

Markov Chains

Example 1: Suppose I flip a biased coin which is heads w.p. p

Let $X = \#$ of flips until I see my first heads.

$$E[X] = ?$$

Zoo/Reference Sheet:

Alternative calculation:

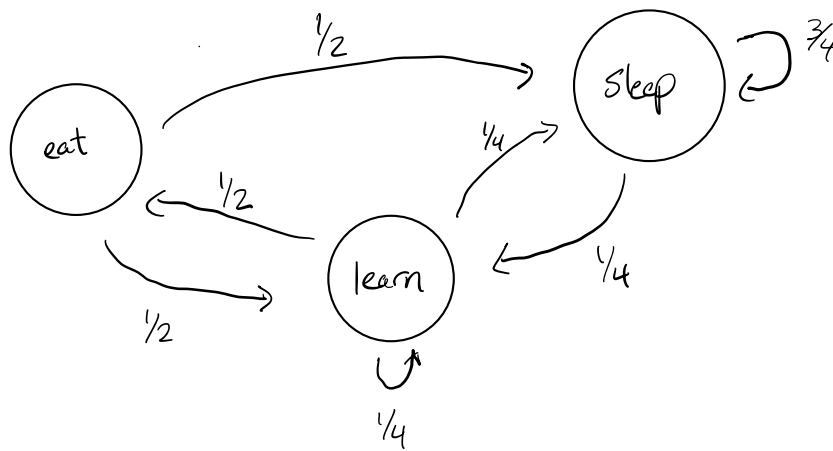
Example 2: Same setup, but let $Y = \#$ of flips until I see 2 heads in a row

$$E[Y] = ?$$

idea 1: geometric RV?

idea 2: condition on most recent flip?

Example 3



At each time step t :

I am in one of four states:

$\{ \text{gym, eat, sleep, learn} \}$

$$\Pr[\text{in state } s' \text{ at time } t+1 \mid \text{in state } s \text{ at time } t]$$

=

This random process is called a

Markov Chain

[remark: Looks kind of like DFA/NFA from 311 ... except labels are probabilities, not input symbols.]

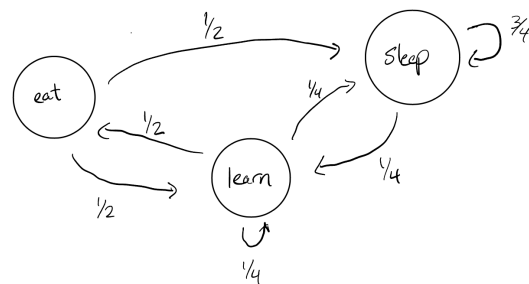
Define random variable $X_t = \text{state we are in at time } t$.

Questions

1) $\Pr[X_1 = \text{sleep} \mid X_0 = \text{sleep}] =$

2) $\Pr[X_2 = \text{sleep} \mid X_0 = \text{sleep}] =$

3) $\Pr[X_t = \text{sleep} \mid X_0 = \text{sleep}] = ?$

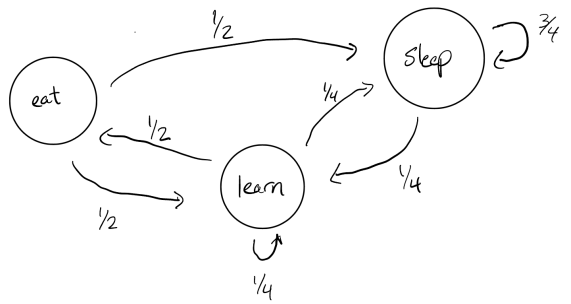


4) How long do I expect to wait before I get to **eat**? (assuming still $X_0 = \text{sleep}$)

Y_S = amount of time until eat starting in **sleep**

Y_L = amount of time until eat starting from **Learn**

Y_E = amount of time until eat starting from **Eat**



LTE: $E[Y_S] =$

"first-step equations"

Definition A **Markov Chain** is a sequence of random variables

X_0, X_1, X_2, \dots satisfying

$$1) \Pr[X_{t+1} = s_{t+1} \mid X_t = s_t, \dots, X_0 = s_0] = \Pr[X_{t+1} = s_{t+1} \mid X_t = s_t]$$

$$2) \Omega_{X_i} = S \quad (\text{for example, } S = \{\text{eat, sleep, learn}\})$$

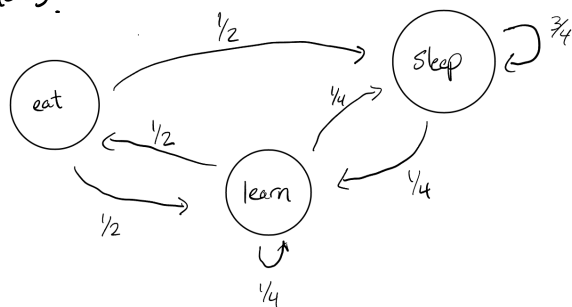
$$3) p_{X_0} \text{ is an arbitrary pmf on } S$$

Let's write PMF's for X_t 's as (row) vectors.

$$q^{(0)} = \begin{bmatrix} \text{eat} & \text{sleep} & \text{learn} \\ 0 & 1 & 0 \end{bmatrix}$$

$$q^{(1)} = \begin{bmatrix} \end{bmatrix}$$

$$q^{(2)} = \begin{bmatrix} \end{bmatrix}$$



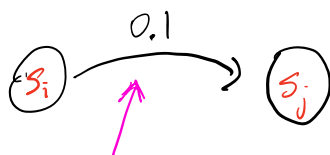
Question: How to get $q^{(t)}$ (PMF of X_t) from $\overbrace{q^{(0)}, q^{(1)}, \dots, q^{(t-1)}}^{\text{PMF's for } X_0, X_1, \dots, X_{t-1}}$?

Definition Let X_0, X_1, \dots be a Markov chain over state space

$S = \{s_1, \dots, s_n\}$. Define the transition probability matrix P

to be the unique matrix s.t.

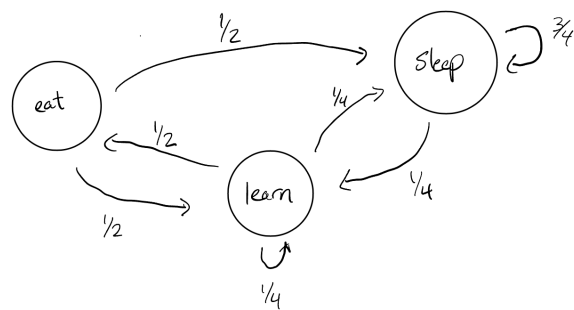
$$P_{ij} = \Pr[X_t = s_j \mid X_{t-1} = s_i]$$



$P_{ij} = 0.1$ in this example

example :

$$P = \begin{matrix} & \begin{matrix} \text{eat} & \text{sleep} & \text{learn} \end{matrix} \\ \begin{matrix} \text{eat} \\ \text{sleep} \\ \text{learn} \end{matrix} & \begin{bmatrix} 0 & 1/2 & 1/2 \\ 0 & 3/4 & 1/4 \\ 1/2 & 1/4 & 1/4 \end{bmatrix} \end{matrix}$$



$$q_{\text{eat}}^{(t)} = \Pr[X_t = \text{eat}] = \Pr[X_t = \text{eat} \cap X_{t-1} = \text{eat}]$$

$$\Pr[X_t = \text{eat} \cap X_{t-1} = \text{sleep}] + \Pr[X_t = \text{eat} \cap X_{t-1} = \text{learn}]$$

observation $q^{(t)} = q^{(t-1)} P$

claim $q^{(t)} = q^{(0)} P^t$

proof

question What does $q^{(t)}$ look like as $t \rightarrow \infty$?

equivalently: what does $q^{(0)} P^t$ look like as $t \rightarrow \infty$?

$$q^{(0)} = \begin{matrix} & \text{eat} & \text{sleep} & \text{learn} \\ \begin{bmatrix} 0 & 1 & 0 \end{bmatrix} \end{matrix}$$

$$q^{(1)} = \begin{bmatrix} 0 & 3/4 & 1/4 \end{bmatrix}$$

$$q^{(2)} = \begin{bmatrix} 1/8 & 5/8 & 1/4 \end{bmatrix}$$

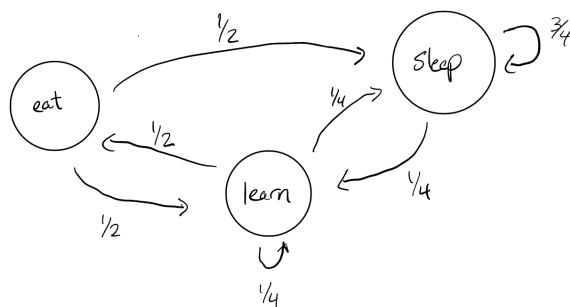
$$q^{(3)} = \begin{bmatrix} 1/8 & 19/32 & 9/32 \end{bmatrix}$$

$$q^{(4)} = \begin{bmatrix} 9/64 & 37/64 & 9/32 \end{bmatrix}$$

$$\vdots \quad \vdots \quad \vdots \quad \vdots$$

$$q^{(10)} \approx [0.142853, 0.571442, 0.285706]$$

$$q^{(11)} = [0.142853, 0.571434, 0.285713]$$



$$P = \begin{matrix} & \text{eat} & \text{sleep} & \text{learn} \\ \begin{matrix} \text{eat} \\ \text{sleep} \\ \text{learn} \end{matrix} & \begin{bmatrix} 0 & 1/2 & 1/2 \\ 0 & 3/4 & 1/4 \\ 1/2 & 1/4 & 1/4 \end{bmatrix} \end{matrix}$$

observation if $q^{(t+1)} = q^{(t)}$ then distribution never changes again!

called a stationary distribution

solution to $\pi = \pi P$

so a (left) eigenvector with eigenvalue 1!

Let's solve!

$$\begin{matrix} \pi & = & \pi & P \end{matrix}$$

$$[\pi_E, \pi_S, \pi_L] = [\pi_E, \pi_S, \pi_L] \begin{bmatrix} 0 & 1/2 & 1/2 \\ 0 & 3/4 & 1/4 \\ 1/2 & 1/4 & 1/4 \end{bmatrix}$$

Big Theorem for Markov Chains For any sufficiently nice^(*)

Markov Chain, no matter what $q^{(0)}$ is,

$$\lim_{t \rightarrow \infty} q^{(0)} P^t = \lim_{t \rightarrow \infty} q^{(t)} = \pi$$

↑
solution to $\pi = \pi P$

(*): "nice" being irreducible, aperiodic, and positive recurrent.