# Stochastic Processes

MATH 447

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# CONTENTS

We assume working knowledge of probability and no knowledge of measure theory (though a grasp of analysis is essential). See these MATH 356 notes, also taught by Louigi!

# I    Markov Chains

Conditional expectations will be important in this course. Recall $\mathbb{E}[X|Y = y_0]$, where $X, Y$ are random variables. If $Y$ is continuous, writing $\mathbb{E}[X|Y = y_0] = \frac{\mathbb{P}(X, Y=y_0)}{\mathbb{P}(Y=y_0)}$, will not work. Instead, we consider the slice of the joint density function $f(x, y)$ at $y = y_0$. The result is a one dimensional function $g(x)$ which may not have probability 1. Hence, we divide by $\int g(x)$ to make it into a density function:

$$\mathbb{E}[X|Y = y_0] = \int_{\mathbb{R}} \frac{f(x, y_0)}{\int_{\mathbb{R}} f(x, y_0)dx} x\, dx$$

DEF 1.1    We frequently write $f_{X|Y}(x) = f(x, y)/\int_{\mathbb{R}} f(x, y)dx$, and call this the *conditional density* of $X$ given $Y$. For fixed $y$, then, $\mathbb{E}[X|Y = y] = \mathbb{E}[Z]$, where $Z \sim f_{X|Y}$.

## INTRODUCTION

Before providing definitions, we give some examples of stochastic processes:

> **Eg. 1.1** A simple random walk: $S_{i+1} = S_i + X_i$, where $X_i \sim \text{Ber}(p)$ and $S_0 = 0$. We might ask: does $S_i$ ever return to 0, i.e.
>
> $$\mathbb{P}(\exists i > 0 : S_i = 0)$$
>
> **Eg. 1.2** A branching process: as in asexual reproduction, we have an initial node. Each node $n$ has a number of children $X_n$, where $\frac{X_n}{2} \sim \text{Ber}(p)$. We denote $Z_i$ to be the number of inidiuals in the $i$-th generation. We might ask: does $Z_i$ ever have no children, i.e.
>
> $$\mathbb{P}(\exists i > 0 : Z_i = 0)$$
>
> **Eg. 1.3** Choose $k$ independent random points in the square $[0, \sqrt{k}]^2$. On average, then, there is 1 point within any unit square $U \subseteq [0, \sqrt{k}]^2$.

DEF 1.2
DEF 1.3    Given a finite or countable set $V$, a *Markov chain* with *state space* $V$ is a sequence $X_n : n \geq 0$ of random variables, with $X_n \in V$, such that:

$$\mathbb{P}(\underbrace{X_{n+1} = v_{n+1}}_{\text{future}} | \underbrace{X_0 = v_0, ..., X_{n-1} = v_{n-1}}_{\text{past}}, \underbrace{X_n = v_n}_{\text{present}}) = \mathbb{P}(X_{n+1} = v_{n+1}|X_n = v_n)$$

In other words, the future only depends on the past via the present. This is called the DEF 1.4    *Markov property*.

Sometimes we allow Markov chains to be only finitely large (i.e. $0 \leq n \leq m$). For instance, we limit ourselves to one weekend of gambling in Las Vegas. A graphical example would look something like:



By repeated Bayes' Law, we observe

$$\mathbb{P}(X_1 = v_1, ..., X_n = v_n | X_0 = v_0)$$
$$= \mathbb{P}(X_1 = v_1 | X_0 = v_0) \cdot \mathbb{P}(X_2 = v_2 | X_0 = v_0, X_1 = v_1) \cdots \mathbb{P}(X_n = v_n | X_0 = v_0, ..., X_{n-1} = v_{n-1})$$
$$= \mathbb{P}(X_1 = v_1 | X_0 = v_0) \cdot \mathbb{P}(X_2 = v_2 | X_1 = v_1) \cdots \mathbb{P}(X_n = v_n | X_{n-1} = v_{n-1}) \quad \text{by Markov property}$$

## TIME-HOMOGENEOUS MARKOV CHAINS

We often write
THMC
We say that a Markov chain is *time-homogeneous* if, for all $u, v \in V$ and $n \geq 0$

$$\mathbb{P}(X_{n+1} = v | X_n = u) = \mathbb{P}(X_1 = v | X_0 = u)$$

In other words, the chain's behavior is described entirely by $\mathbb{P}(X_1 = v | X_0 = u)$ for each $(v, u) \in V \times V$. In this case, we can describe such probabilities in a *transition matrix* $P$:

$$P = \left( p_{u,v} \right)_{(u,v) \in V^2} = \left( \mathbb{P}(X_1 = v | X_0 = u) \right)_{(u,v) \in V^2}$$

---

**Eg. 1.4** Recall the game Snakes and Ladders. A $6 \times 6$ grid is indexed $1, ..., 36$. Players start at the 1 cell. The game ends when a player reaches the 36 cell. A die roll dictates how many spots one advances. The are some directed edges between cells (increasing: "ladders", decreasing: "snakes"). One must follow these edges when one lands at its tail. Suppose a ladder exists from 11 to 27. Then

$$\mathbb{P}(X_{11} = 27 | X_{10} = 6, X_9 = 3) = \frac{1}{6} = \mathbb{P}(X_{11} = 27 | X_{10} = 6) = \mathbb{P}(X_2 = 27 | X_1 = 6)$$

We see that Snakes and Ladders is naturally modeled as a time-homogeneous Markov chain.

**Eg. 1.5** Sampling without replacement is *not* a Markov chain. If we sample from

$|X| = 10$, we have

$$\mathbb{P}(X_3 = a \,|X_2 = b) = 1/9$$
$$\mathbb{P}(X_3 = a \,|X_2 = b, X_1 = c) = 1/8$$
$$\mathbb{P}(X_3 = a \,|X_2 = b, X_1 = a) = 0$$

so we do not satisfy the Markov property.

DEF 1.7

**Eg. 1.6** Returning to the Snakes and Ladders example, consider $S \subseteq V$. Let $T_S = \inf\{n \geq 0 : X_n \in S\}$, which we call the "*hitting time*" of $S$. We may ask...

- What is the average number of rounds to finite? We can write this as $\mathbb{E}[T_{\{36\}}|X_0 = 1]$.
- What is the probability of landing on 18 or 19 before the game ends? We can write this as $\mathbb{P}(T_{\{18,19\}} < T_{\{36\}}|X_0 = 1)$.
- What is the average number of visits to 6 before the game ends? We can write this as
$$\mathbb{E}[\#\{n \in [T_{\{36\}}] : X_n = 6\}|X_0 = 1]$$
- What is the expected proportion of time spent on state 5 before the game ends?
- If we allow two players, what is the probability that player 1 wins? Is this still a Markov chain?

DEF 1.8    A matrix $P = \left(p_{u,v}\right)_{(u,v)\in V^2}$ is called a *stochastic matrix* if every row sums to 1, i.e.

$$\forall\, u \in V, \sum_{v \in V} p_{u,v} = 1$$

Note that any stochastic matrix is the transition matrix of some time-homogeneous Markov chain with state space $V$ and transition probabilities

$$\mathbb{P}(X_{n+1} = v|X_n = u) = \mathbb{P}(X_1 = v|X_0 = u) = p_{u,v}$$

A directed graph, together with its stochastic matrix, can visualize any THMC:

**Eg. 1.7** Random walks on an undirected weighted graph, where edge weights dictate the proportional probability of transitioning between two states, are a special class of THMCs. In particular, given a graph $G = (V, E)$ with weights $w(e) > 0 : e \in E$, we set

$$p_{u,v} = \frac{w(\{u, v\})}{\sum_{z \in N(u)} w(\{u, z\})}$$

If there are no edges $u \leftrightarrow v$, we write $p_{u,v} = 0$.

Not every THMC can be represented by a random walk on an undirected weighted graph. In particular, see the directed graph listed above, or any transition matrix which is not symmetric.

As a concrete example, we can consider a random walk on the number line $\mathbb{Z}$, where, if $w(k, k+1) = \alpha$, $w(k-1, k) = \frac{\alpha}{2}$.

$$\cdots \overset{\frac{1}{16}}{\quad} -3 \overset{\frac{1}{8}}{\quad} -2 \overset{\frac{1}{4}}{\quad} -1 \overset{\frac{1}{2}}{\quad} 0 \overset{1}{\quad} 1 \overset{2}{\quad} 2 \overset{4}{\quad} 3 \overset{8}{\quad} \cdots$$

## *Multi-Step Transition Probabilities*

Given a THMC $X = X_n : n \geq 0$ with a transition matrix $P$, we write

$$\mathbb{P}(X_2 = v | X_0 = u) = \sum_{w \in V} \mathbb{P}(X_2 = v, X_1 = w | X_0 = u)$$

$$= \sum_{w \in V} \mathbb{P}(X_1 = w | X_0 = u) \mathbb{P}(X_2 = v | X_1 = w, \cancel{X_0 = u}) \quad \text{by Markov property}$$

$$= \sum_{w \in V} p_{u,w} p_{w,v} = (P^2)_{u,v} \quad \text{or write } P_{u,v}^2$$

Hence, to determine a two-step transition probability, and by extension an $n$-step transition probability from $u$ to $w$, we consider $P_{u,v}^n$.

**PROP 1.2**

**PROOF.**

See Prop 1.1 to expand probabilities, using Bayes', as needed. We get that

$$\mathbb{P}(X_n = v | X_0 = u) = \sum_{v_1, \ldots, v_{n-1} \in V} \mathbb{P}(X_1 = v_1, \ldots, X_{n-1} = v_{n-1}, X_n = v | X_0 = u)$$

$$= \sum_{v_1, \ldots, v_{n-1} \in V} p_{u,v_1} p(v_1, v_2) \cdots p(v_{n-1}, v) = (P^n)_{u,v} \quad \square$$

Thus, if $P$ is a stochastic matrix, then so is $P^n$.

**PROP 1.3**

**PROOF.**

$\sum_{v \in V} P_{u,v}^n = \sum_{v \in V} \mathbb{P}(X_n = v | X_0 = u) = 1.$ $\quad \square$

> **Theorem 1.1   Markov Property**
>
> If $X_n : n \geq 0$ is a THMC with state space $V$, then for all $u_0, ..., u_{n-1}, u, v \in V$,
>
> $$\mathbb{P}(X_{n+m} = v | X_0 = u_0, ..., X_{n-1} = u_{n-1}, X_n = u) = \mathbb{P}(X_{n+m} = v | X_n = u) = P_{u,v}^m$$

PROOF.

> One shows this by combining the Markov property with Prop 1.2 via induction.   □

Somewhat nonsensically, we *also* call this the Markov property. When talking about THMCs, this will be the default notion.

DEF 1.9   We say that a Markov chain has an *initial distribution* $\alpha = (\alpha_v : v \in V)$ if $\mathbb{P}(X_0 = v) = \alpha_v$ for each $v \in V$. If this is the case, we often write $\alpha$ as a subscript of our state probabilities. For instance,

$$\mathbb{P}_\alpha(X_n = v) = \sum_{u \in V} \mathbb{P}_\alpha(X_0 = u, X_n = v) = \sum_{u \in V} \mathbb{P}_\alpha(X_0 = u)\mathbb{P}_\alpha(X_n = v | X_0 = u) = \sum_{u \in V} \alpha_u P_{u,v}^n$$

PROP 1.4   For any event $E$ depending only on $X_0, ..., X_n$, with $\mathbb{P}(X_n = u, E) > 0$, we have

$$\mathbb{P}(X_{n+m} = v | X_n = u, E) = P_{u,v}^m$$

PROOF.

> For any such event $E$, we can determine whether $E$ occurs exactly when we know the realized values $u_i$ of $X_i$ for $i = 1, ... n - 1$. Hence, we may write $\mathcal{S}$ to be the set of tuples $(u_0, ..., u_{n-1})$ that guarantee $E$. It follows that
>
> $$\mathbb{P}(X_n = u, E) = \sum_{\mathbf{s} \in \mathcal{S}} \mathbb{P}(\mathbf{x} = \mathbf{s}, X_n = u)$$
>
> Similarly, we have
>
> $$\mathbb{P}(X_{n+m} = v, X_n = u, E) = \sum_{\mathbf{s} \in \mathcal{S}} \mathbb{P}(X_{n+m} = v, X_n = u, \mathbf{x} = \mathbf{s})$$
> $$= \sum_{\mathbf{s} \in \mathcal{S}} \mathbb{P}(X_{n+m} = v | X_n = u, \mathbf{x} = \mathbf{s})\mathbb{P}(X_n = u, \mathbf{x} = \mathbf{s})$$
> $$= P_{u,v}^m \sum_{\mathbf{s} \in \mathcal{S}} \mathbb{P}(X_n = u, \mathbf{x} = \mathbf{s}) = P_{u,v}^m \mathbb{P}(X_n = u, E)$$
>
> Divide and use Bayes, and the result follows.   □

PROP 1.5   If $X$ is a THMC with transition matrix $P$, then, for all $k \geq 1$, $X_{kn} : n \geq 0$ is a THMC with transition matrix $P^k$.

For any $n \neq 0$, any sequence $u_0, ..., u_{n+1} \in V$ satisfies

$$\mathbb{P}(X_{(n+1)k} = u_{n+1} | X_0 = u_0, X_k = u_1, ..., X_{nk} = u_n) = P^k_{u_n, u_{n+1}} \qquad \square$$

**Theorem 1.2    Chapman-Kolmogorov**

For any Markov chain $X$ with state space $V$, any $m, n \geq 0$, and $u, v \in V$,

$$\mathbb{P}(X_{m+n} = v | X_0 = u) = \sum_{w \in V} \mathbb{P}(X_n = w | X_0 = u)\mathbb{P}(X_{m+n} = v | X_n = w)$$

If the $X$ is time homogeneous, then this is $P^{n+m}_{u,v}$, which agrees with Prop 1.2.

## *Long Term Behavior*

Recall from probability the *law of large numbers*: if $Y_n : n \geq 1$ are IID with common mean $\mu$, then $\frac{S_n}{n} \to \mu$ in probability, where $S_n = \sum_{i=1}^n Y_i$, i.e. $\forall \varepsilon > 0$,

$$\limsup_{n \to \infty} \mathbb{P}\left( \left| \frac{S_n}{n} - \mu \right| > \varepsilon \right) = 0$$

If $Y_i \in \mathbb{Z}$ then, for $k, \ell, u_i \in \mathbb{Z}$ and $i = 1, ..., n-1$,

$$\begin{aligned}
\mathbb{P}(S_{n+1} = \ell | S_n = k, S_i = u_i \; \forall i) &= \mathbb{P}(Y_{n+1} = \ell - k | S_n = k, S_i = u_i \; \forall i) \\
&= \mathbb{P}(Y_{n+1} = \ell - k | Y_1 = u_1 - u_0, Y_2 = u_2 - u_1, ..., Y_n = k - u_{n-1}) \\
&= \mathbb{P}(Y_{n+1} | \ell - k) = \mathbb{P}(Y_1 = \ell - k) = P_{k,\ell}
\end{aligned}$$

where $S_n : n \geq 0$ has transition matrix $P$, noting that it may be viewed as a THMC.

From now on, we denote by $\mathbb{P}_v(E)$ the probability $\mathbb{P}(E|v)$.

**Eg. 1.8** A general two-state chain, with states $A$ and $B$, can be described by

$$P = \begin{pmatrix} 1 - \alpha & \alpha \\ \beta & 1 - \beta \end{pmatrix}$$

Let $q_n = \mathbb{P}_A(X_n = A) = \mathbb{P}(X_n = A | X_0 = A)$. Then

$$\begin{aligned}
q_{n+1} &= \mathbb{P}_A(X_{n+1} = A, X_n = A) + \mathbb{P}_A(X_{n+1} = A, X_n = B) \\
&= \mathbb{P}_A(X_{n+1} = A | X_n = A)\mathbb{P}_A(X_n = A) + \mathbb{P}_A(X_{n+1} = A | X_n = B)\mathbb{P}_A(X_n = B) \\
&= (1 - \alpha)q_n + \beta(1 - q_n) = \beta + (1 - \alpha - \beta)q_n
\end{aligned}$$

This recurrence has a unique solution. In particular, one can find

$$q_n = \frac{\beta}{\alpha + \beta} + (1 - \alpha - \beta)^n \frac{\alpha}{\alpha + \beta}$$

It follows that $q_n \to \frac{\beta}{\alpha+\beta}$, and hence $\mathbb{P}_A(X_n = B) = 1 - q_n \to \frac{\alpha}{\alpha+\beta}$. Likewise:

$$\mathbb{P}_B(X_n = B) = \frac{\alpha}{\alpha + \beta} + (1_\alpha - \beta)^n \frac{\beta}{\alpha + \beta}$$

So $\mathbb{P}_B(X_n = B) \to \frac{\alpha}{\alpha+\beta}$.

Let $\pi := (\pi_A, \pi_B) := \left(\frac{\beta}{\alpha+\beta}, \frac{\alpha}{\alpha+\beta}\right)$ be the distribution of our initial state $X_0$, Then

$$\mathbb{P}_\pi(X_1 = A) = \pi_A \mathbb{P}_A(X_1 = A) + \pi_B \mathbb{P}_B(X_1 = A) = \pi_A$$

and, similarly, $\mathbb{P}_\pi(X_1 = B) = \pi_B$. Hence, if $X_0$ has initial distribution $\pi$, then $X_1$ also has distribution $\pi$. By induction, $X_n$ has distribution $\pi$ $\forall n \geq 0$.

When we say $X = \text{Markov}(P)$, we mean that $X$ is a THMC with transition matrix $P$.

DEF 1.11    A probability distribution $\pi$ is called *stationary* if $\pi P = \pi$. Similarly, a probability
DEF 1.12    distribution $\lambda$ is called a *limiting distribution* if, for each $u, v \in V$

$$(P^n)_{u,v} \to \lambda_v \text{ as } n \to \infty$$

In other words, $\mathbb{P}_u(X_n = v) \to \lambda_v$. Note that, for any initial distribution $\alpha$, we have $\alpha P^n \to \lambda$, i.e. $(\alpha P^n)_v \to \lambda_v$, where $\lambda$ is limiting.

PROP 1.6    If $\lambda$ is a limiting distribution for $P$, then $\lambda$ is stationary for $P$.

PROOF.

Fix any initial distribution $\alpha$, we have

$$\lambda = \lim_{n\to\infty}(\alpha P^n) = \lim_{n\to\infty}(\alpha P^{n-1}P) = \left(\lim_{n\to\infty}\alpha P^{n-1}\right)P = \lambda P \qquad \square$$

Stationary distributions need not be unique, but limiting distributions are (as the limit $\lim_{n\to\infty}\alpha P^n$ is well-defined). In general, then, stationary distributions need not be limiting distributions.

When $n = 0, P^n = I$, which encapsulates the idea that, at timestep 0, we will be at our initial positions.

DEF 1.13    A stochastic matrix $P$ is called *regular* if $\exists n \geq 1$ such that $P^n > 0$ on all entries.

> **Theorem 1.3    Fundamental Theorem of Markov Chains**
>
> Every regular stochastic matrix $P$ has a limiting distribution $\pi$.

Incorporating some of the formulations above, this is equivalent to saying: *For a regular stochastic matrix, there exists a unique distribution $\pi = (\pi_v : v \in V)$ such that $\pi P = \pi$ and $\mathbb{P}_u(X_n = v) \to \pi_v$ $\forall u, v \in V$.*

In this case, there is a unique stationary distribution, and it is the unique limiting distribution.

### A stationary distribution always exists!

Let $\rho = \langle 1, ..., 1 \rangle$. Then note that $P\rho = \rho$, since the sum of any row in $P$ must be 1. Hence, $P$ has eigenvalue 1. It follows that it has a left eigenvector, i.e. $\pi : \pi P = \pi$. This is exactly a stationary distribution, as long as we scale suitably such that $\pi$ is a distribution.

However, then process of scaling into a distribution is non-trivial. Since $\pi$ may have negative coordinates, and hence $\sum \pi_i = 0$, we must consider instead $|\pi|$, i.e. prove it is also an eigenvalue.

*This is true, but requires the fact that $P$ is stochastic*

## Periodicity of States

For $u, v \in V$, we say that $v$ is *accessible* from $u$ if $\exists n \geq 0$ such that $(P^n)_{u,v} > 0$. Equivalently, in the directed graph generated by $P$, there is a directed path from $u$ to $v$. When $v$ is accessible from $u$, we write $u \to v$.

DEF 1.14

States $u$ and $v$ *communicate* if $u \to v$ and $v \to u$. When $u$ and $v$ communicate, we write $u \leftrightarrow v$. Observe that communication is a equivalence relation. Hence, the state space $V$ can be written as a disjoint union of mutually-communicating states, called a *communication class*. Note that, in the directed graph generated by $P$, these correspond to the strongly connected components.

DEF 1.15

DEF 1.16

*Clearly, if $P$ is regular, then it is irreducible*

We say that $P$ is *irreducible* if there is only one communication class.

DEF 1.17

$$u \to v \iff \mathbb{P}_u(T_{\{v\}} < \infty) > 0.$$

PROP 1.7

The *period* of a state $u \in V$ is

DEF 1.18

$$d(u) := \gcd(n > 0 : P_{u,u}^n > 0)$$

If $d(u) = 1$, we call $u$ *aperiodic*. By extension, $P$ is aperiodic if $d(u) = 1 \ \forall u \in V$, and $X$ is aperiodic if $X = \text{Markov}(P)$ for $P$ aperiodic.

DEF 1.19

If $u \leftrightarrow v$, then $d(u) = d(v)$.

PROP 1.8

PROOF.

Let $I = \{n > 0 : P_{u,u}^n > 0\}$, and similarly $J$ for $v$. Hence, $d(u) = \gcd(I)$ and $d(v) = \gcd(J)$. Let $a, b > 0$ such that $P_{u,v}^a > 0$ and $P_{v,u}^b > 0$. Then

$$P_{u,u}^{a+b} \geq P_{u,v}^a P_{v,u}^b > 0$$

$\implies a + b \in I$, so $d(u)|a + b$. Now, if $n \in J$, then

$$P_{u,u}^{a+b+n} \geq P_{u,v}^a P_{v,v}^n P_{v,u}^b > 0$$

$\implies a + b + n \in I$, so $d(u)|n + a + b$. But, by the previous line, $d(u)|n$. Since $n \in J$ is arbitrary, we can write $d(u)| \gcd(J) = d(v)$.

Symmetrically, we could conclude that $d(v)|d(u)$, so indeed $d(v) = d(u)$. □

Let $I = \{n > 0 : P_{u,u}^n > 0\}$. If $\gcd(I) = 1$, then $\exists a, b \in I$ such that $\gcd(a, b) = 1$.

PROP 1.9

PROOF.

This is not true for any $I$ (and thus relies not only on number theory). Let $\ell, m \in I$, with $\ell < m$. Let $k = m - \ell$. If $k = 1$, then $\gcd(\ell, m) = 1$. Otherwise, since $\gcd(I) = 1$, there is an $n \in I$ with $k \nmid n$. We then write $n = qk + r$, with $r \in [k - 1]$. Then $m' \in (q + 1)m \in I$, since $P_{u,u}^{(q+1)m} \geq (P_{u,u}^m)^{q+1}$. Symmetrically, we can argue $\ell' = (q + 1)\ell \in I$.

Similarly, $\ell^* := \ell' + n \in I$, since $P_{u,u}^{\ell'+n} \geq P_{u,u}^{\ell'} P_{u,u}^n$. We have

$$m' - \ell^* = (q+1)m - (q+1)\ell - n = (q+1)(m-\ell) - n$$
$$= (q+1)k - n = k - r \in [k-1]$$

TODO...                                                                                    □

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**Theorem 1.4   Postage Stamp Lemma**

If $P$ is irreducible and aperiodic, then $\forall u, v \in V, \exists N$ such that $P_{u,v}^n > 0 \ \forall n \geq N$.

---

Before proving this, we note that, for $a, b \geq 1$ with $\gcd(a, b) = 1$, then for any $q \geq ab$, we can write $q = ja + kb$ for integers $j, k \geq 0$.

PROOF.

Fix $u, v \in V$. Since $P$ is aperiodic, there are $a, b \geq 1$ with $P_{u,u}^a, P_{u,u}^b > 0$ and $\gcd(a, b) = 1$, by Prop 1.9. Since $P$ is irreducible, there is some $m > 0$ with $P_{u,v}^m > 0$. Thus, let $N = m + ab$. For any $n \geq N$, let $q = n - m$. We have that $q \geq ab$, so we can find $j, k \geq 0$ with $q = ja + kb$. Then

$$P_{u,v}^n = P_{u,v}^{q+m} = P_{u,v}^{ja+kb+m} \geq P_{u,u}^{ja} P_{u,u}^{kb} P_{u,v}^m \geq (P_{u,u}^a)^j (P_{u,u}^b)^k P_{u,v}^m$$

All are positive, so $P_{u,v}^n > 0$, as desired.                                          □

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**Theorem 1.5   Characterization of Regular Markov Chain**

Let $P = (p_{u,v})_{u,v \in V}$ be a stochastic matrix, where $|V| < \infty$. Then

$$P \text{ is regular} \iff P \text{ is irreducible and aperiodic}$$

---

PROOF.

We first note why finiteness is necessary. Consider:



with all edges having weight 1. This graph is clearly aperiodic and irreducible, but not regular.

($\implies$) We start with the "easy" direction. If $P$ is regular, then $\exists n > 0$ s.t. $P_{u,v}^n > 0$ for all $u, v \in V$. Then, for all $u, v \in V$, we have $u \to v$ and $v \to u$. Hence, $P$ is irreducible. Now, if $P$ is irreducible, then for all $u \in V$, there is some $v \in V$ such that $P_{v,u} > 0$ (think about this in graph theoretic terms). Then, let $n > 0$ be such that $P_{u,u}^n$ is positive. We have

$$P_{u,u}^{n+1} \geq P_{u,v}^n P_{u,v} > 0$$

So, with $I = \{m > 0 : P_{u,u}^m > 0\}$, $d(u) = \gcd(I) \leq \gcd(n, n+1) = 1$. It follows that

$d(u) = 1$, so $u$ is aperiodic (and hence $P$ is aperiodic).

( $\Longleftarrow$ ) By Thm 1.4, for each $u, v \in V$, there exists $N : P_{u,v}^n > 0 \; \forall n \geq N$. Let $N^*$ be the maximum value of $N$ determined over all pairs $(u, v) \in V^2$. Then, for $n \geq N^*$ and all $u, v \in V$, $P_{u,v}^n > 0$. It follows that all entries of $P^n$ are positive, and we are done. $\qquad \square$

## *Finding Stationary Distributions*

Recall that $x = (x_v : v \in V)$ is a stationary distribution if $xP = x$. Let $V$ be finite. Then, for a stationary distribution $x$, we have

$$x_1 p_{1,1} + \cdots + x_n p_{n,1} = x_1$$
$$x_1 p_{1,2} + \cdots + x_n p_{n,2} = x_2$$
$$\vdots$$
$$x_1 p_{1,n} + \cdots + x_n p_{n,n} = x_n$$

We have $n$ equations, $n$ unknowns, and a homogeneous system, so there is not a unique solution. If

$$P = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0.5 & 0.5 \\ 0.5 & 0 & 0.5 \end{pmatrix}$$

We can compute $x = \langle t, 2t, 2t \rangle$. But, noting that $x$ is a probability distribution, and hence $5t = 1$, this yields $x = \langle 1/5, 2/5, 2/5 \rangle$. We'll consider some special cases.

UNDIRECTED GRAPHS

This is distinct from Example 1.7

Let $G = (V, E)$ be undirected. Then we define a THMC by

$$P_{u,v} = \begin{cases} \frac{1}{\deg(u)} & \{u, v\} \in E \\ 0 & \text{o.w.} \end{cases}$$

Let $x = (\deg(v) : v \in V)$. We have

$$(xP)_v = \sum_{u \in V} \deg(u) P_{u,v} = \sum_{u \in N(v)} \deg(u) \cdot \frac{1}{\deg(u)}$$
$$= \deg(v)$$

Hence, $xP = x$. Recalling that $\sum_{v \in V} \deg(v) = 2|E|$, we conclude that

$$\left( \frac{\deg(v)}{2|E|} : v \in V \right)$$

is a stationary distribution.

UNDIRECTED WEIGHTED GRAPHS

Let $G = (V, E)$ be undirected. Then, we define a THMC by

This is not distinct from Example 1.7

$$P_{u,v} = \begin{cases} \frac{w(\{u,v\})}{\sum_{z \in N(u)} w(\{u,z\})} & v \in N(u) \\ 0 & \text{o.w.} \end{cases}$$

Let $x = (\sum_{e:e \ni v} w(e) : v \in V)$. Then we can compute $xP = x$, and similar to above,

$$x = \left( \frac{\sum_{e:e \ni v} w(e)}{2 \sum_{e \in E} w(e)} : v \in V \right)$$

is a stationary distribution.

## Transience and Recurrence

DEF 1.20
Recall $T_S = \inf\{n \geq 0 : X_n \in S\}$, the "hitting time" of $S$. We let $R_S = \inf\{n > 0 : X_n \in S\}$. Note that if $T_S > 0$, $T_S = R_S$. Otherwise, $R_S$ gives the first "*return time*" to the set $S$.

DEF 1.21
DEF 1.22
A state $v \in V$ is called *recurrent* if $\mathbb{P}_v(R_{\{v\}} < \infty) = 1$. If all states of $v$ are recurrent, we may $P$ and $X = \text{Markov}(P)$ recurrent. Otherwise, we call $v$ *transient*, and similarly extend the notion to the transition matrix and chain when all state are transient.

DEF 1.23
For a given state $v \in V$, we call $L_v = |\{n \geq 0 : X_n = v\}|$ the *local time* of $v$. This notion is not probabilistic: we simply consider a realized walk on the chain (or a part of the chain). Note that, if $v = X_j$ and $v$ is recurrent, then $L_v = \infty$.

PROP 1.10
Let $X = \text{Markov}(P)$. For any state $v \in V$ and $k > 1$,

Intuitively, if $L_v > k$ when $X_0 = v$, then $L_v > k - 1$ when $X_{i_1} = v$, where $i_1$ is the first time we return to $v$.

$$\mathbb{P}_v(L_v > k) = \mathbb{P}_v(L_v > 1)^k$$

PROOF.

Using the law of total probability:

$$\mathbb{P}_v(L_v > k) = \mathbb{E}\left[\mathbb{P}_v(L_v > k | R_v)\right] = \sum_{t=1}^{\infty} \mathbb{P}_v(R_v = t)\mathbb{P}_v(L_v > k | R_v = t)$$

$$= \sum_{t=1}^{\infty} \mathbb{P}_v(R_v = t)\mathbb{P}_v(L_v > k | R_v = t, X_t = v)$$

As $R_v = t \iff R_v = t \wedge X_t = v$

$$= \sum_{t=1}^{\infty} \mathbb{P}_v(R_v = t)\mathbb{P}_v(L_v > k - 1)$$

$$= \mathbb{P}_v(L_v > k - 1) \sum_{t=1}^{\infty} \mathbb{P}_v(R_v = t)$$

$$= \mathbb{P}_v(L_v > k - 1)\mathbb{P}_v(R_v < \infty) = \mathbb{P}_v(L_v > k - 1)\mathbb{P}_v(L_v > 1)$$

The result follows by induction.                                                                $\square$

$$\mathbb{P}_v(L_v = \infty) = \begin{cases} 1 & v \text{ recurrent} \\ 0 & v \text{ transient} \end{cases}$$

This follows directly from Prop 1.10 + monotonicity of probability. □

$$\sum_{n=0}^{\infty} P_{v,v}^n = \begin{cases} \infty & v \text{ recurrent} \\ \frac{1}{1 - \mathbb{P}_v(R_{\{v\}} < \infty)} & v \text{ transient} \end{cases}$$

This follows from linearity of expectation, and the fact that, for a non-negative integer variable $Z$,

$$\mathbb{E}[Z] = \sum_{k=0}^{\infty} \mathbb{P}(Z > k)$$

In particular... [TODO] □

If $u \leftrightarrow v$, then $u$ is transient $\iff$ $v$ is transient.
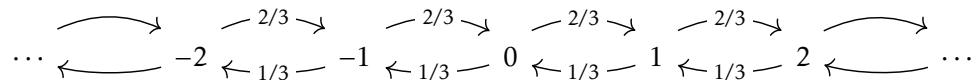
Fix $a, b \geq 0$ with $P_{u,v}^a, P_{v,u}^b > 0$. Then

$$\sum_{n=0}^{\infty} P_{v,v}^n \geq \sum_{n=0}^{\infty} P_{v,v}^{a+b+n} = \sum_{n=0}^{\infty} P_{v,u}^b P_{u,u}^n P_{u,v}^a$$

$$= P_{v,u}^b P_{u,v}^a \sum_{n=0}^{\infty} P_{u,u}^n$$

Thus, if $v$ is transient, then $\sum_{n=0}^{\infty} P_{v,v}^n < \infty$, so it must be that $\sum_{n=0}^{\infty} P_{u,u}^n < \infty$, i.e. $u$ is transient. The argument is identical in reverse. □

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**Eg. 1.9** If $u \leftrightarrow v$ and $u$ is recurrent, then $\mathbb{P}_u(T_{\{v\}} < \infty) = 1$.

**Eg. 1.10** The following chain is completely transient:



In fact, we could replace ⅔ by $p$, and ⅓ by $1 - p$. In this case, the chain is irreducible. To see that it is transient, we have

$$P_{0,0}^{2n} = \binom{2n}{n} p^n (1-p)^n$$

Then

$$\sum_{n=0}^{\infty} P_{0,0}^{2n} < \sum_{n=0}^{\infty} 2^{2n} p^n (1-p)^n = \sum_{n=0}^{\infty} (4p(1-p))^n < \infty \quad \text{if } p \neq \frac{1}{2}$$

By <span style="color:crimson">Prop 1.12</span>. Notice that $\sum_{n=0}^{\infty} P_{0,0}^n = \sum_{n=0}^{\infty} P_{0,0}^{2n}$, since it is only possible to return on even-length cycles.

We conclude that the chain is transient when $p \neq \frac{1}{2}$.

**FACT**   Stirling's Formula provides

$$m! \sim \left(\frac{m}{e}\right)^m \sqrt{2\pi m}$$

in that

$$\lim_{m \to \infty} \frac{m!}{\left(\frac{m}{e}\right)^m \sqrt{2\pi m}} = 1$$

This fact implies

$$e\left(\frac{n}{e}\right)^n \leq n! \leq \frac{e(n+1)}{4}\left(\frac{n+1}{e}\right)^n$$

These facts, though out of the scope of this course, can be derived from a careful treatment of Reimann sums

**Eg. 1.11**   We return to the previous example, letting $p = \frac{1}{2}$. Then

$$\sum_{n=0}^{\infty} P_{0,0}^{2n} = \sum_{n=0}^{\infty} \frac{(2n)!}{(n!)^2}[p(1-p)]^n \sim \sum_{n=0}^{\infty} \frac{\left(\frac{2n}{e}\right)^{2n}\sqrt{2\pi(2n)}}{\left[\left(\frac{n}{e}\right)^n \sqrt{2\pi n}\right]^2}[p(1-p)]^n$$

$$= \sum_{n=0}^{\infty} \frac{[4p(1-p)]^n}{\sqrt{\pi n}} = \sum_{n=0}^{\infty} \frac{1}{\sqrt{\pi n}} = \infty$$

We conclude that the chain is recurrent when $p = \frac{1}{2}$.

**PROP 1.14**   If $V$ is finite, then there is at least one recurrent state.

**PROOF.**

Fix an initial distribution $\alpha = (\alpha_v : v \in V)$. Then $\mathbb{P}_\alpha \left( \sum_{v \in V} L_v = \infty \right) = 1$. We conclude

that there is at least one state $v \in V$ with $\mathbb{P}_\alpha(L_v = \infty) > 0$. But also:

$$
\begin{aligned}
\mathbb{P}_\alpha(L_v = \infty) &= \sum_{n=0}^\infty \mathbb{P}_\alpha(L_v = \infty, T_v = n) = \sum_{n=0}^\infty \mathbb{P}_\alpha(L_v = \infty | T_v = n)\mathbb{P}_\alpha(T_v = n) \\
&= \sum_{n=0}^\infty \mathbb{P}_\alpha(L_v = \infty | T_v = n, X_n = v)\mathbb{P}_\alpha(T_v = n) \\
&= \sum_{n=0}^\infty \mathbb{P}_\alpha(L_v = \infty | X_n = v)\mathbb{P}_\alpha(T_v = n) \\
&= \sum_{n=0}^\infty \mathbb{P}_v(L_v = \infty)\mathbb{P}_\alpha(T_v = n)
\end{aligned}
$$

So $\mathbb{P}_v(L_v = \infty) > 0 \implies \mathbb{P}_v(L_v = \infty) = 1$, by Prop 1.11. □

Finite, irreducible chains are recurrent. **PROP 1.15**

**PROOF.**

Since the chain is finite it has at least one recurrent state, by Prop 1.14. Then all states must be recurrent, since the chain is irreducible, by Prop 1.13. □

## Canonical Decompositions

Fix a transition matrix $P$ and list the communication classes of $V$ as

$$D_1, D_2, \ldots \quad \text{(transient)} \qquad C_1, C_2, \ldots \quad \text{(recurrent)}$$

Note that we can split the chain up in this way by Prop 1.13. Set $D = \cup_{i \geq 0} D_i$. Then the *canonical decomposition* of the chain is defined to be **DEF 1.24**

$$D \sqcup C_1 \sqcup C_2 \sqcup \cdots$$

We say that a communication class $C$ is *closed* if, for any $u \in C, v \notin C, p_{u,v} = 0$. Intuitively, **DEF 1.25** if $X_0 \in C$, or we enter $C$ at some later time, we will never leave $C$.

If $C$ is a recurrent communication class, then $C$ is closed. **PROP 1.16**

# INDEX OF DEFINITIONS