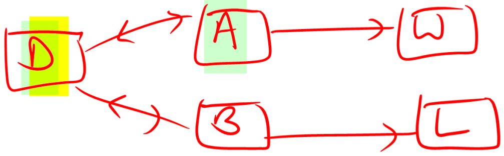
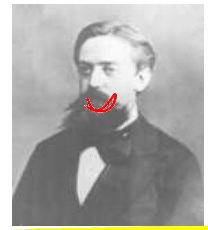


$X_0 = D$
$X_1 = A$
$X_2 = D$ etc.

Chapter 5: Markov Chains

it only matters where you are, not where you've been...

5.1 Introduction



A.A.Markov
1856-1922

So far, we have examined several stochastic processes using transition diagrams and First-Step Analysis.
The processes can be written as $\{X_0, X_1, X_2, \ldots\}$,
where X_t is the state at time t.

On the transition diagram, X_t corresponds to which box we are in at step t.

In the Gambler's Ruin (Section 2.7), X_t is the amount of money the gambler possesses after toss t. In the model for gene spread (Section 3.7), X_t is the number of animals possessing the harmful allele A in generation t.

The processes that we have looked at via the transition diagram have a crucial property in common: X_{t+1} depends only on X_t.

It does not depend upon $X_0, X_1, \ldots, X_{t-1}$.

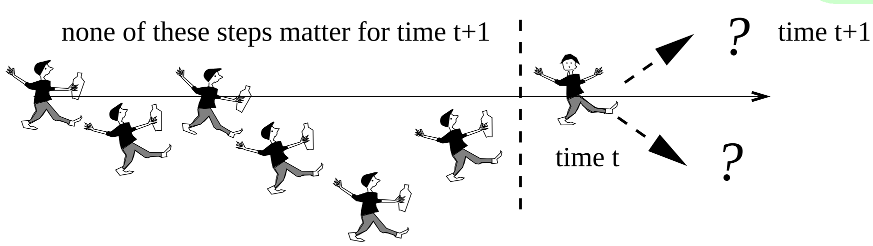
} Markov Property.

Processes like this are called Markov Chains.

$X_0 \quad X_1 \quad X_2 \quad X_3 \quad X_4$

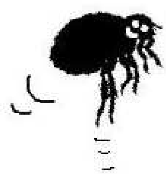
(compare with IID random variables where none depend on any others)

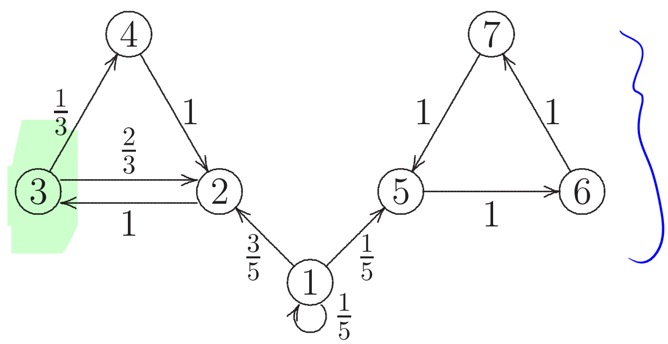
Example: Random Walk (see Chapter 7)



In a Markov Chain, the future depends only upon the present:
NOT upon the past.

The text-book image of a Markov chain has a flea hopping about at random on the vertices of the transition diagram, according to the probabilities shown.





The transition diagram above shows a system with 7 possible states:

State space, $S = \{1, 2, 3, 4, 5, 6, 7\}$.

Questions of interest

Ch2
- Starting from state 1, what is the probability of ever reaching state 7?

Ch3
- Starting from state 2, what is the expected time taken to reach state 4?

Ch6
- Starting from state 2, what is the long-run proportion of time spent in state 3? Equilibrium:

Ch5
- Starting from state 1, what is the probability of being in state 2 at time t? Does the probability converge as $t \to \infty$, and if so, to what?

Ch 6

We have been answering questions like the first two using first-step analysis since the start of STATS 325. In this chapter we develop a unified approach to all these questions using the matrix of transition probabilities, called the transition matrix.

5.2 Definitions

The Markov chain is the process $X_0, X_1, X_2, \dots$

Definition: The **state** of a Markov chain at time t is the value of X_t.

For example, if $X_t = 6$, we say the process is in state 6 at time t.

Definition: The **state space** of a Markov chain, S, is the set of values that each X_t can take. For example, $S = \{1, 2, 3, 4, 5, 6, 7\}$.

Let S have size N (possibly infinite).

"path"

Definition: A **trajectory** of a Markov chain is a particular set of values for $X_0, X_1, X_2, \dots$

For example, if $X_0 = 1$, $X_1 = 5$, and $X_2 = 6$, then the trajectory up to time $t = 2$ is 1, 5, 6.

More generally, if we refer to the trajectory $s_0, s_1, s_2, s_3, \dots$, we mean that $X_0 = s_0$, $X_1 = s_1$, $X_2 = s_2$, $X_3 = s_3$, ...

'Trajectory' is just a word meaning "path".

Markov Property

The basic property of a Markov chain is that only the most recent point in the trajectory affects what happens next.

This is called the Markov Property.
It means that X_{t+1} depends on X_t, but it does NOT depend on $X_{t-1}, X_{t-2}, \dots, X_1, X_0$ (if X_t is known).

Remember p. 29 : we said $\mathbb{P}_D(V \mid A) = \mathbb{P}(V \mid A)$

this was ignored because of Markov property.

We formulate the Markov Property in mathematical notation as follows:

most recent part of history is used

$$\boxed{\mathbb{P}(X_{t+1} = s \,|\, X_t = s_t, X_{t-1} = s_{t-1}, \ldots, X_0 = s_0) \;=\; \mathbb{P}(X_{t+1} = s \,|\, X_t = s_t),}$$

rest of history is ignored.

for all $t = 1, 2, 3, \ldots$ and for all states $s_0, s_1, \ldots, s_t, s$.

Explanation:

$$\mathbb{P}(X_{t+1} = s \quad | \quad X_t = s_t, \quad \underbrace{\cancel{X_{t-1} = s_{t-1}, X_{t-2} = s_{t-2}, \ldots, X_1 = s_1, X_0 = s_0}}\,)$$

distribution of X_{t+1} ...

... depends on X_t

... but whatever happened before time t doesn't matter.

Definition: Let $\{X_0, X_1, X_2, \ldots\}$ be a sequence of discrete random variables. Then $\{X_0, X_1, X_2, \ldots\}$ is a <u>**Markov chain**</u> if it satisfies the Markov property:

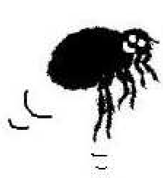
$$\mathbb{P}(X_{t+1} = s \mid X_t = s_t, \ldots, X_0 = s_0) = \mathbb{P}(X_{t+1} = s \mid X_t = s_t)$$

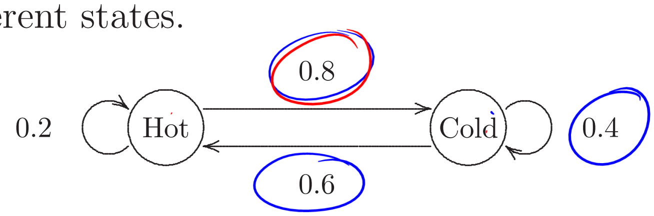
for all $t = 1, 2, 3, \ldots$ and for all states $s_0, s_1, \ldots, s_t, s$.

5.3 The Transition Matrix

"transition" = "movement"

We have seen many examples of <u>**transition diagrams**</u> to describe Markov chains. The transition diagram is so-called because it shows the <u>transitions</u> between different states.





We can also summarize the probabilities in a <u>**matrix:**</u>

X_{t+1} (next state)

$$\begin{array}{cc} & \begin{array}{cc} \text{Hot} & \text{Cold} \end{array} \\ X_t \text{ (current state)} \left\{ \begin{array}{c} \text{Hot} \\ \text{Cold} \end{array} \right. & \begin{pmatrix} 0.2 & 0.8 \\ 0.6 & 0.4 \end{pmatrix} \begin{array}{l} \leftarrow \text{sum to } 1 \\ \leftarrow \text{sum to } 1 \end{array} \end{array}$$

The matrix describing the Markov chain is called the transition matrix.
It is the most important tool for analysing Markov chains.

Transition Matrix

$$
\begin{array}{ccc}
 & \overbrace{\longleftarrow \text{ list all states } \longrightarrow}^{X_{t+1} \quad \text{To}} & \\
\text{From } X_t \left\{ \begin{array}{c} \text{list} \\ \text{all} \\ \text{states} \end{array} \right. \Big\updownarrow & \left(\begin{array}{c} \texttt{insert} \\ \texttt{probabilities} \\ p_{ij} \end{array} \right) & \begin{array}{l} \longleftarrow \text{rows add to 1} \\ \longleftarrow \text{rows add to 1} \end{array}
\end{array}
$$

The transition matrix is usually given the symbol $P = (p_{ij})$ (matrix of probabilities)

In the transition matrix P:

- the ROWS represent NOW, or FROM (X_t).
- the COLUMNS represent NEXT, or TO (X_{t+1}).
- entry (i, j) is the CONDITIONAL probability that NEXT $= j$ given that NOW $= i$: the prob. of going FROM state i TO state j.

$$\boxed{p_{ij} = \mathbb{P}(X_{t+1} = j \mid X_t = i) = \mathbb{P}_{X_t = i}(X_{t+1} = j)}$$

Notes: 1. The transition matrix P must list *all* possible states in the state space S.

2. P is a *square matrix* $(N \times N)$, because X_{t+1} and X_t both take values in the same state space S (of size N).

3. The <u>**rows**</u> of P should each sum to 1:

arrows out of any box always sum to 1

$$\sum_{j=1}^{N} p_{ij} = \sum_{j=1}^{N} \mathbb{P}(X_{t+1} = j \mid X_t = i) = \sum_{j=1}^{N} \mathbb{P}_{\{X_t = i\}}(X_{t+1} = j) = 1.$$

This simply states that X_{t+1} *must* take one of the listed values.

4. The <u>**columns**</u> of P do <u>**not**</u> in general sum to 1.

might do by chance.

Definition: Let $\{X_0, X_1, X_2, \ldots\}$ be a Markov chain with state space S, where S has size N (possibly infinite). The **transition probabilities** of the Markov chain are

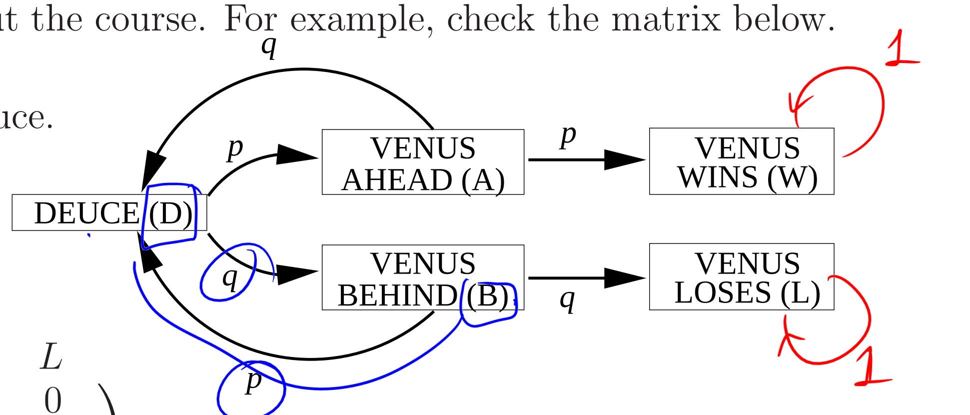
$$p_{ij} = \mathbb{P}(X_{t+1} = j \mid X_t = i) \quad \text{for } i, j \in S, \quad t = 0, 1, 2, \ldots$$

Definition: The **transition matrix** of the Markov chain is $P = (p_{ij})$.

5.4 Example: setting up the transition matrix

We can create a transition matrix for any of the transition diagrams we have seen in problems throughout the course. For example, check the matrix below.

Example: Tennis game at Deuce.

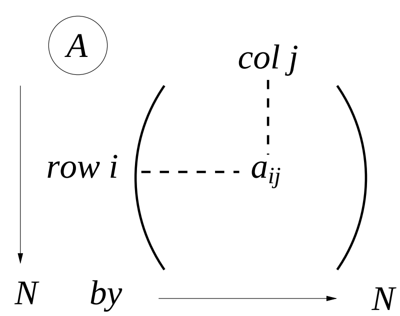


To

$$\text{From} \quad \begin{array}{c} \\ D \\ A \\ B \\ W \\ L \end{array} \begin{array}{c} \begin{array}{ccccc} D & A & B & W & L \end{array} \\ \begin{pmatrix} 0 & p & q & 0 & 0 \\ q & 0 & 0 & p & 0 \\ p & 0 & 0 & 0 & q \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \end{array}$$

5.5 Matrix Revision

Read



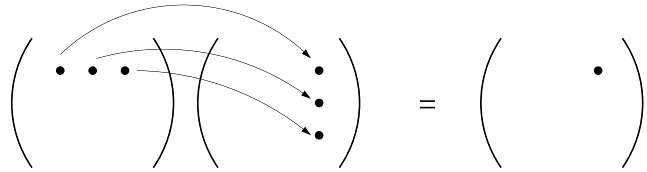
Notation

Let A be an $N \times N$ matrix.

We write $A = (a_{ij})$,
i.e. A comprises elements a_{ij}.

The (i, j) element of A is written both as a_{ij} and $(A)_{ij}$:
e.g. for matrix A^2 we might write $(A^2)_{ij}$.

Matrix multiplication



Let $A = (a_{ij})$ and $B = (b_{ij})$ be $N \times N$ matrices.

The product matrix is $A \times B = AB$, with elements $(AB)_{ij} = \sum_{k=1}^{N} a_{ik} b_{kj}$.

Summation notation for a matrix squared

Let A be an $N \times N$ matrix. Then

$$(A^2)_{ij} = \sum_{k=1}^{N} (A)_{ik}(A)_{kj} = \sum_{k=1}^{N} a_{ik} a_{kj}.$$

Pre-multiplication of a matrix by a vector

Let A be an $N \times N$ matrix, and let $\boldsymbol{\pi}$ be an $N \times 1$ column vector: $\boldsymbol{\pi} = \begin{pmatrix} \pi_1 \\ \vdots \\ \pi_N \end{pmatrix}$.

We can pre-multiply A by $\boldsymbol{\pi}^T$ to get a $1 \times N$ row vector, $\boldsymbol{\pi}^T A = \big((\boldsymbol{\pi}^T A)_1, \ldots, (\boldsymbol{\pi}^T A)_N\big)$, with elements

$$(\boldsymbol{\pi}^T A)_j = \sum_{i=1}^{N} \pi_i a_{ij}.$$

5.6 The t-step transition probabilities

Let $\{X_0, X_1, X_2, \ldots\}$ be a Markov chain with state space $S = \{1, 2, \ldots, N\}$.

Recall that the elements of the transition matrix P are defined as:

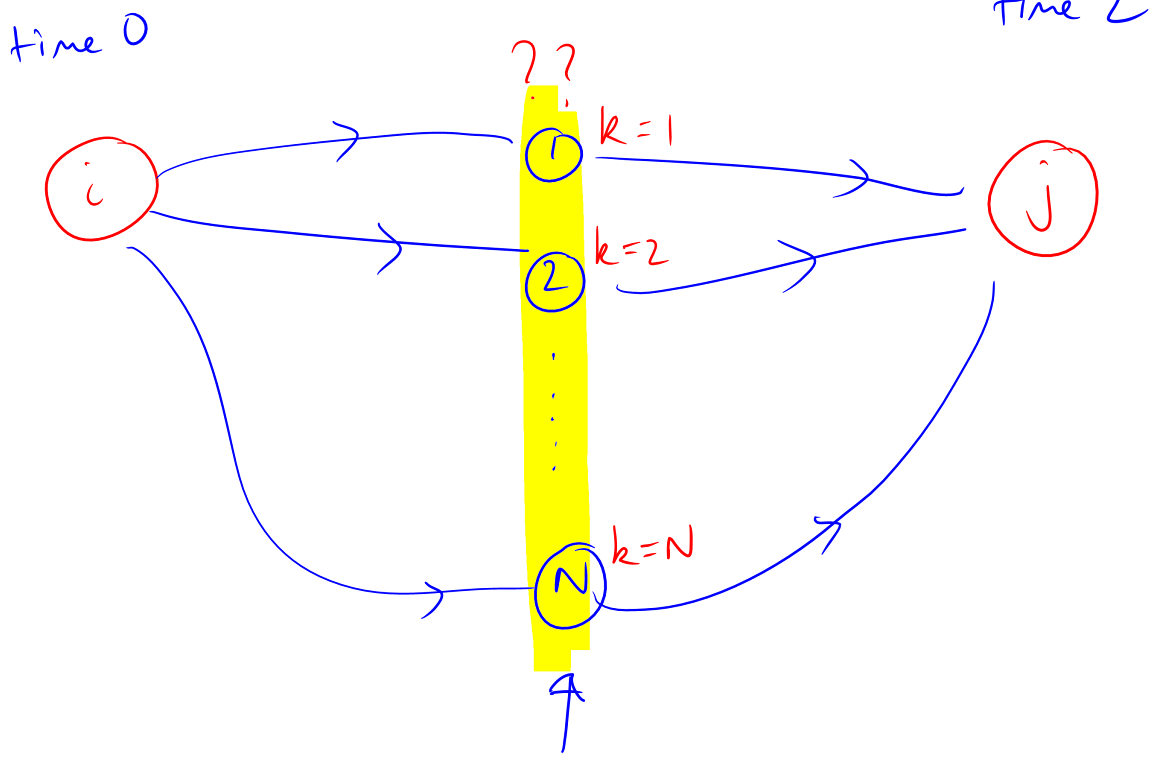
$$(P)_{ij} = p_{ij} = \mathbb{P}(X_1 = j \mid X_0 = i) = \mathbb{P}(X_{n+1} = j \mid X_n = i) \quad \text{for any } n.$$

p_{ij} is the probability of making a transition FROM state i TO state j in a SINGLE step.

Question: what is the probability of making a transition from state i to state j over **two** steps?

i.e. what is $\mathbb{P}(X_2 = j \mid X_0 = i)$?

Missing at time 1



partition $= \{$all possible states at time $1\}$

$$\mathbb{P}(X_{127} = j \mid X_0 = i) = (P^{127})_{ij}$$

Note: $(P^2)_{ij}$ NOT $(P_{ij})^2$

element ij of the matrix P^2

the square of element ij of matrix P.

We are seeking $\mathbb{P}(X_2 = j \mid X_0 = i)$. Use the Partition Theorem.

$$\mathbb{P}(X_2 = j \mid X_0 = i) = \mathbb{P}_i(X_2 = j) \qquad \text{(notation of Ch 2)}$$

$$= \sum_{k=1}^{N} \mathbb{P}_i(X_2 = j \mid X_1 = k)\,\mathbb{P}_i(X_1 = k) \qquad \text{Partition Thm.}$$

$$= \sum_{k=1}^{N} \mathbb{P}(X_2 = j \mid \underbrace{X_1 = k}_{\text{this matters}} \text{ AND } \underbrace{X_0 = i}_{\text{this doesn't matter}})\,\mathbb{P}(X_1 = k \mid X_0 = i) \qquad \text{(Markov Property)}$$

$$= \sum_{k=1}^{N} \underbrace{\mathbb{P}(X_2 = j \mid X_1 = k)}_{p_{kj}}\,\underbrace{\mathbb{P}(X_1 = k \mid X_0 = i)}_{p_{ik}} \qquad \text{(Markov property)} \leftarrow \text{by definitions}$$

$$= \sum_{k=1}^{N} p_{ik}\,p_{kj} \qquad \leftarrow \text{rearranging}$$

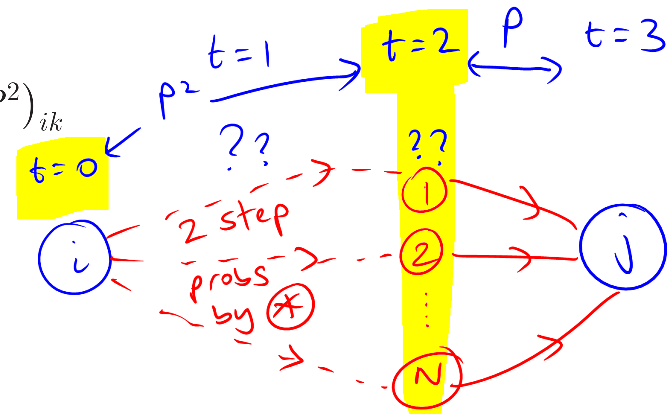
$$= (P^2)_{ij} \qquad \text{See Matrix Revision.}$$

The two-step transition probabilities are therefore given by the matrix P^2:

$$(*) \quad \boxed{\mathbb{P}(X_2 = j \mid X_0 = i) = \mathbb{P}(X_{n+2} = j \mid X_n = i) = (P^2)_{ij} \quad \text{for any } n.}$$

3-step transitions: We can find $\mathbb{P}(X_3 = j \mid X_0 = i)$ similarly, but conditioning on the state at time 2: which we know probs for by (*) above.

$$\begin{aligned}
\mathbb{P}(X_3 = j \mid X_0 = i) &= \sum_{k=1}^{N} \mathbb{P}(X_3 = j \mid X_2 = k)\mathbb{P}(X_2 = k \mid X_0 = i) \\
&= \sum_{k=1}^{N} p_{kj}\,(P^2)_{ik} \\
&= (P^3)_{ij}.
\end{aligned}$$



$(P^t)_{ij}$, NOT $(P_{ij})^t$.

The three-step transition probabilities are therefore given by the matrix P^3:

$$\boxed{\mathbb{P}(X_3 = j \,|\, X_0 = i) = \mathbb{P}(X_{n+3} = j \,|\, X_n = i) = \left(P^3\right)_{ij} \quad \text{for any } n.}$$

General case: t-step transitions

The above working extends to show that the t-step transition probabilities are given by the matrix P^t for any t:

$$\boxed{\mathbb{P}(X_t = j \,|\, X_0 = i) = \mathbb{P}(X_{n+t} = j \,|\, X_n = i) = (P^t)_{ij} \quad \text{for any } n.}$$

We have proved the following Theorem.

Theorem 5.6: Let $\{X_0, X_1, X_2, \ldots\}$ be a Markov chain with $N \times N$ transition matrix P. Then the t-step transition probabilities are given by the matrix P^t. That is,

$$\mathbb{P}(X_t = j \,|\, X_0 = i) = \left(P^t\right)_{ij}.$$

It also follows that

$$\mathbb{P}(X_{n+t} = j \,|\, X_n = i) = \left(P^t\right)_{ij} \quad \text{for any } n. \qquad \square$$

5.7 Distribution of X_t = where we will be at time t

Let $\{X_0, X_1, X_2, \ldots\}$ be a Markov chain with state space $S = \{1, 2, \ldots, N\}$.

Now each X_t is a random variable, so it has a probability distribution.

We can write the probability distribution of X_t as an $N \times 1$ vector.

For example, consider X_0. Let $\boldsymbol{\pi}$ be an $N \times 1$ vector denoting the probability distribution of X_0:

$$\underset{\sim}{\pi} = \begin{pmatrix} \pi_1 \\ \pi_2 \\ \pi_3 \\ \vdots \\ \pi_N \end{pmatrix} = \overset{\leftarrow 1 \text{ column} \rightarrow}{\begin{pmatrix} \mathbb{P}(X_0 = 1) \\ \mathbb{P}(X_0 = 2) \\ \mathbb{P}(X_0 = 3) \\ \vdots \\ \mathbb{P}(X_0 = N) \end{pmatrix}} \; N \text{ rows}$$

In the flea model, this corresponds to the flea choosing at random which vertex it starts off from, such that

$$\mathbb{P}(\text{flea chooses vertex } i \text{ to start}) = \pi_i \,.$$

Notation: we will write $X_0 \sim \underset{\sim}{\pi}^T$ to denote that the row vector of probabilities is given by the row vector $\boldsymbol{\pi}^T$.

Probability distribution of X_1

Use the Partition Rule, conditioning on X_0:

π_i by previous

$$\mathbb{P}(X_1 = j) = \sum_{i=1}^{N} \underbrace{\mathbb{P}(X_1 = j \mid X_0 = i)}\,\mathbb{P}(X_0 = i)$$

$$= \sum_{i=1}^{N} p_{ij}\,\pi_i \quad \text{by definitions}$$

$$= \sum_{i=1}^{N} \pi_i\, p_{ij} \quad \text{rearranging}$$

$$= \left(\underset{\sim}{\pi}^T P\right)_j \quad \text{premultiplication by a vector: see Matrix Revision §5.5.}$$

$X_0 \sim \underset{\sim}{\pi}^T$

$X_1 \sim \underset{\sim}{\pi}^T P$

$\vdots$

$X_t \sim \underset{\sim}{\pi}^T P^t$

This shows that $\mathbb{P}(X_1 = j) = \left(\underset{\sim}{\pi}^T P\right)_j$ for all j.

The row vector $\boldsymbol{\pi}^T P$ is therefore the probability distribution of X_1:

$$\boxed{\begin{aligned} X_0 &\sim \underset{\sim}{\pi}^T \\ X_1 &\sim \underset{\sim}{\pi}^T P \end{aligned}}$$

$$\underset{1\times N}{\underset{\sim}{\pi}^T} \quad \underset{N\times N}{P} \quad = \underset{1\times N}{\underset{\sim}{\pi}^T P}$$

Probability distribution of X_2

Using the Partition Rule as before, conditioning again on X_0:

$$\mathbb{P}(X_2 = j) = \sum_{i=1}^{N} \mathbb{P}(X_2 = j \mid X_0 = i)\mathbb{P}(X_0 = i) = \sum_{i=1}^{N} \left(P^2\right)_{ij} \pi_i = \left(\boldsymbol{\pi}^T P^2\right)_j .$$

X_t

The row vector $\boldsymbol{\pi}^T P^2$ is therefore the probability distribution of X_2:

$$\boxed{\begin{array}{rcl} X_0 & \sim & \boldsymbol{\pi}^T \\ X_1 & \sim & \boldsymbol{\pi}^T P \\ X_2 & \sim & \boldsymbol{\pi}^T P^2 \\ & \vdots & \\ X_t & \sim & \boldsymbol{\pi}^T P^t. \end{array}}$$

a, b numbers then $a * b = b * a$

A, B matrices then $AB \neq BA$ in general.

These results are summarized in the following Theorem.

Theorem 5.7: Let $\{X_0, X_1, X_2, \ldots\}$ be a Markov chain with $N \times N$ transition matrix P. If the probability distribution of X_0 is given by the $1 \times N$ row vector $\boldsymbol{\pi}^T$, then the probability distribution of X_t is given by the $1 \times N$ row vector $\boldsymbol{\pi}^T P^t$. That is,

$$X_0 \sim \underset{\sim}{\pi}^T \quad \Rightarrow \quad X_t \sim \underset{\sim}{\pi}^T P^t. \quad \text{for all } t = 0, 1, 2, \ldots$$

Note: The distribution of X_t is $X_t \sim \underset{\sim}{\pi}^T P^t$

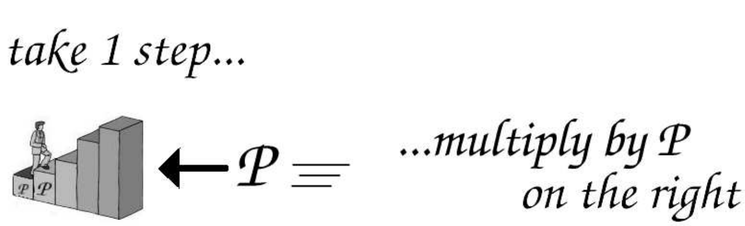
The distribution of X_{t+1} is $X_{t+1} \sim \underset{\sim}{\pi}^T P^{t+1}$ i.e. $\underset{\sim}{\pi}^T P^t * P$

Taking one step in the Markov chain corresponds to multiplying by P on the right.

Note: The t-step transition matrix is P^t (Theorem 5.6)

The $(t+1)$-step transition matrix is P^{t+1}

Again, taking one step in the Markov chain corresponds to multiplying by P on the right.

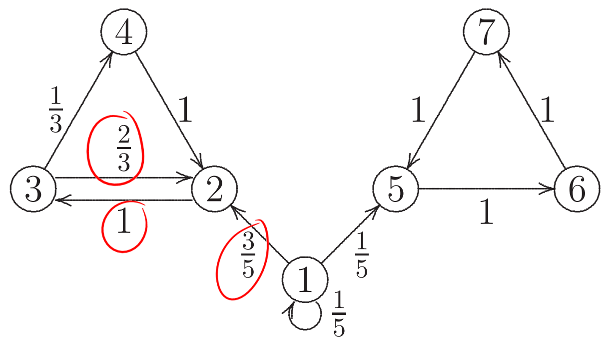


// path

5.8 Trajectory Probability

Recall that a trajectory is a sequence of values for $X_0, X_1, \ldots, X_t$.

Because of the Markov Property, we can find the probability of any trajectory by multiplying together the starting probability and all subsequent single-step probabilities.



Example: Let $X_0 \sim (\frac{3}{4}, 0, \frac{1}{4}, 0, 0, 0, 0)$. What is the probability of the trajectory 1, 2, 3, 2, 3, 4?

$\mathbb{P}(1, 2, 3, 2, 3, 4) = \mathbb{P}(X_0 = 1) \; p_{12} \; p_{23} \; p_{32} \; p_{23} \; p_{34}$

$= \frac{3}{4} * \frac{3}{5} * 1 * \frac{2}{3} * 1 * \frac{1}{3}$

$= \frac{1}{10}$

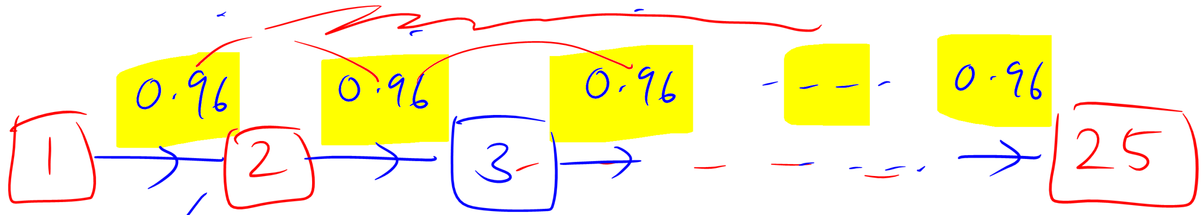
Proof in formal notation using the Markov Property:

Let $X_0 \sim \boldsymbol{\pi}^T$. We wish to find the probability of the trajectory $s_0, s_1, s_2, \ldots, s_t$.

$\mathbb{P}(X_0 = s_0, X_1 = s_1, \ldots, X_t = s_t)$ it's an intersection: $\mathbb{P}(X_0 = s_0 \cap X_1 = s_1 \cap \ldots \cap X_t = s_t)$

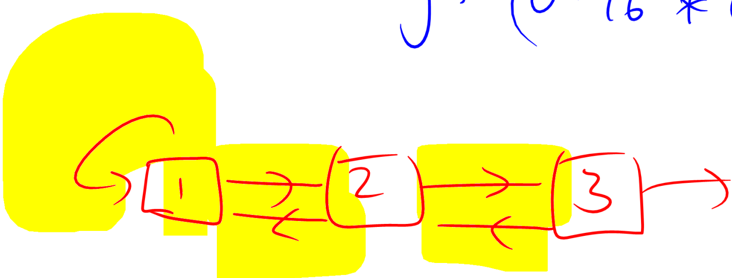
$$\begin{aligned}
&= \mathbb{P}(\overset{A}{X_t = s_t} \mid \overset{B}{X_{t-1} = s_{t-1}, \ldots, X_0 = s_0}) \times \mathbb{P}(\overset{B}{X_{t-1} = s_{t-1}, \ldots, X_0 = s_0}) \\
&= \mathbb{P}(X_t = s_t \mid X_{t-1} = s_{t-1}) \times \mathbb{P}(X_{t-1} = s_{t-1}, \ldots, X_0 = s_0) \quad \text{(Markov Property)} \\
&= p_{s_{t-1},s_t}\mathbb{P}(X_{t-1} = s_{t-1} \mid X_{t-2} = s_{t-2}, \ldots, X_0 = s_0) \times \mathbb{P}(X_{t-2} = s_{t-2}, \ldots, X_0 = s_0) \\
&\vdots \\
&= p_{s_{t-1},s_t} \times p_{s_{t-2},s_{t-1}} \times \ldots \times p_{s_0,s_1} \times \mathbb{P}(X_0 = s_0) \\
&= p_{s_{t-1},s_t} \times p_{s_{t-2},s_{t-1}} \times \ldots \times p_{s_0,s_1} \times \pi_{s_0}.
\end{aligned}$$

$\mathbb{P}(A \cap B) = \mathbb{P}(A \mid B)\,\mathbb{P}(B)$



→ complicated 2nd difference eqn.

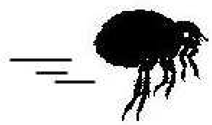
easy: $(0.96 * 0.96 * \ldots * 0.96) = (0.96)^{24}$

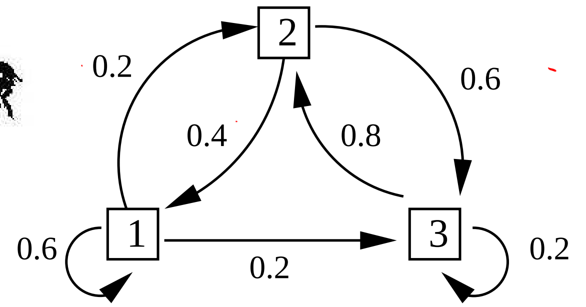


Check yourselves

5.9 Worked Example: distribution of X_t and trajectory probabilities

Purpose-flea zooms around the vertices of the transition diagram opposite. Let X_t be Purpose-flea's state at time t $(t = 0, 1, \ldots)$.





(a) Find the transition matrix, P.

$$\textit{Answer: } P = \begin{pmatrix} 0.6 & 0.2 & 0.2 \\ 0.4 & 0 & 0.6 \\ 0 & 0.8 & 0.2 \end{pmatrix}$$

(b) Find $\mathbb{P}(X_2 = 3 \mid X_0 = 1)$.

$$\mathbb{P}(X_2 = 3 \mid X_0 = 1) = (P^2)_{13} = \begin{pmatrix} 0.6 & 0.2 & 0.2 \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \end{pmatrix} \begin{pmatrix} \cdot & \cdot & 0.2 \\ \cdot & \cdot & 0.6 \\ \cdot & \cdot & 0.2 \end{pmatrix}$$

$$= 0.6 \times 0.2 + 0.2 \times 0.6 + 0.2 \times 0.2$$

$$= 0.28.$$

Note: we only need one element of the matrix P^2, so don't lose exam time by finding the whole matrix.

(c) Suppose that Purpose-flea is equally likely to start on any vertex at time 0. Find the probability distribution of X_1.

From this info, the distribution of X_0 is $\boldsymbol{\pi}^T = \left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)$. We need $X_1 \sim \boldsymbol{\pi}^T P$.

$$\boldsymbol{\pi}^T P = \begin{pmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{pmatrix} \begin{pmatrix} 0.6 & 0.2 & 0.2 \\ 0.4 & 0 & 0.6 \\ 0 & 0.8 & 0.2 \end{pmatrix} = \begin{pmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{pmatrix}.$$

Thus $X_1 \sim \left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)$ and therefore X_1 is also equally likely to be 1, 2, or 3.

(d) Suppose that Purpose-flea begins at vertex 1 at time 0. Find the probability distribution of X_2.

The distribution of X_0 is now $\boldsymbol{\pi}^T = (1, 0, 0)$. We need $X_2 \sim \boldsymbol{\pi}^T P^2$.

$$\boldsymbol{\pi}^T P^2 = (1 \quad 0 \quad 0) \begin{pmatrix} 0.6 & 0.2 & 0.2 \\ 0.4 & 0 & 0.6 \\ 0 & 0.8 & 0.2 \end{pmatrix} \begin{pmatrix} 0.6 & 0.2 & 0.2 \\ 0.4 & 0 & 0.6 \\ 0 & 0.8 & 0.2 \end{pmatrix}$$

$$= (0.6 \quad 0.2 \quad 0.2) \begin{pmatrix} 0.6 & 0.2 & 0.2 \\ 0.4 & 0 & 0.6 \\ 0 & 0.8 & 0.2 \end{pmatrix}$$

$$= (0.44 \quad 0.28 \quad 0.28)\,.$$

Thus $\mathbb{P}(X_2 = 1) = 0.44$, $\mathbb{P}(X_2 = 2) = 0.28$, $\mathbb{P}(X_2 = 3) = 0.28$.

Note that it is quickest to multiply the vector by the matrix first: we don't need to compute P^2 in entirety.

(e) Suppose that Purpose-flea is equally likely to start on any vertex at time 0. Find the probability of obtaining the trajectory (3, 2, 1, 1, 3).

$$\begin{aligned} \mathbb{P}(3,2,1,1,3) &= \mathbb{P}(X_0 = 3) \times p_{32} \times p_{21} \times p_{11} \times p_{13} \quad \textit{(Section 5.8)} \\ &= \tfrac{1}{3} \times 0.8 \times 0.4 \times 0.6 \times 0.2 \\ &= 0.0128. \end{aligned}$$

5.10 Class Structure

The state space of a Markov chain can be partitioned into a set of non-overlapping communicating classes.

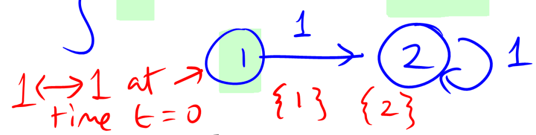
States i and j are in the same communicating class if there is some way of getting from state i to state j, AND there is some way of getting from state j to state i. It needn't be possible to get between i and j in a ***single*** step, but it must be possible over some number of steps to travel between them both ways.

We write $i \leftrightarrow j$.

Definition: Consider a Markov chain with state space S and transition matrix P, and consider states $i, j \in S$. Then **state i communicates with state j** if:

1. there exists some t such that $(P^t)_{ij} > 0$, AND
2. there exists some u such that $(P^u)_{ji} > 0$.

} t, u can be $= 0$

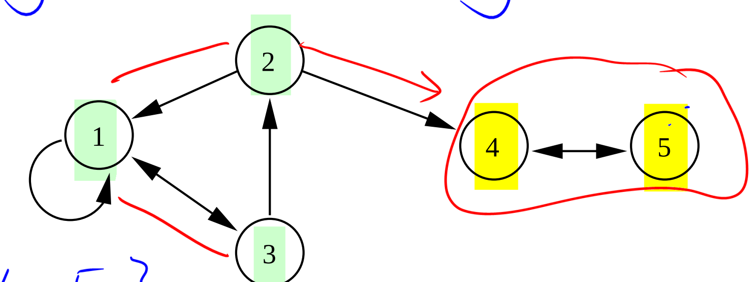


Mathematically, it is easy to show that the communicating relation $\leftrightarrow$ is an **equivalence relation**, which means that it partitions the sample space S into non-overlapping equivalence classes.

Definition: States i and j are in the same **communicating class** if $i \leftrightarrow j$, i.e. if each state is accessible from the other.

Every state is a member of exactly one communicating class.

Example: Find the communicating classes associated with the transition diagram shown.



Solution: $\{1, 2, 3\}$ $\{4, 5\}$.

State $2 \to 4$, but not the reverse, so they are in different communicating classes.

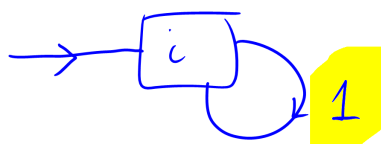
Definition: A communicating class of states is **closed** if it is not possible to leave that class. (opposite of usual meaning of "closed": we can get in, but we can't get out!)

That is, the communicating class C is closed if $p_{ij} = 0$ whenever $i \in C$ and $j \notin C$.

Example: In the transition diagram above:

- Class $\{1, 2, 3\}$ is not closed: it is possible to escape to class $\{4, 5\}$.
- Class $\{4, 5\}$ is closed: it is not possible to escape.

Definition: A state i is said to be **absorbing** if the set $\{i\}$ is a closed class:



Definition: A Markov chain or transition matrix P is said to be **irreducible** if $i \leftrightarrow j$ for all $i, j \in S$. That is, the chain is irreducible if the state space S is a single communicating class.

[Can get from anywhere to anywhere given enough steps]

5.11 Hitting Probabilities

We have been calculating hitting probabilities for Markov chains since Chapter 2, using First-Step Analysis. The hitting probability describes the probability that the Markov chain will *ever* reach some state or set of states.

In this section we show how hitting probabilities can be written in a single vector. We also see a general formula for calculating the hitting probabilities. In general it is easier to continue using our own common sense, but occasionally the formula becomes more necessary.

Vector of hitting probabilities

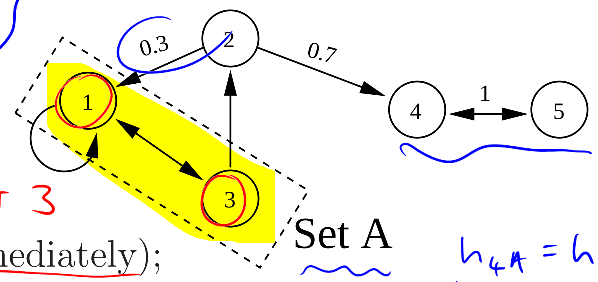
Let A be some subset of the state space S. (A need not be a communicating class: it can be any subset required, including the subset consisting of a single state: e.g. $A = \{4\}$.)

The **hitting probability** from state i to set A is the probability of ever reaching the set A, starting from initial state i. We write this probability as h_{iA}.
Thus

$$h_{iA} = \mathbb{P}(X_t \in A \text{ for some } t \geq 0 \mid X_0 = i).$$

from i ... to set A

Example: Let set $A = \{1, 3\}$ as shown.



$h_{4A} = h_{5A}$
$h_{5A} = h_{4A}$

The hitting probability for set A is:
(hit set A at time $t=0$)

- 1 starting from states 1 or 3
(We are starting in set A, so we hit it immediately);

- 0 starting from states 4 or 5
(The set $\{4, 5\}$ is a closed class, so we can never escape out to set A);

- 0.3 starting from state 2.
(We could hit A at the first step (probability 0.3), but otherwise we move to state 4 and get stuck in the closed class $\{4, 5\}$ (probability 0.7).)

We can summarize all the information from the example above in a vector of hitting probabilities:

$$\underset{\sim}{h}_A = \begin{pmatrix} h_{1A} \\ h_{2A} \\ h_{3A} \\ h_{4A} \\ h_{5A} \end{pmatrix} = \begin{pmatrix} 1 \\ 0.3 \\ 1 \\ 0 \\ 0 \end{pmatrix}.$$

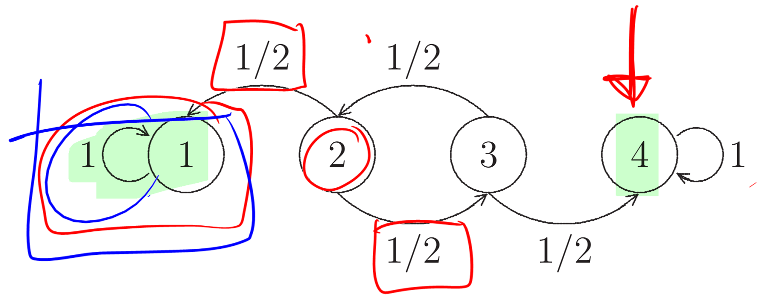
Note: When A is a closed class, the hitting probability h_{iA} is called the absorption probability.

In general, if there are N possible states, the vector of hitting probabilities is

$$\underset{\sim}{h}_A = \begin{pmatrix} h_{1A} \\ h_{2A} \\ \vdots \\ h_{NA} \end{pmatrix} = \begin{pmatrix} \mathbb{P}(\text{hit } A \mid \text{start at state } 1) \\ \mathbb{P}(\text{hit } A \mid \ldots\ldots\ldots\ 2) \\ \vdots \\ \mathbb{P}(\text{hit } A \mid \ldots\ldots\ N) \end{pmatrix}$$

Example: finding the hitting probability vector using First-Step Analysis

Suppose $\{X_t : t \geq 0\}$ has the following transition diagram:



(Gambler's Ruin)

Find the vector of hitting probabilities for state 4.

Solution: Let $h_{i4} = \mathbb{P}(\text{hit state 4 eventually} \mid \text{start from state } i)$.

Clearly, $\boxed{h_{14} = 0}$.
$h_{44} = 1$

Using first-step analysis for the other states:

$$h_{24} = \tfrac{1}{2} h_{14} + \tfrac{1}{2} h_{34} \Rightarrow h_{24} = \tfrac{1}{2} h_{34} \quad (1)$$

$$h_{34} = \tfrac{1}{2} h_{24} + \tfrac{1}{2} h_{44} \Rightarrow h_{34} = \tfrac{1}{2} + \tfrac{1}{2} h_{24} \quad (2)$$

Subst (1) in (2): $h_{34} = \frac{1}{2} + \frac{1}{2}\left\{\frac{1}{2} h_{34}\right\} \Rightarrow h_{34} = \frac{2}{3}$.

Using (1) $\Rightarrow$ $h_{24} = \frac{1}{2} h_{34} = \frac{1}{3}$.

So the vector of hitting prob.s is $\underset{\sim}{h}_{\{4\}} = \left(0, \frac{1}{3}, \frac{2}{3}, 1\right)$.

Formula for hitting probabilities

In the previous example, we used our common sense to state that $h_{14} = 0$. While this is easy for a human brain, it is harder to explain a general rule that would describe this 'common sense' mathematically, or that could be used to write computer code that will work for all problems.

Although it is usually best to continue to use common sense when solving problems, this section provides a general formula that will *always* work to find a vector of hitting probabilities $\boldsymbol{h_A}$.

Theorem 5.11: The vector of hitting probabilities $\boldsymbol{h_A} = (h_{iA} : i \in S)$ is the minimal non-negative solution to the following equations:

Smallest solution ≥ 0 to the first-step analysis eqns, modified to incorporate $h_{iA} = 1$ if $i \in A$.

$$h_{iA} = \begin{cases} 1 & \text{for} \quad i \in A, \\ \sum_{j \in S} p_{ij} h_{jA} & \text{for} \quad i \notin A. \end{cases}$$

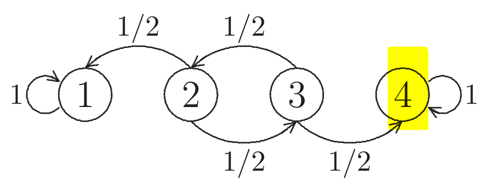
→ hit A immediately because we start in A.

FSA eqns

The 'minimal non-negative solution' means that:

1. the values $\{h_{iA}\}$ collectively satisfy the equations above; ← h_A must be a soln of FSA
2. each value h_{iA} is ≥ 0 (non-negative); (it's a probability!)
3. given any other non-negative solution to the equations above, say $\{g_{iA}\}$ where $g_{iA} \geq 0$ for all i, then $h_{iA} \leq g_{iA}$ for all i (minimal solution).

Example: How would this formula be used to substitute for 'common sense' in the previous example?



The equations give:

$$h_{i4} = \begin{cases} 1 & \textit{if} \quad i = 4, \\ \sum_{j \in S} p_{ij} h_{j4} & \textit{if} \quad i \neq 4. \end{cases}$$

Thus,

$$\begin{aligned} h_{44} &= 1 \\ h_{14} &= h_{14} \quad \textit{unspecified! Could be anything!} \\ h_{24} &= \tfrac{1}{2} h_{14} + \tfrac{1}{2} h_{34} \\ h_{34} &= \tfrac{1}{2} h_{24} + \tfrac{1}{2} h_{44} = \tfrac{1}{2} h_{24} + \tfrac{1}{2} \end{aligned}$$

Problem.

as before

Because h_{14} could be anything, we have to use the minimal non-negative value, which is $h_{14} = 0$.
(Need to check $h_{14} = 0$ does not force $h_{i4<0}$ for any other i: OK.)

The other equations can then be solved to give the same answers as before. $\square$

Proof of Theorem 5.11 (non-examinable): come back to this when we've done Ch 4 (Induction).

Consider the equations $$h_{iA} = \begin{cases} 1 & \text{for } i \in A, \\ \sum_{j \in S} p_{ij} h_{jA} & \text{for } i \notin A. \end{cases} \qquad (\star)$$

We need to show that:

(i) the hitting probabilities $\{h_{iA}\}$ collectively satisfy the equations $(\star)$; (Partition Thm - easy)

(ii) if $\{g_{iA}\}$ is any other non-negative solution to $(\star)$, then the hitting probabilities $\{h_{iA}\}$ satisfy $h_{iA} \leq g_{iA}$ for all i (minimal solution).

Use induction: typical idea for Stoch Processes.

Proof of (i): Clearly, $h_{iA} = 1$ if $i \in A$ (as the chain hits A immediately).

Suppose that $i \notin A$. Then

$$\begin{aligned} h_{iA} &= \mathbb{P}(X_t \in A \text{ for some } t \geq 1 \mid X_0 = i) \\ &= \sum_{j \in S} \mathbb{P}(X_t \in A \text{ for some } t \geq 1 \mid X_1 = j)\mathbb{P}(X_1 = j \mid X_0 = i) \\ &\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \text{(Partition Rule)} \\ &= \sum_{j \in S} h_{jA}\, p_{ij} \qquad \text{(by definitions).} \end{aligned}$$

Thus the hitting probabilities $\{h_{iA}\}$ must satisfy the equations $(\star)$.

Proof of (ii): Let $h_{iA}^{(t)} = \mathbb{P}(\text{hit } A \text{ at or before time } t \mid X_0 = i)$.

g_{iA} = "imposter" soln

We use mathematical induction to show that $h_{iA}^{(t)} \leq g_{iA}$ for all t, and therefore $h_{iA} = \lim_{t \to \infty} h_{iA}^{(t)}$ must also be $\leq g_{iA}$.

Time $t = 0$: $\quad h_{iA}^{(0)} = \begin{cases} 1 & \text{if} \quad i \in A, \\ 0 & \text{if} \quad i \notin A. \end{cases}$

But because g_{iA} is non-negative and satisfies $(\star)$, $\begin{cases} g_{iA} = 1 & \text{if } i \in A, \\ g_{iA} \geq 0 & \text{for all } i. \end{cases}$

So $g_{iA} \geq h_{iA}^{(0)}$ for all i.

The inductive hypothesis is true for time $t = 0$.

Time t: Suppose the inductive hypothesis holds for time t, i.e.

$$h_{jA}^{(t)} \leq g_{jA} \quad \text{for all } j.$$

Consider

$$\begin{aligned} h_{iA}^{(t+1)} &= \mathbb{P}(\text{hit } A \text{ by time } t+1 \,|\, X_0 = i) \\ &= \sum_{j \in S} \mathbb{P}(\text{hit } A \text{ by time } t+1 \,|\, X_1 = j)\mathbb{P}(X_1 = j \,|\, X_0 = i) \\ &\qquad\qquad\qquad\qquad\qquad\qquad \text{(Partition Rule)} \\ &= \sum_{j \in S} h_{jA}^{(t)} p_{ij} \qquad \text{by definitions} \\ &\leq \sum_{j \in S} g_{jA} p_{ij} \qquad \text{by inductive hypothesis} \\ &= g_{iA} \qquad \text{because } \{g_{iA}\} \text{ satisfies } (\star). \end{aligned}$$

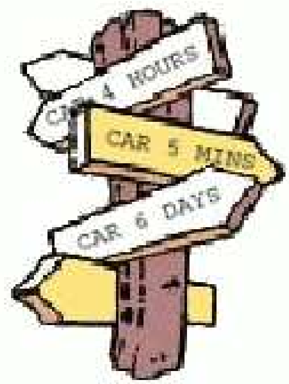
Thus $h_{iA}^{(t+1)} \leq g_{iA}$ for all i, so the inductive hypothesis is proved.

By the Continuity Theorem (Chapter 2), $h_{iA} = \lim_{t \to \infty} h_{iA}^{(t)}$.

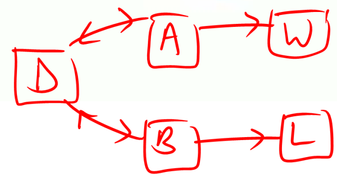
So $h_{iA} \leq g_{iA}$ as required. $\square$

5.12 Expected hitting times

In the previous section we found the **probability** of hitting set A, starting at state i. Now we study **how long** it takes to get from i to A. As before, it is best to solve problems using first-step analysis and common sense. However, a general formula is also available.



$\mathbb{E}(T_W) = \infty$ b/c she might never reach state W. (might lose).



Definition: Let A be a subset of the state space S. The **hitting time** of A is the random variable T_A, where

$$T_A = \min\{t \geq 0 : X_t \in A\}$$

T_A is the time taken before hitting set A for the first time.

The hitting time T_A can take values $0, 1, 2, 3, \ldots$ and ∞.

If the chain *never* hits set A, then $T_A = \infty$.

Note: The hitting time is also called the **reaching time**. If A is a closed class, it is also called the absorption time.

Definition: The **mean hitting time** for A, starting from state i, is

$$m_{iA} = \mathbb{E}(T_A \mid X_0 = i).$$

Note: If there is any possibility that the chain *never* reaches A, starting from i, i.e. if the hitting prob $h_{iA} < 1$, then $\mathbb{E}(T_A \mid X_0 = i) = \infty$.

Calculating the mean hitting times

Theorem 5.12: The vector of expected hitting times $\boldsymbol{m_A} = (m_{iA} : i \in S)$ is the minimal non-negative solution to the following equations:

$$m_{iA} = \begin{cases} 0 & \text{for } i \in A \quad \text{takes no time if already there} \\ 1 + \sum_{j \notin A} p_{ij} m_{jA} & \text{for } i \notin A. \quad \text{FSA} \end{cases}$$

one step to get out of i - - - - plus whatever happens next

Proof (sketch):

Consider the equations $m_{iA} = \begin{cases} 0 & \text{for} \quad i \in A, \\ 1 + \sum_{j \notin A} p_{ij} m_{jA} & \text{for} \quad i \notin A. \end{cases} \qquad (\star).$

We need to show that:

(i) the mean hitting times $\{m_{iA}\}$ collectively satisfy the equations $(\star)$;

(ii) if $\{u_{iA}\}$ is any other non-negative solution to $(\star)$, then the mean hitting times $\{m_{iA}\}$ satisfy $m_{iA} \le u_{iA}$ for all i (minimal solution).

We will prove point (i) only. A proof of (ii) can be found online at:
`http://www.statslab.cam.ac.uk/~james/Markov/` , Section 1.3.

Proof of (i): Clearly, $m_{iA} = 0$ if $i \in A$ (as the chain hits A immediately).

Solution $\underset{\sim}{m}_A$ satisfies the FSA eqns.

Suppose that $i \notin A$. Then

$$\begin{aligned} m_{iA} &= \mathbb{E}(T_A \,|\, X_0 = i) \\ &= 1 + \sum_{j \in S} \mathbb{E}(T_A \,|\, X_1 = j)\mathbb{P}(X_1 = j \,|\, X_0 = i) \end{aligned}$$

(conditional expectation: take 1 step to get to state j at time 1, then find $\mathbb{E}(T_A)$ from there)

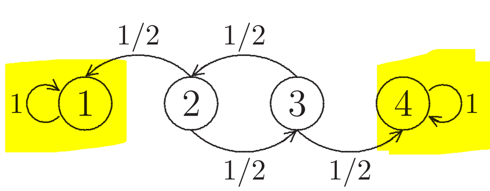
$$\begin{aligned} &= 1 + \sum_{j \in S} m_{jA}\, p_{ij} \qquad \text{(by definitions)} \\ &= 1 + \sum_{j \notin A} p_{ij}\, m_{jA}\,, \qquad \text{because } m_{jA} = 0 \text{ for } j \in A. \end{aligned}$$

Thus the mean hitting times $\{m_{iA}\}$ must satisfy the equations $(\star)$.

□

Example: Let $\{X_t : t \ge 0\}$ have the same transition diagram as before:

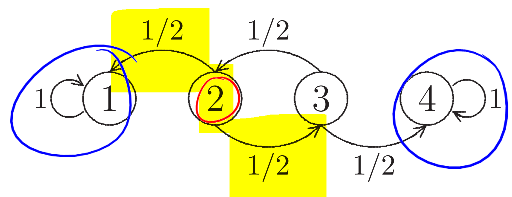
Starting from state 2, find the expected time to absorption.



Solution: Looking for m_{2A} where $A = \{1, 4\}$ (absorbing states).

Now $m_{iA} = \begin{cases} 0 & \text{if } i \in \{1,4\} \\ 1 + \sum_{j \notin A} p_{ij} m_{jA} & \text{if } i \notin \{1,4\}. \end{cases}$ FSA eqns.

So $\left.\begin{array}{l} m_{1A} = 0 \\ m_{4A} = 0 \end{array}\right\}$ because $1 \in A$ and $4 \in A$.



$m_{2A} = 1 + \frac{1}{2} \cancel{m_{1A}} + \frac{1}{2} m_{3A}$

$\Rightarrow m_{2A} = 1 + \frac{1}{2} m_{3A}$ ✱

Also $m_{3A} = 1 + \frac{1}{2} m_{2A} + \frac{1}{2} \cancel{m_{4A}}$

$= 1 + \frac{1}{2} m_{2A}$

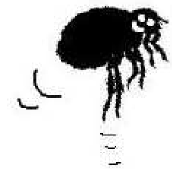
$= 1 + \frac{1}{2} \left\{ 1 + \frac{1}{2} m_{3A} \right\}$ by ✱

$\Rightarrow \frac{3}{4} m_{3A} = \frac{3}{2}$

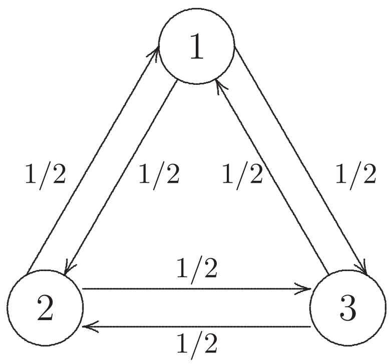
$\therefore$ $m_{3A} = 2$. By ✱, $m_{2A} = 2$ also.

$\therefore$ Expected time to absorption is $\mathbb{E}(T_A) = 2$ steps.

Example: Glee-flea hops around on a triangle. At each step he moves to one of the other two vertices at random. What is the expected time taken for Glee-flea to get from vertex 1 to vertex 2?



Solution:



transition matrix, $P = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & 0 & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & 0 \end{pmatrix}$.

We wish to find m_{12}.

Now $m_{i2} = \begin{cases} 0 & \textit{if} \quad i = 2, \\ 1 + \sum_{j \neq 2} p_{ij} m_{j2} & \textit{if} \quad i \neq 2. \end{cases}$

Thus

$$\begin{aligned} m_{22} &= 0 \\ m_{12} &= 1 + \tfrac{1}{2} m_{22} + \tfrac{1}{2} m_{32} \;=\; 1 + \tfrac{1}{2} m_{32}. \\ m_{32} &= 1 + \tfrac{1}{2} m_{22} + \tfrac{1}{2} m_{12} \\ &= 1 + \tfrac{1}{2} m_{12} \\ &= 1 + \tfrac{1}{2}\left(1 + \tfrac{1}{2} m_{32}\right) \\ \Rightarrow \quad m_{32} &= 2. \end{aligned}$$

Thus $m_{12} = 1 + \frac{1}{2} m_{32} = 2$ *steps.*