

DISCRETE TIME MARKOV CHAIN

STATE CLASSIFICATION

- Stochastic process

Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space and (E, \mathcal{E}) a measure space.
A stochastic process with values in E is a collection of random variables $X_t : \Omega \rightarrow E$ and its denoted by $(X_t)_{t \in \mathbb{N}}$.

- Markov Process

A stochastic process $(X_t)_{t \in \mathbb{N}}$ is a Markov process if it holds the Markov property:

$$\mathbb{P}(X_{t+1} \in E_{t+1} | X_{t+2} \in E_{t+2}, \dots, X_2 \in E_2) = \mathbb{P}(X_{t+1} \in E_{t+1} | X_t \in E_t)$$

$$\forall t_2 < t_3 < \dots < t_m < t_{m+1}, \quad \forall E_1, \dots, E_m \in \mathcal{E}.$$

- Transition probabilities:

$$p_{ij}(t, s) := \mathbb{P}(X_t = j | X_s = i) \quad s < t$$

The process $(X_t)_{t \in \mathbb{N}}$ is time homogeneous if $p_{ij}(t, s)$ depends only on $t-s$.

Transition matrix: $(p_{ij})_{i,j \in E}$, where $p_{ij} = p_{ij}(4)$ are the 1-step transition probabilities

- properties:

$$\begin{aligned} & 0 \leq p_{ij} \leq 1 \\ & \sum_{j \in E} p_{ij} = 1 \quad \forall i \in E \quad (\text{= } \sum_{j \in E} \mathbb{P}(X_t = j | X_0 = i) = 1) \end{aligned}$$

$$\mathbb{P}(X_{t+2} = j | X_t = i) = p_{ij}^{(2)} = \sum_{k \in E} p_{ik} p_{kj}$$

power 2 of the

step transition matrix

$$\mathbb{P}(X_{t+m} = j_m, X_{t+m-1} = j_{m-1}, \dots, X_0 = j_0) = \mathbb{P}(X_0 = j_0)^{(t_1)} p_{j_0 j_1} \cdots p_{j_{m-1} j_m}^{(t_{m-1})}$$

- Accessible state : j accessible from i if $\exists n > 0$: $\mathbb{P}(X_n = j | X_0 = i) = p_{ij}^{(n)} > 0$

- Communicating states: i and j communicate if each one is accessible from the other one

Class of states: $C \subseteq E$ is a class of state if all states in C communicate and they do not communicate with states in $E \setminus C$

- Inversible MC : a MC is irreversible if all the states communicate

- Recurrent state: $(X_n)_{n \in \mathbb{N}}$ discrete MC:

$$\mathbb{P}(\cup_{n=1}^{\infty} \{X_n = i\} | X_0 = i) = 1$$

the probability of return to i in finite time starting from i is 1.

- If a state is not recurrent then is transient.

- First entrance/visit time: $T_i = \begin{cases} \min \{n : X_n = i\} & \text{if } \{n \geq 1 : X_n = i\} \neq \emptyset \\ +\infty & \text{otherwise} \end{cases}$

(first entrance/visit time in $i \in E$)

$$f_{ij}(n) = \mathbb{P}(T_i = n | X_0 = j) = \text{probability of entering in } i \text{ in } n\text{-th step starting from } j$$

- Renewal equation:

$$p_{ij}^{(n)} = \sum_{i=1}^n f_{ij}^{(n)} p_{jj}^{(n-i)}$$

probability of entering in j after n steps and remain in j in n steps
(the Z represents all possible cases)

- Thus. $(X_n)_{n \in \mathbb{N}}$ discrete Markov chain

i recurrent $\iff \sum_{n \geq 0} p_{ii}^{(n)} = +\infty$

We never come back to i
the average time spent in i is infinite

$$\sum_{n \geq 0} p_{ii}^{(n)} = \sum_{n \geq 0} \mathbb{E}[1_{\{X_n = i\}}] = \mathbb{E}[\sum_{n \geq 0} 1_{\{X_n = i\}}]$$

Otherwise (if $\sum_{n \geq 0} p_{ii}^{(n)} < \infty$) the state is transient and:

$$\sum_{n \geq 0} p_{ii}^{(n)} = \frac{1}{1 - \mathbb{P}_i(\bullet)}, \quad \mathbb{P}_i(\bullet) = \mathbb{P}(\bullet | X_0 = i)$$

probability of never returning in i

\Rightarrow a MC visits a transient state only a finite number of times

- Two communicating states are both recurrent or transient

\Rightarrow the elements of a class of states are all recurrent or transient

j transient $\iff \begin{cases} \sum_{n \geq 0} p_{ij}^{(n)} < +\infty & \forall i \\ \lim_{n \rightarrow \infty} \mathbb{P}_i(X_n = j) = \mathbb{P}(X_n = j | X_0 = i) = 0 & (\text{the MC goes through } j \text{ only a finite number of times a.s.}) \end{cases}$

\Rightarrow \exists at least one recurrent state

INARIANT LAWS & ASYMPTOTIC BEHAVIOUR

Invariant distribution

$(X_n)_{n \in \mathbb{N}}$ MC with transition matrix $(p_{ij})_{i,j \in E}$. Let $\pi = (\pi_i)_{i \in E}$ be a probability density on E ($0 \leq \pi_i \leq 1, \sum_{i \in E} \pi_i = 1$).

π is an invariant distribution if $X_{n+1} \sim \pi$ whenever $X_n \sim \pi$ $\forall n$.

$$\pi \text{ invariant} \iff \pi_j = \sum_{i \in E} \pi_i p_{ij} \quad \iff \pi P = \pi$$

the density is the left eigenvector of P (eigenvalue = 1)

Properties:

- E finite $\iff \exists \pi$ (at least one)
- E infinite $\iff \exists! \pi$

(iii) π probability density is reversible if: $\pi_i p_{ij} = \pi_j p_{ji} \quad \forall i, j \in E$
If $(\pi_i)_{i \in E}$ is reversible \iff $(\pi_i)_{i \in E}$ is invariant

Thm. Existence and unicity of invariant distributions:

- If limits $\lim_{n \rightarrow \infty} \pi_j(n)$ exists and are strictly positive
- the MC has an unique invariant distribution $(\pi_i)_{i \in E}$

moreover:

$$\lim_{n \rightarrow \infty} \mathbb{E}[f(X_n)] = \int f d\pi = \sum_{i \in E} f(i) \pi_i$$

for all f bounded.

In this situation: $X_n \xrightarrow{n \rightarrow \infty} \pi$ in distribution ($\mathbb{P}(X_n = j) \rightarrow \pi_j$ $\forall j$)

- Period of a state: defined as $\text{MCD} \{n \geq 1 | p_{ii}^{(n)} > 0\}$.

If the period is 1 we call the state aperiodic.

States of the same class have the same period (to the case of irreducible MC we can talk about periodic/aperiodic MC)

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STRONG MARKOV PROPERTY

- Thus. Probability of staying forever in transient states

Stopping time: $T: \Omega \rightarrow \mathbb{N}$ is a stopping time of the MC $(X_n)_{n \geq 0}$ if the random variable $\{T \leq n\}$ belongs to the σ -algebra generated by $\{X_n = i_n, X_{n-1} = i_{n-1}, \dots, X_0 = i_0\}$. (with i_1, \dots, i_0 arbitrary states)

The stopping time is \mathbb{I} from the future.

- First entrance time : $T_j = \inf \{n \geq 1 : X_n = j\}$
- If $\{n \geq 2 : X_n = j\} = \emptyset \Rightarrow T_j = +\infty$

- First exit time : $U_j = \inf \{n \geq 1 : X_n \neq j\}$
- If $\{n \geq 1 : X_n \neq j\} = \emptyset \Rightarrow U_j = +\infty$

law of the first exit time:

If $(X_n)_{n \geq 0}$ is a MC with $(p_{ij})_{i,j \in E}$ s.t. $p_{jj} \in (0,1) \quad \forall j \in E$

- the stopping time $U_j : U_j \sim \mathcal{Y}_j(1-p_{jj})$ (geometric distribution)

$$\bullet (X_{U_j})(\omega) = \sum_{n \geq 1} X_n(\omega) \quad \text{if } U_j = n \quad (\omega \text{ satisfies :} \\ P_j(X_{U_j} = k) = \frac{p_{jk}}{1-p_{jj}} \quad \forall k \neq j)$$

• Thus. Restarted MC:

$$\left. \begin{array}{l} \bullet (X_n)_{n \geq 0} \text{ MC} \\ \bullet T \text{ stopping time} \\ \bullet (X_n)_{n \geq 0} \text{ restarted MC :} \\ \quad Y_n(\omega) = \begin{cases} X_{T(\omega)+n}(\omega) & \text{if } T(\omega) < \infty \\ \text{arbitrary} & \text{else} \end{cases} \end{array} \right\} \Rightarrow (X_{Tn})_{n \geq 0} \quad \text{the same } (p_{ij}), i, j \in \text{of } (X_n)_{n \geq 0}$$

• Thus. Strong Markov Property:

$$\left. \begin{array}{l} \bullet (X_n)_{n \geq 0} \text{ MC} \\ \bullet T \text{ stopping time} \\ \bullet (p_{ij})_{i,j \in E} \text{ transition matrix} \end{array} \right\} \Rightarrow (X_{Tn})_{n \geq 0} \quad \text{restarted MC} \\ \text{w.r.t. } \mathbb{P}(\omega | X_T = i, T < \infty) \quad \downarrow$$

where $(Tn)(\omega) = \min \{T(\omega), \infty\}$

TRANSIENCY, RECURRENCE, ABSORPTION

- Thus. The number of visits of a recurrent state is infinite almost surely.

proof: $N_i := \sum_{n \geq 1} \mathbb{1}_{\{X_n=i\}}$ = number of returns in the state i .
 let $(T_i(n))_{n \geq 1}$ be s.t. : $\begin{cases} T_i^{(1)} = \inf \{n \geq 1 : X_n = i\} \\ T_i^{(k+1)} = \inf \{n > T_i^{(k)} : X_n = i\} \end{cases}$ time of the 1^{st} return
 time of the $(k+1)^{\text{th}}$ return

i recurrent $\Leftrightarrow \mathbb{P}_i(T_i^{(k)} < +\infty) = 1 \Leftrightarrow \mathbb{P}_i(N_i > k) = 1$.

$T_i^{(1)}$ is the first visit time in i for the MC restarted from time $T_i^{(2)}$, but the transition matrix is the same $\Rightarrow \mathbb{P}_i(T_i^{(2)} < +\infty) = 1$.

By induction:

$$\mathbb{P}_i(T_i^{(n)} < +\infty) = 1 \quad \forall k \Leftrightarrow \mathbb{P}_i(N_i > k) = 1 \quad \forall k$$

$$\Rightarrow \mathbb{P}_i(N_i > +\infty) = 1$$

- Thus. Probability of staying forever in transient states

$$U_i = \mathbb{P}_i(\cap_{n \geq 1} \{X_n \neq T\}) \quad \forall i \in T$$

= probability of remaining in transient states forever

$\Rightarrow (U_i)_{i \in T}$ is the biggest solution st. $0 \leq U_i \leq 1 \quad \forall i \in T$ that satisfies the system of equations :

$$U_i = \sum_{j \in T} p_{ij} U_j$$

(Remark: generally there is no unique solution, but if T is finite $\Rightarrow \exists!$ sol : $U_i = 0 \quad \forall i \in T$)

Proof.

$$\text{We define } U_i^{(n)} = \mathbb{P}_i(X_n \in T, \dots, X_1 \in T)$$

= probability of staying in transient states from 1 to n

$(U_i^{(n)})_{n \geq 1}$ is a non increasing sequence (the prob. of staying longer is lower)

$U_i = \lim_{n \rightarrow \infty} U_i^{(n)} = \lim_{n \rightarrow \infty} \mathbb{P}_i(X_n \in T, \dots, X_1 \in T)$

= $\mathbb{P}_i(\cap_{n \geq 1} \{X_n \in T, \dots, X_1 \in T\})$

$U_i^{(n+1)} = \underbrace{\mathbb{P}_i(X_{n+1} \in T, \dots, X_2 \in T, X_1 \in T)}_{\text{n steps staying from } X_2 = j}$

= $\mathbb{P}_i(X_{n+1} \in T, \dots, X_2 \in T) \mathbb{P}_i(X_1 \in T)$

= $\sum_{j \in T} \underbrace{\mathbb{P}_i(X_{n+1} \in T, \dots, X_2 \in T | X_1 = j)}_{\text{probability of remaining in } T} \mathbb{P}_i(X_1 = j)$

$$\text{Applying the limits on both sides: } U_i = \sum_{j \in T} p_{ij} U_j \quad \forall i \in T$$

Now we want to prove that $(U_i)_{i \in T}$ is the biggest $[0,1]$ -valued solution. Suppose we have a bigger solution $V_i = \sum_{j \in T} p_{ij} V_j \quad \forall i \in T$,

$$\Rightarrow U_i^{(1)} = \mathbb{P}_i(X \in T) = \sum_{j \in T} p_{ij} \geq \sum_{j \in T} p_{ij} V_j = V_i$$

$$\Rightarrow U_i^{(2)} > V_i \quad \forall i \in T$$

$$\text{By induction: } U_i^{(n+1)} = \sum_{j \in T} p_{ij} U_j^{(n)} \geq \sum_{j \in T} p_{ij} V_j = V_i$$

by considering the limit: $U_i^{(n)} \rightarrow U_i \Rightarrow U_i > V_i$, contradiction.

We also prove the reusable T (true $\Rightarrow U_i = 0$ $\forall i$)

$$U_i = \sum_{j \in T} p_{ij} U_j = \sum_{j \in T} \mathbb{P}_j(\sum_{k \in T} p_{jk} U_k) = \sum_{j \in T} \sum_{k \in T} p_{jk} p_{kj} U_k$$

$\leq \sum_{k \in T} (Z_{j \in E} p_{jk} p_{kj}) U_k = \sum_{k \in T} p_{jk} U_k$

By iterating n times:

$$U_i = \sum_{k_1, \dots, k_n \in T} (p_{ik_1} \dots p_{k_{n-1} k_n}) U_{k_n} \leq \sum_{k_1, \dots, k_n \in E} (p_{ik_1} \dots p_{k_{n-1} k_n}) U_{k_n} =$$

$$= \sum_{k \in T} p_{ik}^{(n)} U_k$$

$$\Rightarrow \forall n: U_i \leq \sum_{j \in T} p_{ij}^{(n)} U_j \leq \sum_{j \in T} p_{ij} U_j \leq 1$$

And since $\forall i \in T \quad p_{ij}^{(n)} \rightarrow 0$ (transient) $\Rightarrow U_i = 0 \quad \forall i \in T$.

• Example: Gambler's ruin vs. a bank

$(X_n)_{n \geq 0}$: X_n = capital of the player at time n , $C = \mathbb{N}$

Classes: • $\{0\}$ recurrent

• $\{1, 2, 3, \dots\}$ transient
 $P_i(N_{i+1} = (X_0 = i)) < 1 - q_i < 1$

We want to evaluate the probability that the gambler is never ruined, i.e. the probability of ruin in $T = \{1, 2, 3, \dots\}$

$$U_i = \sum_{j \in T} p_{ij} U_j \quad \text{(since } U_0 = 0\text{)}$$

Characteristic equation: $p\lambda^2 - \lambda + q = 0 \implies \lambda_1 = 1, \lambda_2 = \frac{q}{p}$

\bullet $p+q = 1$: $U_i = A(1)_i + B(\frac{q}{p})_i$

Since $U_0 = 0 \implies A = -B \implies U_i = A(1 - (\frac{q}{p}))_i$

If $p < q$ then $A = 0$ and so $U_i = 0$ (we need $0 \leq U_i \leq 1$)

If $p > q$ then limit $\rightarrow U_i = A$ and in order to get the longer solution $A = 1 \implies U_i = 1 - (\frac{q}{p})_i$

\bullet $p = q = \frac{1}{2}$: $U_i = A + Bi \implies U_0 = 0 \implies A = 0 \implies U_i = 0$

$$U_1 = pU_2 \implies B = 0 \implies U_i = 0$$

• Thus: Absorption probability in a recurrent class

$T = \text{set of transient states}$

$V_i = \text{probability of absorption in a recurrent class } C \text{ starting from } i \in T$

$\implies (V_i)_{i \in T}$ is the smallest $[0, 1]$ -valued solution of:

$$V_i = \sum_{j \in C} p_{ij} V_j$$

(Remark: T finite $\implies \exists! (V_i)_{i \in T}$)

We define: $V_i^{(n)} = P_i(X_n \in C, X_{n-1} \notin C, \dots, X_1 \notin C)$

= probability of absorption in C at time n and then being absorbed to a transient state

\bullet Thus: Mean absorption time in a recurrent class

$$V_i = \sum_{j \in C} p_{ij} \quad n \gg 2$$

V_i = probability of absorption in a recurrent class C starting from $i \in T$

$\implies (V_i)_{i \in T}$ is the smallest $[0, 1]$ -valued solution of:

$$V_i = \sum_{j \in T} p_{ij} + \sum_{j \in C} p_{ij} V_j$$

(Remark: T finite $\implies \exists! (V_i)_{i \in T}$)

proof.

For every $n \geq 1$: $P_i(V_i > n) = P_i(X_n \in C, \dots, X_T \in C)$

The event "absorption in C^n " = $\bigcup_{k=n+1}^T \{X_k \in C, X_{k-1} \notin C, \dots, X_1 \notin C\}$

disjoint union

$$V_i = P_i(\bigcup_{k=n+1}^T \{X_k \in C, X_{k-1} \notin C, \dots, X_1 \notin C\})$$

$$= \sum_{k=n+1}^T P_i(\{X_k \in C, X_{k-1} \notin C, \dots, X_1 \notin C\})$$

$$= V_i^{(n)} + \sum_{k=n+2}^T V_i^{(n)}$$

$$= \sum_{j \in C} p_{ij} + \sum_{k=n+2}^T \left(\sum_{j \in C} p_{ij} V_j^{(n-k)} \right) P_i$$

$$= \sum_{j \in C} p_{ij} + \sum_{j \in C} p_{ij} V_j$$

Moreover $(V_i)_{i \in T}$ is the smaller $[0, 1]$ -valued solution. Let (X_i) be another $[0, 1]$ -valued solution of: $X_i = \sum_{j \in C} p_{ij} + \sum_{j \in C} p_{ij} X_j$

$$\implies X_i = \sum_{j \in C} p_{ij} + \sum_{j \in T} p_{ij} X_j = V_i^{(1)} + \sum_{j \in T} p_{ij} X_j > V_i^{(1)} \quad \forall i \in T$$

Suppose $X_i \geq \sum_{k=1}^n V_i^{(k)}$:

$$X_i = \sum_{j \in C} p_{ij} + \sum_{j \in T} p_{ij} X_j \geq \underbrace{\sum_{j \in T} p_{ij}}_{V_i^{(1)}} + \underbrace{\sum_{k=1}^n \sum_{j \in C} p_{ij} V_j^{(k)}}_{V_i^{(n)}}$$

$$V_i^{(1)} + \sum_{k=1}^n V_i^{(k)}$$

By induction we showed $X_i \geq \sum_{k=1}^n V_i^{(k)}$ the limit with $n \rightarrow \infty$ we obtain $X_i \geq V_i$. And so by taking the limit, continuation.

- Example: Gambler's ruin vs. a bank
- We want to determine the ruin probability (absorption to 0):

$$V_i = \sum_{j \in C} p_{ij} + \sum_{j \in T} p_{ij} V_j \quad \text{General solution: } V_i = A + B(\frac{q}{p})^i \quad \implies \begin{cases} V_0 = 1 \\ V_1 = A + B(\frac{q}{p}) \end{cases} \quad \begin{cases} V_0 = 1 \\ V_1 = A + B = 1 \end{cases}$$

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From the first step to the n th

From the n th step to the $n+1$ th

From the $n+1$ th step to the $n+2$ th

From the $n+2$ th step to the $n+3$ th

$$\begin{aligned}
U_i(n) &\leq \sum_{j \in T} p_{ij}(n) U_j(n-w) \\
&\leq \max_{j \in T} U_j(n-w) \sum_{j \in T} p_{ij}(n) \\
&\leq \max_{j \in T} U_j(n-w) M \quad \Rightarrow \text{the probability of remaining forever in transient states is exponentially decreasing} \\
\text{According to:} \\
\max_{i \in T} U_i(n) &\leq M^w \max_{i \in T} U_i(n-w) \leq \dots \leq M^w \max_{i \in T} U_i(n - \lfloor \frac{w}{M} \rfloor w) \\
&\leq 4 \text{ since it's a probability} \\
\Rightarrow P_i(V>n) &\leq \max_{i \in T} U_i(n) \leq M^w \leq M^{\frac{w}{M}} = M^{-1} \quad \text{since } M = (M^{\frac{w}{M}})^M \\
\Rightarrow E_i[V] &= \sum_{n \geq 0} P_i(V>n) \leq M^{-1} \sum_{n \geq 0} (M^{\frac{w}{M}})^n = (M(1 - M^{\frac{w}{M}}))^{-1} < +\infty \\
\Rightarrow w_i \text{ are finite.}
\end{aligned}$$

Now we want to prove the formula.

$$\begin{aligned}
w_i &= E_i[V] = \sum_{n \geq 1} n \cdot P_i(V=n) \\
&= \sum_{n \geq 1} n \cdot \underbrace{P_i(V=n, X_1 \in C)}_{\text{if } X_2 \in T \text{ then } V \geq 2 \text{ at least 2}} + \sum_{n \geq 1} n \cdot \underbrace{P_i(V=n, X_1 \in C)}_{\text{since } X_2 \in C \text{ then it cannot be, for instance, } V=2 \text{ (since we're already in } C\text{)}} \\
&= \left[\sum_{n \geq 2} n \cdot \sum_{j \in T} P_i(V=n, X_1=j) \right] + \sum_{j \in C} p_{ij} \\
&= \left[\sum_{n \geq 2} n \cdot \sum_{j \in T} P_i(V=n | X_1=j) P_{ij} \right] + \sum_{j \in C} p_{ij} \\
&= P(V=n | X_2=j, X_1=i) = P(V=n | X_1=i) \\
&= P(V=n-1 | X_0=j) \\
&= P_j(V=n-1) \\
&= \left[\sum_{n \geq 1} (n+1) \sum_{j \in T} P_i(V=n) P_{ij} \right] + \sum_{j \in C} p_{ij} \\
&= \left[\sum_{j \in T} \sum_{n \geq 1} n P_j(V=n) P_{ij} \right] + \left[\sum_{j \in T} P_j(V=n) \right] + \left[\sum_{j \in C} P_{ij} \right] \\
&= \underbrace{\sum_{j \in T} P_j W_j}_{E_j[V]} + \sum_{j \in C} p_{ij} \\
&= \sum_{j \in T} w_j P_{ij} + 1
\end{aligned}$$

- Example: coupons collector. The collection is made of N pictures. At time w we buy an envelope containing a random picture. How many pictures do we have to buy to complete the collection?
- $(X_n)_{n \geq 0}$ MC: $X_n = \# \text{ different pictures collected at time } n \quad (X_0 = 0)$

Transition probabilities:

$$\begin{aligned}
P(X_{n+1} = k+1 | X_n = k) &= \frac{N-k}{N} \\
P(X_{n+1} = k | X_n = k) &= \frac{k}{N}
\end{aligned}$$

$$P(X_{n+1} = j | X_n = k) = 0 \quad j \neq k, k+1$$

$$\begin{bmatrix} 0 & 1 & 0 & 0 & \dots \\ 0 & \frac{1}{N} & \frac{N-2}{N} & 0 & \dots \\ 0 & 0 & \frac{2}{N} & \frac{N-2}{N} & 0 & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \frac{N-1}{N} & 0 & 1 \end{bmatrix}$$

$$\begin{aligned}
T &= \text{transient states} = \{0, 1, 2, \dots, N-1\} \\
C &= \text{recurrent class} = \{N\} \\
w_i &= \text{mean time for reaching } N \text{ starting from } i \\
&\quad \begin{cases} w_i = 1 + \sum_{j \in T} P_{ij} w_{i,j} \\ w_N = 0 \end{cases} \quad i = 0, \dots, N-1 \\
\Rightarrow w_i &= 1 + \frac{1}{N} w_i + \frac{N-i}{N} w_{i+1} \\
\Rightarrow w_i &= \frac{N}{N-i} + \frac{N}{N-i-1} + \dots + \frac{N}{N-(N-1)} \\
\Rightarrow w_0 &= \sum_{k=0}^{N-1} \frac{N}{N-k} = N \sum_{k=1}^N \frac{1}{k} \approx N \log(N)
\end{aligned}$$

- Example: Gambler's ruin.

We consider the fair case $p=q=\frac{1}{2}$.

$$\begin{bmatrix} 4 & 0 & 0 & 0 & 0 & \dots \\ 1/2 & 0 & 1/2 & 0 & 0 & \dots \\ 0 & 1/2 & 0 & 1/2 & 0 & \dots \\ 0 & 0 & 1/2 & 0 & 1/2 & 0 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

We want to compute the mean win time knowing that the ruin will occurs eventually, we want the mean w.r.t. $P_i(\{V \geq T \mid X_0 \neq N\})$ (we have to exclude the other absorbing class $\{N\}$)

$$\begin{aligned}
w_0 &= 0 \\
w_i &= 1 + \frac{1}{2} w_{i-1} + \frac{1}{2} w_{i+1} \quad i=1, \dots, N-1 \\
w_{N-1} &= 1 + w_{N-2} \quad \text{we exclude the possibility of going to } N \\
\text{Homogeneous} &\Rightarrow w_i = A + Bi \\
\text{Particular} &\Rightarrow w_i = a + bi + c \quad \Rightarrow [..] \quad \Rightarrow a = -1, b = 0, c = 0 \\
\text{Complete} &\Rightarrow w_i = A + Bi - i^2 \\
\text{Boundaries} &\Rightarrow w_0 = 0 \quad \Rightarrow w_{N-1} = 1 + w_{N-2} \quad \Rightarrow w_i = -i^2 + 2(N-1)i \\
&\quad \text{mean duration of the game if we'll be ruined}
\end{aligned}$$

- Thus. Transience criterion

$(X_n)_{n \geq 0}$ irreducible MC (with countable space E)
 $(X_n)_{n \geq 0}$ transient \iff bounded non-constant solution of:

$$(*) \quad \sum_{k \in E} p_{ik} y_k = y_j \quad \forall j \in E \text{ last one}$$

proof.

(\Rightarrow) Suppose that $(X_n)_{n \geq 0}$ is transient.
We denote \mathbb{E} the unique state for which $(*)$ doesn't hold.
We consider a transformed MC in which \mathbb{E} is absorbing:

$$\tilde{p}_{ij} = \begin{cases} p_{ij} & j = \mathbb{E} \\ 0 & \text{else} \end{cases}$$

Since the original MC is transient (the transformed is not), there exist $i \in E$ such that:
 $\tilde{Y}_i = P_i(T_{\mathbb{E}} < +\infty) < 1$
 $T_{\mathbb{E}}$ = first entrance time in E

If wait be < 1, otherwise, if $P_i(\tau_{e^*} + \infty) = 1 \quad \forall i :$
 $P_e(\tau_e < +\infty) = p_{ee} + \sum_{k \neq e} p_{ek} P_k(\tau_e < +\infty) = p_{ee} + \sum_{k \neq e} p_{ek} = 1$
 which contradicts the transience of $(X_n)_n$.

- $\Rightarrow V_i < 1$ for some i and $V_e = 1$
- $\Rightarrow (V_i)_{i \in E}$ is $[0,1]$ -valued (bounded) and was constant
- Moreover, $(V_i)_{i \in E}$ are the absorption probabilities in e for the transient MC, and so:

$$V_i = \tilde{p}_{ie} + \sum_{k \neq e} \tilde{p}_{ik} V_k \quad \Rightarrow \quad \tilde{V}_i = \sum_{k \in E} \tilde{p}_{ik} V_k$$

since $\tilde{p}_{ik} = \tilde{p}_{ik}$
 (for $k \neq e$) and
 $V_e = 1$

and so $(*)$ holds.

(\Leftarrow) We suppose $\sum_{k \in E} \tilde{p}_{ik} y_k = y_i \quad \forall i \in E$ (i.e. bounded and was constant).

If we consider $(\tilde{p}_{ij})_{i,j \in E}$ as before we get: $\sum_{k \in E} \tilde{p}_{ik} y_k = y_i \quad \forall i \in E$
 Iterating: $\sum_{k \in E} \tilde{p}_{ik} \tilde{p}_{kh} y_h = \sum_{k \in E} (\sum_{j \in E} \tilde{p}_{jk} \tilde{p}_{kh}) y_h = \tilde{p}_{ih} y_h = y_i$

Iterating n times: $\sum_{k \in E} \tilde{p}_{ik}^{(n)} y_k = y_i$

If the original MC was recurrent, we would have:

$$\begin{aligned} \lim_{n \rightarrow \infty} \tilde{p}_{ik}^{(n)} &= \lim_{n \rightarrow \infty} |\mathbb{P}_j(\tilde{X}_n = e)| = \lim_{n \rightarrow \infty} \mathbb{P}_j(\tau_e \leq n) = 1 \\ \Rightarrow \forall j \neq e : \quad |y_j - y_e| &= \lim_{n \rightarrow \infty} |\tilde{p}_{je}^{(n)} - \tilde{p}_{je}^{(m)} y_e| \\ &= \lim_{n \rightarrow \infty} |\tilde{p}_{je}^{(n)} - (\tilde{p}_{je}^{(m)} - \sum_{k \in E} \tilde{p}_{jk}^{(m)} y_k)| \\ &= \lim_{n \rightarrow \infty} |\sum_{k \in E} \tilde{p}_{jk}^{(m)} y_k| \\ &\leq \sup_k |\tilde{p}_{jk}| \cdot \lim_{n \rightarrow \infty} |\sum_{k \in E} \tilde{p}_{jk}^{(m)}| \\ &\leq \sup_k |\tilde{p}_{jk}| \cdot \lim_{n \rightarrow \infty} (1 - \tilde{p}_{je}^{(m)}) = 0 \end{aligned}$$

$\Rightarrow y_j = y_e \quad \forall j \neq e \Rightarrow (y_i)_{i \in E}$ constant \Rightarrow contradiction.

- Thus. Recurrence criterion $(X_n)_{n \geq 0}$ irreducible MC.
 If $\exists (y_i)_{i \in E}$ s.t. : $\sum_{k \in E} \tilde{p}_{ik} y_k \leq y_i \quad \forall j \neq e$ but one
- $\lim_{n \rightarrow \infty} y_k = +\infty$

\Rightarrow the MC $(X_n)_{n \geq 0}$ is recurrent.

Example: Queue model

- One customer per unit of time
- number of customers arriving at each time : A_n

$$P(A_n = k) = a_k, \quad a_k \in [0,1], \quad \sum_k a_k = 1$$

- number of customers arriving at different times are \mathbf{A}

Transition matrix:

$$\left[\begin{array}{cccc} a_0 & a_1 & a_2 & \dots \\ a_0 & a_1 & a_2 & \dots \\ a_0 & a_1 & a_2 & \dots \\ 0 & 0 & a_1 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{array} \right] \quad \begin{array}{l} a_0 > 0 \\ 0 < a_1 < 1 \end{array}$$

The MC is irreducible (there is always the possibility of coming back to 0)

Is the MC transient or recurrent? (transient \rightarrow the queue explodes)

Let $\lambda = \sum_{k \geq 0} K_a a_k$ = average number of arriving customers

- $\lambda > 1$: (intuitively transient)
 We use the first criteria: we look for sol. of $\sum_{k \geq 0} \tilde{p}_{ik} y_k = y_i \quad \forall i > 0$
- $\Rightarrow \sum_{k \geq j-1} a_{k-(j-1)} \xi^k = \xi^j$
- $\sum_{k \geq j-1} a_{k-(j-1)} \xi^{k-(j-1)} = \xi^j$

$$\sum_{k \geq 0} a_k \xi^k = \xi^j \quad \text{Consider } f(\xi) = \sum_{k \geq 0} a_k \xi^k : \quad \begin{array}{c} f(\xi) \\ \nearrow \text{increasing} \end{array}$$

$$\begin{array}{l} \text{We know that } f(1) = \sum_{k \geq 0} a_k = \lambda \\ \text{Moreover, by Abel: } f'(1) = \sum_{k \geq 0} k a_k = \lambda \quad \Rightarrow \text{For } \lambda > 1 \quad \exists \xi \in (0,1) \text{ s.t.} \\ \quad f'(\xi) = \xi \quad \text{and we have } (y_i) \\ \text{with } y_i = \xi^i \text{ bounded and} \\ \text{was constant} \end{array}$$

- $\lambda \leq 1$: (intuitively recurrent)

We look for an unbounded solution of $\sum_{k \geq 0} \tilde{p}_{ik} y_k \leq y_i \quad \forall i > 0$
 and we chose $y_k = k$:

$$\begin{aligned} \sum_{k \geq 0} \tilde{p}_{ik} y_k &= \sum_{k \geq j-1} a_{k-(j-1)} k \\ &= \sum_{k \geq 0} a_k (h + (j-1)) \\ &= \sum_{k \geq 0} a_k h + \sum_{k \geq 0} a_k (j-1) \\ &= \lambda + (j-1) = (\lambda - 1) + j \leq y_j \quad \text{for } \lambda \leq 1 \end{aligned}$$

Thus the MC is recurrent.

- Thus. Sufficient condition for $\exists \pi$ (invariant distribution)

$(X_n)_{n \geq 0}$ irreducible MC.

If $\exists (y_j)_{j \in E}$ both unbounded ($y_j, x_j \xrightarrow{j \rightarrow +\infty}$ both that):

$$\sum_{k \geq 0} \tilde{p}_{ik} y_k \leq y_i - x_j \quad \forall j$$

- Thus. The MC admits a unique invariant density

Example: Queue model

$$\begin{aligned} \text{We assume } \sum_{k \geq 0} k^2 a_k < \infty &\quad \sum_{k \geq 0} \tilde{p}_{ik} y_k = \sum_{k \geq j-1} a_{k-(j-1)} k^2 \\ &= \sum_{k \geq 0} a_k (h + (j-1))^2 \\ &= \sum_{k \geq 0} h^2 a_k + 2(j-1) \sum_{k \geq 0} a_k h + (j-1)^2 a_k \\ &= m_2 + 2(j-1) \lambda + (j-1)^2 \\ &= j^2 - (2(1-\lambda))j - (2(1-\lambda) + m_2) \\ &= y_j - x_j \end{aligned}$$

Since both y_j and x_j goes to ∞ \Rightarrow $\exists \pi$. invariant distribution (if $\lambda < 1$)

- Sojourn time
- We call T = tot of transient states. Let $S \subseteq T$. we define the sojourn time in S the total time spent in S : $T_S = \sum_{k \geq 0} \mathbb{1}_{\{X_k \in S\}}$

- Moment generating function of a random var. T : $m_i = E_i[z^T] \quad \forall i \in E$

Note: if S is finite $\Rightarrow m_i = E_i[z^T]$ is well defined

Properties:

- $m_i(z) = \sum_{k=0}^{\infty} z^k p_i(T=k)$
- $m_i(z) = E_i[z^{T+1}]$
- $\begin{cases} m_i(z) = 1 \\ m_i(z) = \sum_j p_{ij} m_j(z) \\ m_i(z) = \sum_j p_{ij} m_j(z) \end{cases}$

proof.

$$\begin{aligned} & \bullet \text{ recurrent } \Rightarrow T=0 \Rightarrow E_i[z^T] = 1 \\ & \bullet i \in T : T_3 = 4 \mathbb{1}_{X_0 \neq i} + \sum_{k \geq 1} 4 \mathbb{1}_{X_k \neq i} = 4 \mathbb{1}_{X_0 \neq i} + \tilde{T} \\ & E_i[z^T] = \sum_j E_i[z^T | X_0=j] P_i(X_0=j) \\ & = \sum_j E_i[z^4 | X_0=i] z^4 | X_1=j | P_i(X_1=j) \\ & = z^4 \mathbb{1}_{X_0=i} \sum_j \mathbb{E}[z^4 | X_1=j, X_0=i] p_{ij} \\ & = z^4 \mathbb{E}[z^4 | X_0=i] \sum_j E_j[z^4] p_{ij} \end{aligned}$$

$$\Rightarrow \begin{cases} i \in S : m_i(z) = z \sum_j E_j[z^4] p_{ij} \\ i \notin S : m_i(z) = \sum_j E_j[z^4] p_{ij} \end{cases}$$

Example: Gambler's ruin

Symmetric case $p=q=\frac{1}{2}$
Finite state space: $\{1, 2, 3\}$

$$\begin{bmatrix} 1 & 0 & 0 \\ 1/2 & 0 & 1/2 \\ 0 & 1/2 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Moment generating function of the total time spent in $S=\{1\}$ starting from $i\{1\}$:

$$\begin{cases} m_0(z) = m_3(z) = 1 \\ m_1(z) = z \left(\frac{1}{2} m_2(z) + \frac{1}{2} m_0(z) \right) \\ m_2(z) = \frac{1}{2} m_3(z) + \frac{1}{2} \end{cases} \Rightarrow m_2(z) = \frac{3/4 z}{1 - 2/4}, \quad m_1(z) = \frac{1 + 2/2}{2(1 - 2/4)}$$

CONTINUOUS TIME MARKOV CHAIN TRANSITION PROBABILITIES & RATES

- Markov property: $P(X_{t+h}=j | X_{t+h}=i, \dots, X_t=i) = P(X_{t+h}=j | X_{t+h}) = P(X_{t+h}=j | X_{t+h}=i)$
- Time homogeneity: $P(X_{t+s}=j | X_s=i) = P(X_t=j | X_0=i) = p_{ij}(t)$
- Transition semi-group: $P_t = (p_{ij}(t))_{i,j \in E}$
- Properties:
 - $0 \leq p_{ij}(t) \leq 1 \quad \forall i, j \in E, \forall t > 0$
 - $\sum_{j \in E} p_{ij}(t) = 1$
 - $P_{t+s} = P_t P_s$
 - $P_0 = I$

Proof.

$$\begin{aligned} & \bullet \text{ Chapman-Kolmogorov equation: } p_{ij}(t+s) = \sum_{k \in E} p_{ik}(t) p_{kj}(s) \\ & \bullet \text{ In regular situations we know that the following limits exist:} \\ & q_{ij} = \lim_{t \rightarrow 0^+} \frac{p_{ij}(t)}{t} \quad i \neq j, \quad q_{ii} = \lim_{t \rightarrow 0^+} \frac{-4 + p_{ii}(t)}{t} \\ & \text{They are the derivatives of transition probabilities in 0 (since } p_j(0) = \delta_{ij} \text{)} \\ & \text{and they're called transition rates. Moreover: } q_{ii} \leq 0, \quad q_{ii} > 0 \end{aligned}$$

Kolmogorov equations

$$\begin{aligned} & \bullet \text{ Forward KE: } p_{ij}'(t) = \sum_{k \in E} p_{ik}(t) q_{kj} \\ & \bullet \text{ Backward KE: } p_{ij}'(t) = \sum_{k \in E} q_{ik} p_{kj}(t) \\ & \bullet \text{ Transition rate matrix: } Q = (q_{ij})_{i,j \in E} \\ & \text{ properties:} \quad \bullet \sum_{j \in E} q_{ij} = 0 \\ & \bullet q_{ij} \geq 0, \quad q_{ii} \leq 0 \\ & \bullet (\text{from FKE}): \quad P_t' = P_t Q \end{aligned}$$

Thus, solution of Kolmogorov equations
 $\text{If } \sup |q_{ij}| < \infty \Rightarrow \text{FKE and BKE have the same solution: } P_t = e^{tQ}$

EXIT TIME & DISCRETE SKELETON

$\bullet T_i = \inf \{t > 0 : X_t \neq i\} = \text{exit time from the state } i \quad (i \in E)$

$$\begin{cases} T_i = \infty & \text{if } q_{ii} = 0 \\ -\infty < q_{ii} < 0 \end{cases} \Rightarrow T_i \sim \mathbb{E}(-q_{ii}) \Rightarrow P_i(X_{T_i} = j) = \frac{q_{ij}}{-q_{ii}} \quad \forall j \neq i$$

where X_{T_i} = state we visit after leaving i

$$\begin{cases} \text{If } q_{ii} = +\infty \Rightarrow i \text{ is an instantaneous state} \\ \text{If } q_{ii} = 0 \Rightarrow i \text{ is absorbing: } p_{ii}(t) = 1 \quad \forall t \end{cases}$$

We can associate a discrete MC to a continuous one through the Discrete Skeleton: $(\hat{P}_{ij})_{i,j \in E}$

$$\hat{P}_{ij} = \begin{cases} \frac{q_{ij}}{-q_{ii}}, & i \neq j \\ 1 - q_{ii}, & i=j \\ 0, & (q_{ii}=0, i \neq j) \vee (q_{ii} \neq 0, i=j) \end{cases}$$

POISSON PROCESS

$$Q = \begin{bmatrix} -\lambda & \lambda & 0 & 0 & 0 & \dots \\ 0 & 0 & -\lambda & \lambda & 0 & \dots \\ 0 & 0 & 0 & -\lambda & \lambda & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix} \rightarrow P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & \dots \\ 0 & 0 & 1 & 0 & 0 & \dots \\ 0 & 0 & 0 & 1 & 0 & \dots \\ 0 & 0 & 0 & 0 & 1 & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix}$$

- The states are $0, 1, 2, \dots$ and the filtration is: $\mathcal{F}_t = \sigma(X_s : s \leq t)$

We go out of the state i after an exponential time (ε_i) . We define the MC $(N_t)_{t \geq 0}$ and we set $\lambda > 0$.

- $(N_t)_{t \geq 0}$ MC with $Q = (q_{ij})_{i,j \in \mathbb{N}}$ is such that:

$$P_i(N_t=n \mid N_0=0) = e^{-\lambda t} \frac{(\lambda t)^n}{n!}$$

- Moreover: $N_{t_k} - N_{t_{k-1}} \sim P(\lambda(t_k - t_{k-1}))$

POPULATION DYNAMICS

$(X_t)_{t \geq 0}$ MC: $X_t = \# \text{individuals at time } t$
Generic case of BIRTH-DEATH PROCESS:

$$\underbrace{(n)}_{(n-1)} \rightsquigarrow \underbrace{(n+1)}_{(n+2)}$$

In every moment we can:

$$Q = \begin{bmatrix} -\lambda_0 & \lambda_0 & 0 & 0 & \dots \\ \mu_1 & -(\lambda_1 + \mu_1) & \lambda_1 & 0 & \dots \\ 0 & \mu_2 & -(\lambda_2 + \mu_2) & \lambda_2 & \dots \\ 0 & 0 & \mu_3 & -(\lambda_3 + \mu_3) & \lambda_3 & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix}$$

$B_n \sim \Sigma(\lambda_n)$, $D_n \sim \Sigma(\mu_n)$

The MC is irreducible iff $\lambda_n > 0 \ \forall n$, $\mu_n > 0 \ \forall n$.

We leave the state n after a random time, which is the minimum of B_n , D_n :

leaving time $\sim \Sigma(\lambda_n + \mu_n)$

$$P(B_n < D_n) = \frac{\lambda_n}{\lambda_n + \mu_n} \quad (= \frac{q_{nn}}{q_{nn} + q_{nn}})$$

Invariant density

$$T_n = \left(\frac{\lambda_0 \lambda_1 \dots \lambda_{n-1}}{\mu_1 \mu_2 \dots \mu_n} \right) \left(\frac{2}{1 + \sum_{k=0}^{n-1} \frac{\lambda_k}{\mu_k}} \right)$$

Exploding in finite time: (pure birth process with λ_n)

If λ_n are such that: $\Sigma_{n=0}^{\infty} \frac{\lambda_n}{\mu_n} < +\infty \Rightarrow$ In finite time $(X_n)_n$ diverges

STATES CLASSIFICATION

- j is accessible from i if $\exists t: p_{ij}(t) > 0$
- i and j communicate if one is accessible from the other
- (def. 2) j accessible from $i \iff \exists n: i_0, i_1, \dots, i_n : q_{i_0 i_1} \dots q_{i_{n-1} i_n} > 0$
- i recurrent: $P_i(\omega \mid t \geq 0 : X_t(\omega) = i \text{ is unbounded}) = 1$
- i transient: $P_i(\omega \mid t \geq 0 : X_t(\omega) = i \text{ is bounded}) = 0$
- Thus, i recurrent (transient) for the continuous MC \iff i recurrent (transient) for the discrete skeleton (associated discrete MC)

INVARIANT DENSITIES

- $(X_t)_{t \geq 0}$ continuous time MC. $(P_t)_{t \geq 0}$ transition matrix.
- $(\mu_i)_{i \in E}$ invariant density $\iff \mu_j = \sum_{i \in E} \mu_i p_{ij}(t) \quad \forall t$
- Properties:

 - $\sum_{i \in E} \mu_i = 1$
 - $\mu_i \geq 0 \quad \forall i \in E$
 - If $q_{ii} > -\infty$ and $(p_{ij}(t))_{i,j}$ is the unique sol. of FPE, BKE \iff (μ_i) is an invariant density $\iff 0 = \sum_{i \in E} \mu_i q_{ii} \forall i \in E$

- $E[Q] = 0$
- E finite $\Rightarrow \exists$ at least 2 invariant density
- Invariant densities of the continuous MC are invariant densities of the discrete skeleton
- (Π_i) : for continuous, $(\Pi_i(-q_{ii}))_i$ for discrete

CONDITIONAL EXPECTATION

- Ergodic theorem
- discrete positive recurrent irreducible MC:

- continuous positive recurrent irreducible MC:

- $\frac{1}{n} \sum_{i=1}^n \frac{1}{t} \chi_{\{X_t=i\}} \xrightarrow{n \rightarrow \infty} \Pi_i$
- $\frac{1}{t} \int_0^t \frac{1}{t} \chi_{\{X_s=i\}} ds \xrightarrow{n \rightarrow \infty} \Pi_i$
- X random variable st. $E[X] < +\infty$. We call conditional expectation of X w.r.t. \mathcal{G} any \mathcal{G} -measurable random variable \mathbf{Y} st.:

 - $\int_G X dP = \int_G Y dP \quad \forall G \in \mathcal{G}_Y$
 - Thus: Existence of conditional expectation $\mathbf{X} \setminus \mathcal{G}$ -measurable, integrable, $E[X \mid \mathcal{G}] < +\infty$, $\mathbf{Y} \subseteq \mathcal{G}$
 - $\exists \mathbf{Y} \setminus \mathcal{G}$ -measurable: $\int_G X dP = \int_G Y dP \quad \forall G \in \mathcal{G}_Y$
 - (unique up to sets $G \in \mathcal{G}_Y : P(G) = 0$)

- Properties:

 - $E[aX_1 + bX_2 \mid \mathcal{G}] = aE[X_1 \mid \mathcal{G}] + bE[X_2 \mid \mathcal{G}]$
 - $X_1 > 0 \Rightarrow E[X_1 \mid \mathcal{G}] \geq 0$
 - $P(X_1 > X_2) = 1 \Rightarrow E[X_1 \mid \mathcal{G}] \geq E[X_2 \mid \mathcal{G}]$
 - X_1 constant $\Rightarrow E[X_1 \mid \mathcal{G}] = X_1 = \text{constant}$
 - $E[\{E[X_1 \mid \mathcal{G}]\} \mid \mathcal{G}] = E[X_1 \mid \mathcal{G}] \quad \text{if } \mathcal{G} \subseteq \mathcal{G}_Y$

- $(X_n)_{n \geq 0}$ discrete MC, P transition matrix, $f: E \rightarrow \mathbb{R}$, $E[f(X_0)] < \infty \quad \forall n$
- $E[f(X_{n+m}) \mid \sigma(X_0, \dots, X_n)] = P^m f(X_n)$
- $(X_t)_{t \geq 0}$ continuous MC, P_t trans. res. group, $f: E \rightarrow \mathbb{R}$, $E[f(X_t)] < \infty \quad \forall t$
- $E[f(X_t) \mid \sigma(X_r : r \leq s)] = (P_{t-s}f)(X_s)$
- Thus: Min square error approximation of a random variable

- X r.v. with $E[X]^2 < \infty$, $\mathbf{Y} \subseteq \mathcal{G}$
- $\Rightarrow E[\{E[X \mid \mathcal{G}]\}^2] < \infty$ and $\min_{\mathcal{G} \setminus \mathcal{G}_Y} E[\{X - E[X \mid \mathcal{G}]\}^2]$
- Thus. Freezing lemma

- X r.v. with density f_1 , $\mathbf{Y} \setminus \mathcal{G}$ ($\sigma(X \setminus \mathcal{G})$), $\mathbf{Y}_1, \dots, \mathbf{Y}_n$ \mathcal{G} -meas.
- $\Rightarrow E[h(X, Y_1, \dots, Y_n) \mid \mathcal{G}] = \int_{\mathcal{G}} h(X, Y_1, \dots, Y_n) f(x) dx$

MARKOV PROCESS

- $(X_t)_{t \geq 0}$ collection of random variables $X_t : \Omega \rightarrow E$ is a Markov Process if

$$P(X_{t+u} \in E_{t+u} | X_{t+1} \in E_1, \dots, X_{t+3} \in E_3) = P(X_{t+u} \in E_{t+u} | X_{t+u} \in E_u)$$

$y_1, y_2, \dots < t_{min}, \quad \forall i_1, \dots, i_{m+1} \in \mathcal{E}$

$(X_t)_{t \geq 0}$ MP homogeneous if: $P(X_{t+s} \in E_2 | X_t \in E_1) = P(X_{t+s} \in E_2 | X_0 = x)$

Transition kernels: $P_t(x, A) = P(X_t \in A | X_0 = x)$

(act. 2) collection of $P_t : E \times \mathcal{E} \rightarrow [0, 1]$ such that:

1. $P_t(x, \cdot)$ is a probability measure on \mathcal{E} $\forall x \in E$

2. $P_t(\cdot, A)$ is \mathcal{E} -measurable $\forall A \in \mathcal{E}$

3. $P(X_{t+s} \in A | X_s = x) = \int_A P_t(x, dy)$

- Thus. MP and conditional expectation

$(X_t)_{t \geq 0}$ MP time homogeneous, P_t transition kernel

$f : E \rightarrow \mathbb{R}$ measurable : $E[f(X_{t+s})] < \infty$

$$\Rightarrow E[f(X_{t+s}) | \sigma(X_s)] = \int_E f(y) P_t(X_s, dy)$$

STATIONARITY let $(Y_t)_{t \geq 0}$ be an MP and μ a measure on \mathcal{E} .

μ is invariant if when $Y_0 \sim \mu$ then $Y_t \sim \mu \quad \forall t > 0$.

$$\mu \text{ is invariant} \Leftrightarrow \mu(A) = \int_E P_t(x, A) \mu(dx) \quad \forall A \in \mathcal{E}$$

- IRREDUCIBILITY

Let $(X_t)_{t \geq 0}$ be an MP with values in (E, \mathcal{E}) and transition kernels (P_t) .
 $(X_t)_{t \geq 0}$ is irreducible w.r.t. a reference measure γ on \mathcal{E} if
 $\forall x \in E, \quad \forall A \in \mathcal{E} \quad \gamma(A) > 0 \quad : \exists t > 0 \text{ s.t. } P_t(x, A) > 0.$

- HARRIS RECURRENT

$(X_n)_{n \geq 0}$ discrete MC, $E \subseteq \mathbb{R}^d$, $\mathcal{E} = \mathcal{B}(E)$.

We set $N_A = \sum_{n \geq 0} \mathbf{1}_{\{X_n \in A\}} = \text{number of visits in the set } A \quad (\forall A \in \mathcal{E})$.

Then: • A is Harris recurrent if $\forall x : P_x(N_A = +\infty) = 1 \quad (\forall x \in A)$

• $(X_n)_{n \geq 0}$ Harris recurrent if $\exists \varphi : \forall A \in \mathcal{E}$ with $\varphi(A) > 0$ are H.R.

- LLN

$(X_n)_{n \geq 0}$ Harris recurrent, φ invariant measure, $f : E \rightarrow \mathbb{R}$ \mathcal{E} -meas. : $\int_E f(x) \varphi(dx) < \infty$

$$\Rightarrow \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=0}^{n-1} f(X_k) = \int_E f(x) \varphi(dx)$$

- (Ω, \mathcal{F}, P) probability space, $(M_t)_{t \geq 0}$ real random variables,

$(\mathcal{F}_t)_{t \geq 0}$ increasing family of sub σ -algebra of \mathcal{F} (set $\Rightarrow \mathcal{F}_t \subseteq \mathcal{F}_t$).

$(M_t)_{t \geq 0}$ is a martingale if :

$$1. \quad E[|M_t|] < +\infty \quad \forall t$$

2. M_t is \mathcal{F} -measurable $\forall t$

3. $\forall s < t : \quad E[M_t | \mathcal{F}_s] = M_s \quad (\text{Martingale property})$

MARTINGALES

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$(X_n)_{n \geq 0}$ discrete MC	$\bullet \quad E[f(X_n)]^{\mathcal{F}_n} = (P^n \omega f)(X_n) \quad (\omega \in \Omega)$
$f : E \rightarrow \mathbb{R}$ measurable	$\bullet \quad M_n := f(X_n) - \sum_{k=0}^{n-1} Pf(X_k) - f(X_0)$
$E[f(X_n)] < +\infty$	$(M_n)_{n \geq 0}$ is a martingale w.r.t. $(\mathcal{F}_n)_{n \geq 0}$
$\mathcal{F}_n = \sigma(X_0, \dots, X_n)$	
$(X_t)_{t \geq 0}$ continuous MC	$\left. \begin{array}{l} \bullet \quad M_t = f(X_t) - \int_0^t (\alpha f)(X_s) ds \\ \bullet \quad (M_t)_{t \geq 0} \text{ martingale} \end{array} \right\} \Rightarrow M_t = f(X_t) - \int_0^t (\alpha f)(X_s) ds \quad \forall t \geq 0$
$f : E \rightarrow \mathbb{R}$ measurable	
$E[f(X_t)] < +\infty$	
$\mathbb{E}[Qf(X_t)] < +\infty \quad \forall t$	$(M_t)_{t \geq 0}$ is a martingale w.r.t. $(\mathcal{F}_t)_{t \geq 0}$
$\mathcal{F}_t = \sigma(X_r : r \leq t)$	
$T : \mathbb{R} \rightarrow [0, +\infty]$ stopping time for the filtration $(\mathcal{F}_t)_{t \geq 0}$ if $\{\tau \leq t\} \in \mathcal{F}_t \quad \forall t$	
\bullet Stopping theorem	
$(M_t)_{t \geq 0}$ martingale (where t belongs to a discrete set)	
$(\mathcal{F}_t)_{t \geq 0}$ filtration	
T stopping time for the filtration	
\Rightarrow the stopped process $(M_{t \wedge T})_t$ is also a martingale	
worther:	
$E[M_{T \wedge T}] = E[M_0] = E[M_T]$	(martingales have constant expectation)
None: by MCT	$E_i[M_{t \wedge T}] \xrightarrow[t]{\text{to}} E_i[M_T]$
by factor	