

Will also be talking about Markov chains but in infinite ^{countable} state spaces
 Will discuss different questions such as how long a ^{random walk} ~~path~~ takes to come back to the starting space.
 (transience and recurrence)

Definition: A sequence of random variables $(X_n)_{n \geq 0}$ taking values in a space E is called a Markov chain if $\forall x_0, \dots, x_n \in E$ such that $P(X_1=x_1, \dots, X_n=x_n) > 0$ we have

$$P(X_{n+1}=x_{n+1} | X_n=x_n, \dots, X_0=x_0) = P(X_{n+1}=x_{n+1} | X_n=x_n) = P(X_1=x_1 | X_0=x_0)$$

"Past is independent of the future given the present" ↑ past & future present ↑ time homogeneous

We'll assume E is countable

The Markov chain is characterized by the transition matrix P $P(i,j) = P(X_1=j | X_0=i)$

Notation: let A be an event. $P_i(A) \stackrel{\text{def}}{=} P(A | X_0=i)$
 $E_i[Y] = E[Y | X_0=i]$

Check: $P(X_n=j | X_0=i) = P^n(i,j) \leftarrow$ also written $P_{ij}(n)$
↑ n-th matrix power

Def: A Markov chain is called irreducible if $\forall x,y \in E \exists n \geq 0$ such that $P^n(x,y) > 0$.

Example: A random walk on a graph can be irreducible only if the graph is connected.

Def: For every i define $T_i = \inf \{n \geq 1 : X_n = i\}$

From now on assume that all Markov chains are irreducible

Def: A state i is called recurrent if $P_i(T_i < \infty) = 1$. Otherwise a state is called transient.

Exercise: If $\exists i$ such that $P_i(T_i < \infty) = 1$ then for all j , $P_j(T_j < \infty) = 1$

So a Markov chain (MC) can be either ~~transient~~ recurrent or transient

Lemma: let $X_0=i$ and $V_i = \sum_{n=0}^{\infty} 1(X_n=i)$ - the total number of visits to i . Then V_i has the geometric

distribution: $P_i(V_i > r) = (P_i(T_i < \infty))^r$

Proof: $P_i(V_i > 1) = P_i(T_i < \infty)$

$P_i(V_i > 2) = P_i(T_i < \infty)^2$ (because of the Markov property) and so on for all r □

So $E_i[V_i] = \frac{1}{1 - P_i(T_i < \infty)}$

Criterion for recurrence: A MC is recurrent iff $\sum_{n=0}^{\infty} P_{ii}(n) = \infty$

Proof: \Rightarrow If $P_i(T_i < \infty) = 1$ then for all r $P_i(V_i > r) = 1$ and so $P_i(V_i = \infty) = 1 \Rightarrow E[V_i] = \infty$

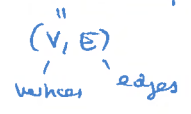
But $E[V_i] = \sum_{n=0}^{\infty} P_i(X_n=i) = \sum_{n=0}^{\infty} P_{ii}(n)$

\Leftarrow If $\sum P_i(n) < \infty$ then $E_i[V_i] < \infty \Rightarrow P_i(T_i < \infty) = 1$ □

Note: Recurrence and transience is only interesting for infinite graphs.

(undirected, locally finite)

Def: A simple random walk on a graph G (always assumed connected)



$$P(i, j) = \begin{cases} \frac{1}{\deg(i)} & \text{if } (i, j) \text{ is an edge} \\ 0 & \text{otherwise.} \end{cases}$$

$(\deg(i) = \# \text{ neighbors of } i)$

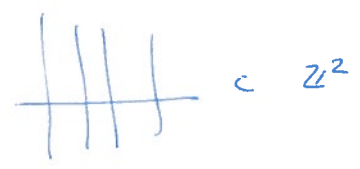
(i, j) means two unordered pair

edges can ~~not~~ connect a vertex to itself and there can be multiple edges.

Theorem (Polya) 1920 A simple random walk on \mathbb{Z}^d is recurrent iff $d=1$ or $d=2$

(this theorem was motivated by the fact that he kept running into his flatmate in the park)

On \mathbb{Z}^d 2 walks meeting in the sense of recurrence because you can subtract but this is not always the case. For instance



\mathbb{Z}^2 is recurrent as we will see later but two random walks do not always meet

Proof: $d=1$:



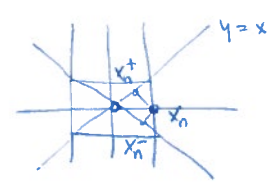
$$P_{00}(2n) = \binom{2n}{n} \left(\frac{1}{2}\right)^{2n}$$

return probability after 2n steps

Stirling's formula: $n! \sim n^n \sqrt{2\pi n} e^{-n}$

Hence $P_{00}(2n) \sim \frac{c}{\sqrt{n}}$ for some $c > 0$. By the Poincaré criterion we see the walk is recurrent.

$d=2$: This was a very nice trick



Let X_n be the walk and
 X_n^+ its projection to $y=x$
 X_n^- " " to $y=-x$

You can easily check that X_n^+, X_n^- are independent simple random walks on $\mathbb{Z}/\sqrt{2}$ so we have decomposed our walk in 2 dimensions into 2 random walks in 1-dimension.

$$P_{00}(2n) = P_0(X_{2n}^+ = 0, X_{2n}^- = 0) = P_0(X_{2n}^+ = 0) P(X_{2n}^- = 0) = \left(\binom{2n}{n} \left(\frac{1}{2}\right)^{2n} \right)^2 \sim \frac{c^2}{n} \Rightarrow d=2 \text{ is recurrent.}$$

$d=3$: Here we can't project and get 3 independent walks

$$P(X_{2n} = 0) = \sum_{\substack{i, j, k \geq 0 \\ i+j+k=n}} \frac{(2n)!}{(i! j! k!)^2} \left(\frac{1}{6}\right)^n = \binom{2n}{n} \frac{1}{2^{2n}} \sum_{\substack{i, j, k \geq 0 \\ i+j+k=n}} \binom{n}{i, j, k}^2 \left(\frac{1}{3}\right)^n$$

$$\sum_{\substack{i, j, k \geq 0 \\ i+j+k=n}} \binom{n}{i, j, k} = 3^n \quad \text{if } n \geq 3m \quad \text{then } \binom{n}{i, j, k} \leq \binom{n}{m, m, m} \text{ [check!]}$$



Hence $P_{00}(2n) \leq \binom{2n}{n} \frac{1}{2^{2n}} \binom{n}{m \ m} \frac{1}{3^n} \stackrel{\text{Stirling}}{\sim} \frac{e^n}{n^{3/2}}$

so this is transient



$d > 3 \rightarrow$ see exercises.

For general graphs this kind of analysis is much harder.

Def: A Markov chain with matrix P has invariant/stationary/equilibrium distribution π if when $X_0 \sim \pi$ then for any n , $X_n \sim \pi$

This means that π has to satisfy $\pi P = \pi$, i.e. π is a left eigenvector of the matrix P

Erick and Persi were talking about convergence to this invariant distribution in their examples.

Def: A MC with P, π is called reversible if for all $n \in \mathbb{N}$, when $X_0 \sim \pi$

$$(X_0, \dots, X_n) \underset{\substack{\sim \\ \text{same distribution}}}{\sim} (X_n, \dots, X_0)$$

Exercise: Reversibility is equivalent to: for all x, y $\pi(x)P(x, y) = \pi(y)P(y, x)$ [detailed balance equation]

~~If we have a finite graph with a stationary distribution, it is reversible.~~

In a finite graph we can let $\pi(i) = \frac{\deg(i)}{\sum_j \deg(j)}$ gives an invariant, reversible distribution.

Next lecture: Electrical networks ; extends to infinite graphs ; spanning trees

