j$$

From the martingale convergence theorem:

$$X_n \xrightarrow[n \rightarrow \infty]{} X_\infty \quad \mathbb{P}_j\text{-a.s. and in } L^2,$$

$$\text{with } \mathbb{E}_j(X_\infty) = \mathbb{E}_j(X_0) = j$$

\* If we can argue (as it is intuitive) that  $X_\infty \in \{0, N\}$ ,

$$\text{then } j = \mathbb{E}_j(X_\infty) = N \cdot \mathbb{P}(X_\infty = N)$$

$$\Rightarrow \mathbb{P}(X_\infty = N) = \frac{j}{N} \quad \text{and} \quad \mathbb{P}(X_\infty = 0) = 1 - \frac{j}{N}$$

b. Evolution of state (e.g. opinion) among interacting individuals  
 $\hookrightarrow$  interacting particle systems

( - individuals / or particles) interact through a

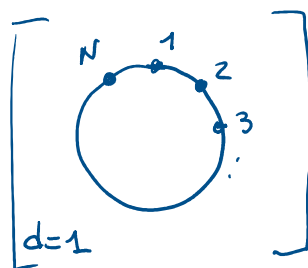
... interacting particles ...

General model assumptions

- individuals (or particles) interact through a "network of friends" that is described by a graph  $G=(V,E)$ , where vertices are the position of individuals and edges correspond to friendship among a couple
- the state (or opinion) takes value on finite  $E$  so that the whole system is described by states in  $E^G \rightarrow$  state or configuration space
- The dynamics change the state of a single individual at each step, and only depends on the state of its neighborhood.

### Voter model

- As a graph of interaction, consider  $\mathbb{T}_N^d = \frac{\mathbb{Z}^d}{N\mathbb{Z}^d}$ , and assume that there is a voter at any vertex of  $\mathbb{T}_N^d$  (hence  $N^d$  in total)
- Any voter holds an opinion  $v \in \{0, 1\}$  (favorable / against) so that the whole system of opinions takes value in  $S = \{0, 1\}^{\mathbb{T}_N^d} \ni \pi = (\pi(i))_{i \in \mathbb{T}_N^d}$  and  $\pi(i) \in \{0, 1\}$
- At each time  $m \in \mathbb{N}$ , an individual, chosen uniformly in  $\mathbb{T}_N^d$ , choose uniformly one of its neighbors and agree with its opinion. Hence the whole set of opinions has changed.



Let  $X_m =$  set of opinions after  $m$  steps  $= (X_m(i))_{i \in \mathbb{T}_N^d}$ ,  $\forall m \in \mathbb{N}$   
 so that  $X_m(i) =$  opinion of voter at site  $i$ ,  $i \in \mathbb{T}_N^d$

Then  $(X_m)_{m \in \mathbb{N}}$  is a MC on  $S$ .

Indeed: let  $(I_m)_{m \in \mathbb{N}}$  iid  $\sim \mathcal{U}(\mathbb{T}_N^d)$

and  $(U_m)_{m \in \mathbb{N}}$  iid  $\sim \mathcal{U}(\pm e_1, \dots, \pm e_d)$  with  $e_k = (0, \dots, \underline{1}, \dots, 0)$   
 $k$ -comp.  
 neighborhood in  $\mathbb{T}_N^d$

neighborhood in  $\mathbb{T}_N^d$

Then  $(X_m)_{m \geq 0}$  is recursively defined so that

$$(*) \quad X_m(i) = \begin{cases} X_{m-1}(i) & \text{if } I_m \neq i \\ X_{m-1}(\underbrace{I_m + U_m}_{\text{chosen neighbor of } I_m}) & \text{if } I_m = i \end{cases}$$

which is clearly a MC with transition prob. that can be obtained from (\*) (try as an exercise).

Remark:

Since the evolution rule "made copy of other opinions", as for the Wright's model there are 2 absorbing states which correspond to the "total agreement", namely the states:

$\underline{0}$  = {all voters have opinion 0} and  $\underline{1}$  = {all voters have opinion 1}

Probability of total agreement

One can consider the sequence  $(M_m)_{m \geq 0}$ , where

$$M_m = \sum_{i \in \mathbb{T}_N^d} X_m(i) = \# \text{ voters with opinion } 1 \in \{0, \dots, N^d\}$$

Then  $(M_m)_{m \geq 0}$  is a sequence of r.v.'s on  $\{0, \dots, N^d\}$

More precisely it is a martingale (bounded in  $L^p$ ,  $\forall p \geq 1$ )

w.r.t.  $\mathcal{F}_m = \sigma(X_k, k \leq m)$ :

$$\begin{aligned} \mathbb{E}(M_m | \mathcal{F}_{m-1}) &= M_{m-1} - \mathbb{E}(X_{m-1}(I_m) | \mathcal{F}_{m-1}) + \mathbb{E}(X_{m-1}(I_m + U_m) | \mathcal{F}_{m-1}) \\ &= M_{m-1} - \sum_{i \in \mathbb{T}_N^d} X_{m-1}(i) \cdot \underbrace{\mathbb{P}(I_m = i)}_{\frac{1}{N^d}} + \sum_{i \in \mathbb{T}_N^d} X_{m-1}(i) \underbrace{\mathbb{P}(I_m + U_m = i)}_{\frac{1}{N^d}} \\ &= M_{m-1} \end{aligned}$$

n u + n " - " "

$$= M_{m-1}$$

By the martingale convergence theorem we then have

$$M_m \xrightarrow{m \rightarrow \infty} M_\infty \quad \mathbb{P}_j\text{-a.s. and in } L^2, \forall j \text{ initial state}$$

$$\text{so that} \quad \mathbb{E}_j(M_\infty) = \mathbb{E}_j(M_0) = j$$

As before, if we can argue that  $M_\infty \in \{0, N^d\}$

$$\Rightarrow \quad \mathbb{P}_j(M_\infty = N^d) = \frac{j}{N^d} \quad \text{and} \quad \mathbb{P}_j(M_\infty = 0) = 1 - \frac{j}{N^d}$$

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