# Jumping Into Markov Chains 

## A PRIMES Exposition

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## Introduction

- A Markov process is characterized by the memoryless property that the future only depends on the current state and not on the previous states.
- For example, a student may follow the chain below every 15 minutes.

- Another example is radioactive decay where the time before the next particle decays does not depend on when the previous particles decayed.


## Necessary Definitions and Theorems

## Definition (State Space)

The state space $I$ is the set of all possible states of the Markov Chain.

## Definition (Measure and Distribution)

A measure is a row vector $\lambda=\left(\lambda_{i}: i \in I\right)$ taking non-negative values in $\mathbb{R}$. A distribution is a measure with $\sum \lambda_{i}=1$.

## Definition (Transition Matrix $P$ )

$P=\left(p_{i j}: i, j \in I\right)$, where $p_{i j}$ is the probability of jumping from state $i$ to state $j \cdot p_{i j}^{(n)}$ is the probability of transitioning from $i$ to $j$ in $n$ steps and is the $i j$ entry of $P^{n}$.

## Definition (Markov Chain)

A sequence of random variables $X_{n}$ taking values in $I$ is $\operatorname{Markov}(\lambda, P)$ if $\mathbb{P}\left(X_{0}=i\right)=\lambda_{i}$ and $\mathbb{P}\left(X_{n+1}=j \mid X_{n}=i\right)=p_{i j}$.

## Hitting Times and Probabilities

## Definition

For a certain subset $A \subset I$ and state $i \in I$, the hitting probability is defined as $h_{i}^{A}=\mathbb{P}_{i}($ hit A$)$ and the hitting time is defined as $k_{i}^{A}=\mathbb{E}_{i}($ time to hit A$)$.

The hitting probabilities satisfy

$$
\begin{cases}h_{i}^{A}=1 & i \in A \\ h_{i}^{A}=\sum_{j \in I} p_{i j} h_{j}^{A} & i \notin A\end{cases}
$$

The hitting times satisfy

$$
\begin{cases}k_{i}^{A}=0 & i \in A \\ k_{i}^{A}=1+\sum_{j \in I} p_{i j} k_{j}^{A} & i \notin A\end{cases}
$$

Moreover, $h_{i}^{A}$ and $k_{i}^{A}$ are the minimal non-negative solutions to these equations.

## Proof for Hitting Probabilities

$$
\begin{cases}h_{i}^{A}=1 & i \in A \\ h_{i}^{A}=\sum_{j \in I} p_{i j} h_{j}^{A} & i \notin A\end{cases}
$$

If $i \in A, h_{i}^{A}=1$ trivially
for $i \notin A$, let $H^{A}(\omega)=\inf \left\{n \mid X_{n}(\omega) \in A\right\}$.

$$
\begin{gathered}
h_{i}^{A}=\mathbb{P}_{i}\left(H^{A}<\infty\right) \\
\mathbb{P}_{i}\left(H^{A}<\infty \mid X_{1}=j\right)=\mathbb{P}_{j}\left(H^{A}<\infty\right) \\
h_{i}^{A}=\sum_{j \in I} p_{i j} \mathbb{P}_{j}\left(H^{A}<\infty\right)=\sum_{j \in I} p_{i j} h_{j}^{A}
\end{gathered}
$$

## A Simple Example



In the chain above, what is the probability of getting to state 4 starting from state 2?

$$
\begin{gathered}
h_{4}=1 \\
h_{1}=h_{1} \\
h_{2}=h_{1} / 2+h_{3} / 2 \\
h_{3}=h_{2} / 2+h_{4} / 2 \\
h_{2}=1 / 3
\end{gathered}
$$

## Gamblers' Ruin

## Problem

Imagine that you enter a casino with a fortune of \$i and gamble, \$1 at a time, with probability $p$ of doubling your stake and probability $q$ of losing it. What is the probability that you leave broke?


Let $h_{i}=\mathbb{P}_{i}$ (hitting 0 ).
We get the system $h_{0}=1, h_{i}=p h_{i+1}+q h_{i-1}$.
General solution: $h_{i}=A+B\left(\frac{q}{p}\right)^{i}$ If $p<q$, then $B=0$, so $h_{i}=1$. Similarly, if $p=q$, then $h_{i}=A+B i$, and $B=0$ once again. Thus, $h_{i}=1$.
If $p>q$, then $h_{i}=\left(\frac{q}{p}\right)^{i}+A\left(1-\left(\frac{q}{p}\right)^{i}\right)$, with the minimal nonnegative
solution being $h_{i}=\left(\frac{q}{p}\right)^{i}$

## Recurrence and Transience

## Definition (Recurrence)

A state $i$ is recurrent if $\mathbb{P}_{i}\left(\left\{t \geq 0: X_{t}=i\right\}\right.$ is unbounded $)=1$

## Definition (Transience)

A state $i$ is transient if $\mathbb{P}_{i}\left(\left\{t \geq 0: X_{t}=i\right\}\right.$ is unbounded $)=0$

## Definition (Communicating States)

State $i$ communicates with state $j$ if $\mathbb{P}_{i}\left(X_{n}=j\right.$ for $\left.n \geq 0\right)>0$ and $\mathbb{P}_{j}\left(X_{n}=i\right.$ for $n \geq 0)>0$

Communicating is an equivalence relation, and partitions the state space into communicating classes. If $I$ is a single class, $P$ is said to be irreducible.

## Definition (Closed Communicating Class)

A communicating class is closed if $i \in C$ and $i$ communicates with $j$ implies that $j \in C$

## Properties of Recurrence and Transience



Figure: Communicating classes : $\{1,2,3\},\{4\},\{5,6\}$

## Definition (First Passage Time to State $i$ )

$$
T_{i}(\omega)=\inf \left\{n \geq 1: X_{n}(\omega)=i\right\}
$$

Definition (Return probability)

$$
f_{i}=\mathbb{P}_{i}\left(T_{i}<\infty\right)
$$

## Definition (Number of visits $V_{i}$ )

$$
V_{i}=\sum_{n=0}^{\infty} 1_{X_{n}=i}, \mathbb{E}_{i}\left(V_{i}\right)=\sum_{n=0}^{\infty} p_{i i}^{(n)}
$$

## Theorem

- If $f_{i}=1$, then $i$ is recurrent and $\sum_{n=1}^{\infty} p_{i i}^{(n)}=\infty$
- If $f_{i}<1$, then $i$ is transient and $\sum_{n=1}^{\infty} p_{i i}^{(n)}<\infty$


## Proof.

If $\mathbb{P}_{i}\left(T_{i}<\infty\right)=1$, then $\mathbb{P}_{i}\left(V_{i}=\infty\right)=1$, so $i$ is recurrent, and $\sum_{n=0}^{\infty} p_{i i}^{(n)}=\mathbb{E}_{i}\left(V_{i}\right)=\infty$. If $f_{i}=\mathbb{P}_{i}\left(T_{i}<\infty\right)<1$, then

$$
\sum_{n=0}^{\infty} p_{i i}^{(n)}=\mathbb{E}_{i}\left(V_{i}\right)=\sum_{r=0}^{\infty} \mathbb{P}_{i}\left(V_{i}>r\right)=\sum_{r=0}^{\infty} f_{i}^{r}=\frac{1}{1-f_{i}}<\infty
$$

## Theorem

All states in a communicating class are either recurrent or transient

## Proof.

Take $i, j \in C$ and assume $i$ is transient. Thus, there exist $n, m \geq 0$ such that $p_{i j}^{(n)}>0$ and $p_{j i}^{(m)}>0$. For all $r \geq 0$,

$$
p_{i i}^{(m+n+r)} \geq p_{i j}^{(n)} p_{j j}^{(r)} p_{j i}^{(m)}
$$

so

$$
\sum_{r=0}^{\infty} p_{j j}^{(r)} \leq \frac{1}{p_{i j}^{(n)} p_{j i}^{(m)}} \sum_{r=0}^{\infty} p_{i i}^{(n+r+m)}<\infty
$$

## Random Walks on $\mathbb{Z}$



Given an odd sequence, $p_{00}^{(2 n+1)}=0$ for all $n$.
Given an even sequence of length $2 n$, the probability of having $n$ steps up and $n$ steps down is $\binom{2 n}{n} p^{n} q^{n}$.
By Stirling's formula,

$$
n!\approx \sqrt{2 \pi n(n / e)^{n}} \text { as } n \rightarrow \infty
$$

Thus,

$$
p_{00}^{(2 n)}=\frac{(2 n)!}{(n!)^{2}}(p q)^{n} \approx \frac{(4 p q)^{n}}{A \sqrt{n / 2}} \text { as } n \rightarrow \infty
$$

For $p=q=\frac{1}{2}$,

$$
p_{00}^{(2 n)} \geq \frac{1}{2 \sqrt{2 \pi n}}, \text { so } \sum_{n=N}^{\infty} p_{00}^{(2 n)} \geq \frac{1}{2 \sqrt{2 \pi}} \sum \frac{1}{\sqrt{n}}=\infty
$$

so the random walk on $\mathbb{Z}$ is recurrent.

## Random Walk on $\mathbb{Z}$ Continued

If $p \neq q, 4 p q<1$, so

$$
\sum_{n=N}^{\infty} p_{00}^{(2 n)} \leq \frac{1}{\sqrt{2 \pi}} \sum_{n=N}^{\infty}(4 p q)^{n}<\infty
$$

so this walk is transient.

## Random Walk on $\mathbb{Z}^{3}$

$$
p_{i j}= \begin{cases}\frac{1}{6} & \text { if }|i-j|=1 \\ 0 & \text { otherwise }\end{cases}
$$

Again, with an odd step sequence, $p_{00}^{(2 n+1)}=0$.
With an even step sequence, we must have $i$ steps up and down, $j$ steps north and south, $k$ steps east and west with $i+j+k=n$.

$$
\begin{aligned}
p_{00}^{(2 n)} & =\sum_{i+j+k=n} \frac{(2 n)!}{(i!j!k!)^{2}}\left(\frac{1}{6}\right)^{2 n} \\
& =\binom{2 n}{n}\left(\frac{1}{2}\right)^{2 n} \sum_{i+j+k=n}\binom{n}{i j k}\left(\frac{1}{3}\right)^{2 n}
\end{aligned}
$$

For $n=3 m,\binom{n}{i j k} \leq\binom{ n}{m m m}$, so

$$
p_{00}^{(2 n)} \leq\binom{ 2 n}{n}\left(\frac{1}{2}\right)^{2 n}\binom{n}{m m m}\left(\frac{1}{3}\right)^{n} \approx \frac{1}{2 \sqrt{2 \pi}^{3}}\left(\frac{6}{n}\right)^{3 / 2} \text { as } n \rightarrow \infty
$$

## Random Walk on $\mathbb{Z}^{3}$ Continued

$\sum_{n=0}^{\infty} p_{00}^{(6 m)}<\infty$ because $\sum n^{-3 / 2}$ converges. Since $p_{00}^{(6 m)} \geq\left(\frac{1}{6}\right)^{2} p_{00}^{(6 m-2)}$ and $p_{00}^{(6 m)} \geq\left(\frac{1}{6}\right)^{4} p_{00}^{(6 m-4)}$,

$$
\sum_{n=0}^{\infty} p_{00}^{(n)}<\infty
$$

and this walk is transient.

## Invariant Distributions and Convergence to Equilibrium

A measure $\pi$ is called invariant if $\pi P=\pi$.
For a process $X$ which is $\operatorname{Markov}(\pi, P)$ for an invariant distribution $\pi, X_{n}$ is also $\operatorname{Markov}(\pi, P)$ for all $n$.
For a fixed state $k$, let $\gamma_{i}^{k}=\mathbb{E}_{k} \sum_{n=0}^{T_{k}-1} 1_{\left\{X_{n}=i\right\}}$ be the expected number of visits to $i$ between visits to $k$. $\gamma^{k}$ turns out to be an invariant measure with $\gamma_{k}^{k}=1$.
If $\sum_{i} \gamma_{i}^{k}=m_{k}$, which is the expected return time to $k$, is finite (positive recurrence), $\gamma^{k} / m_{k}$ is an invariant distribution.
If a chain is irreducible and positive recurrent, the invariant measure turns out to be unique up to scaling and in this case, $\pi_{k}=\frac{1}{m_{k}}$.

## Theorem (Convergence to Equilibrium)

If $P$ is irreducible and aperiodic, $\mathbb{P}\left(X_{n}=j\right) \rightarrow \pi_{j}$ as $n \rightarrow \infty$ for all $j$ regardless of the initial distribution.

Periodic case: $\left(\begin{array}{ll}0 & 1 \\ 1 & 0\end{array}\right)$

## Ergodic Theorem

## Theorem (Ergodic Theorem)

Let $P$ be irreducible and positive recurrent and let $X$ be $\operatorname{Markov}(\lambda, P)$. Then, for any bounded function $f: I \rightarrow \mathbb{R}$,

$$
\mathbb{P}\left(\frac{1}{n} \sum_{k=1}^{n-1} f\left(X_{k}\right) \rightarrow \bar{f} \text { as } n \rightarrow \infty\right)=1
$$

where $\bar{f}=\sum_{i \in I} \pi_{i} f(i)$ regardless of the initial distribution.

## Example of an Invariant Distribution

An opera singer is due to perform a long series of concerts. She is liable to pull out each night with probability $1 / 2$. The promoter sends her flowers every day until she returns. Flowers costing $x$ thousand dollars, $0 \leq x \leq 1$, bring about a reconciliation with probability $\sqrt{x}$. The promoter stands to make $\$ 750$ from each successful concert. How much should he spend on flowers?

$$
\begin{gathered}
P=\left(\begin{array}{cc}
1 / 2 & 1 / 2 \\
\sqrt{x} & 1-\sqrt{x}
\end{array}\right) \\
\lambda_{1}=\lambda_{1} / 2+\sqrt{x} \lambda_{2} \\
\lambda_{2}=\lambda_{1} / 2+(1-\sqrt{x}) \lambda_{2} \\
\lambda_{1}+\lambda_{2}=1 \\
\lambda_{1}=\frac{2 \sqrt{x}}{2 \sqrt{x}+1}, \lambda_{2}=\frac{1}{2 \sqrt{x}+1} \\
\frac{1}{n} \sum_{k=0}^{n-1} f\left(X_{k}\right) \rightarrow 750 \lambda_{1}-1000 x \lambda_{2}=\frac{1500 \sqrt{x}-1000 x}{2 \sqrt{x}+1} \\
x=1 / 4, \mathbb{E}(f) \rightarrow \$ 250
\end{gathered}
$$

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