

Announcements:

- Course Eval ( $> 80\%$  of the class fills out the eval, 1 point of EC post curve)
- HW 7 (next week's hw) released on Friday
  - due a day earlier

## Lecture 6A:

↳ 3 question

long

# Markov Chains

→ 12 days

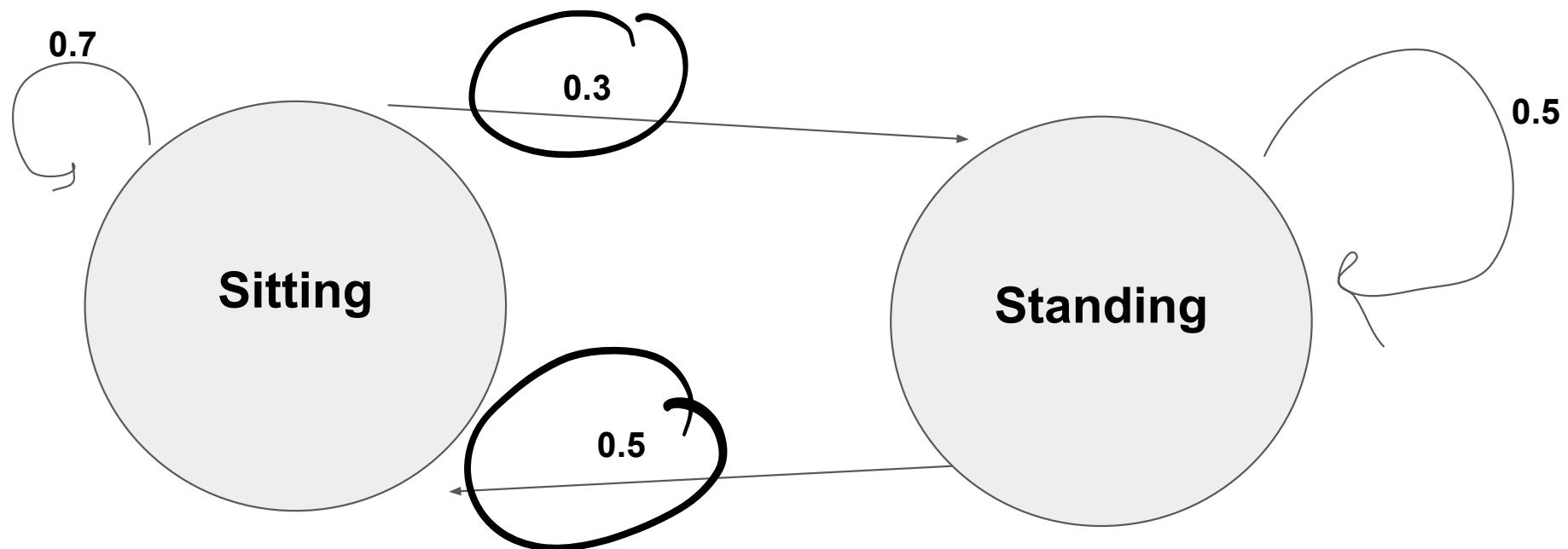
UC Berkeley CS70

Summer 2023

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# Finite Markov Chains

Markov Chains help us to visualize **transitions** between different **states**.



# Finite Markov Chains (Formally)

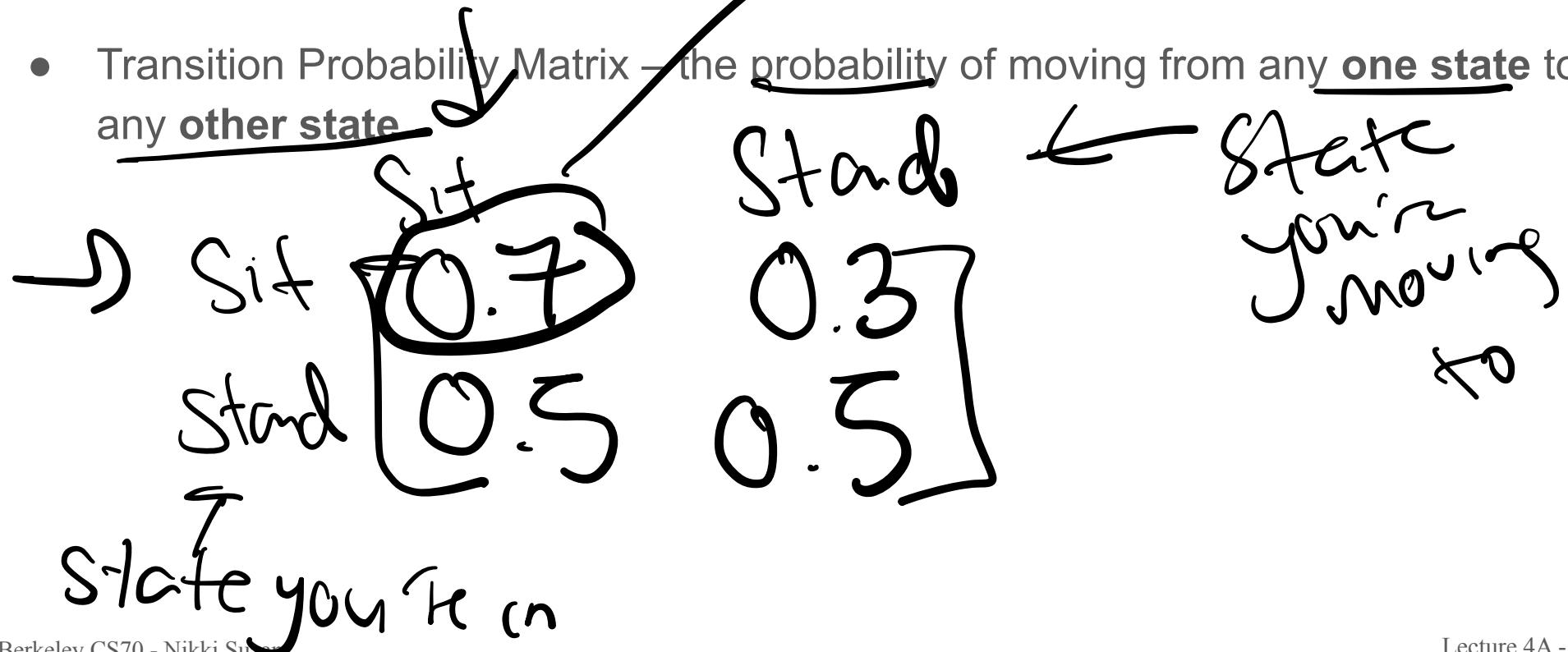
Markov Chains are defined by two key components:

- State Space – set of all possible **states** that your experiment can exist in (all possible values of the random variable in the Markov Chain). i.e. {sitting, standing}.

# Finite Markov Chains (Formally)

Markov Chains are defined by two key components:

- Transition Probability Matrix – the probability of moving from any one state to any other state



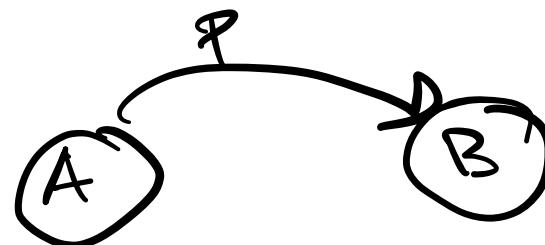
# Key Information!

The **most** important thing about Markov chains, is that the chain is **amnesic** (memoryless) meaning each step should **only** depend on the previous state.

$X_i$  : State that I'm in at step  $i$        $\{A, B, C\}$

$$P(X_n = A \mid X_{n-1} = B, X_{n-2} = A, X_{n-3} = C \dots)$$

$$= P(X_n = A \mid X_{n-1} = B)$$



HHT

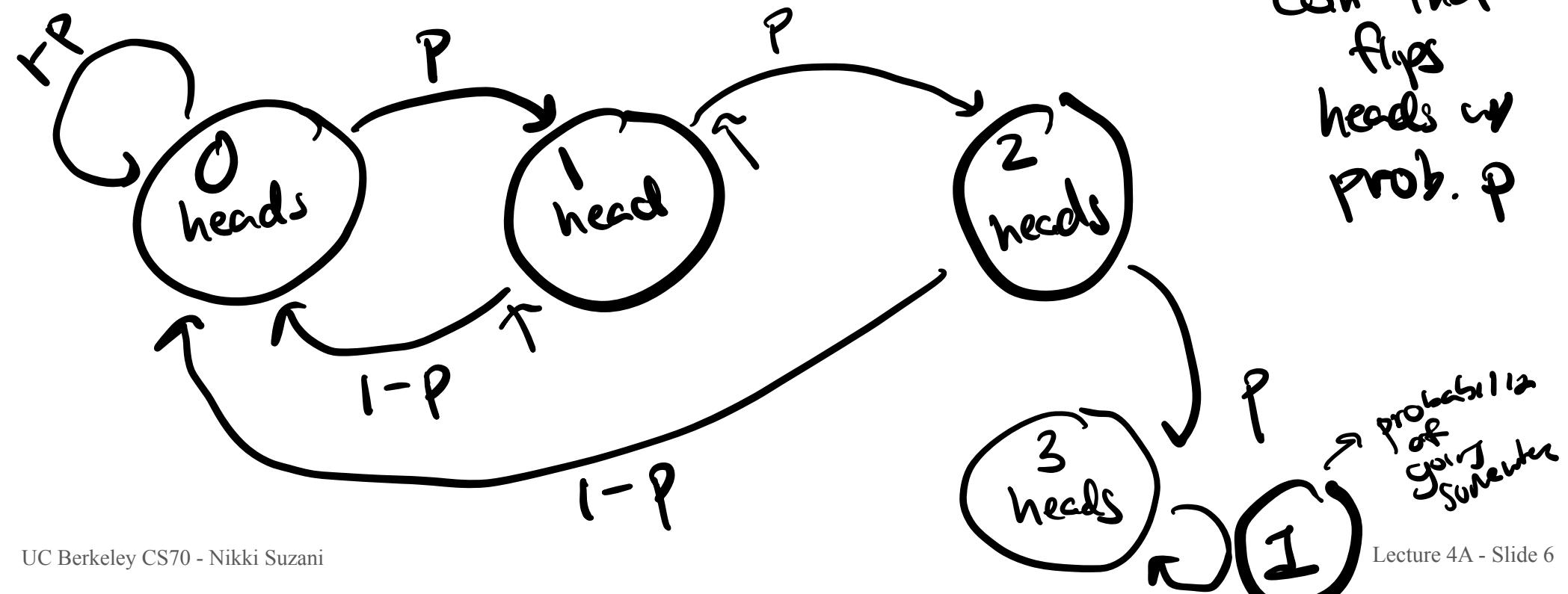
$$1-p+p$$

Can the following be modeled as a Markov Chain?

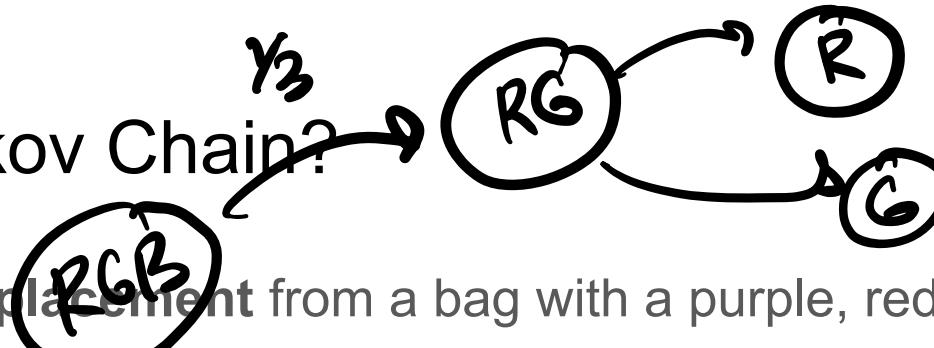
three

You have a coin that you flip continuously until you get ~~two~~ consecutive heads.

can that  
flips  
heads w/  
prob.  $p$



Modeled as a Markov Chain?



You're drawing **without replacement** from a bag with a purple, red, and green ball. Model the outcomes of your draws.

purple ball  
draw 1

green ball

draw 2

↓

100% prob. that  
I got a red ball

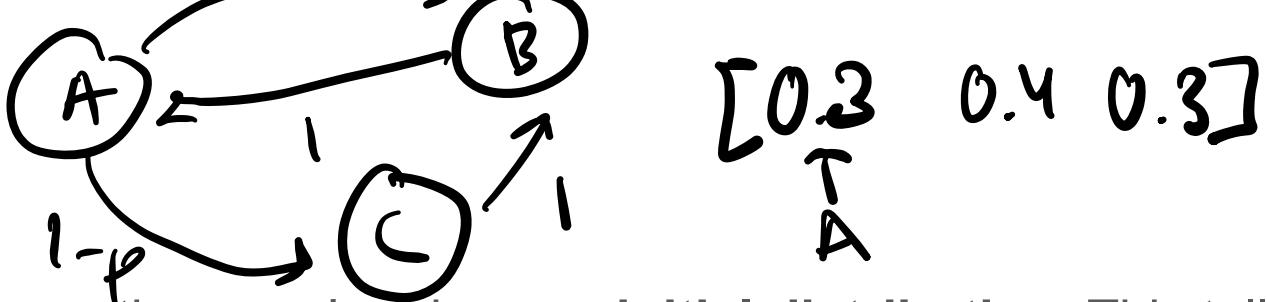
draw 3

↓ 50% prob. of red

~ 50% prob. of purple

φ

## More Vocab!



Often for Markov Chain questions you're given an initial distribution. This tells you the probability of being in **each state** when you start. Each probability should be  $\geq 0$ , and they should sum to 1.

$$\pi = [\pi(0) \quad \pi(1) \quad \dots \quad \pi(n)]^T$$

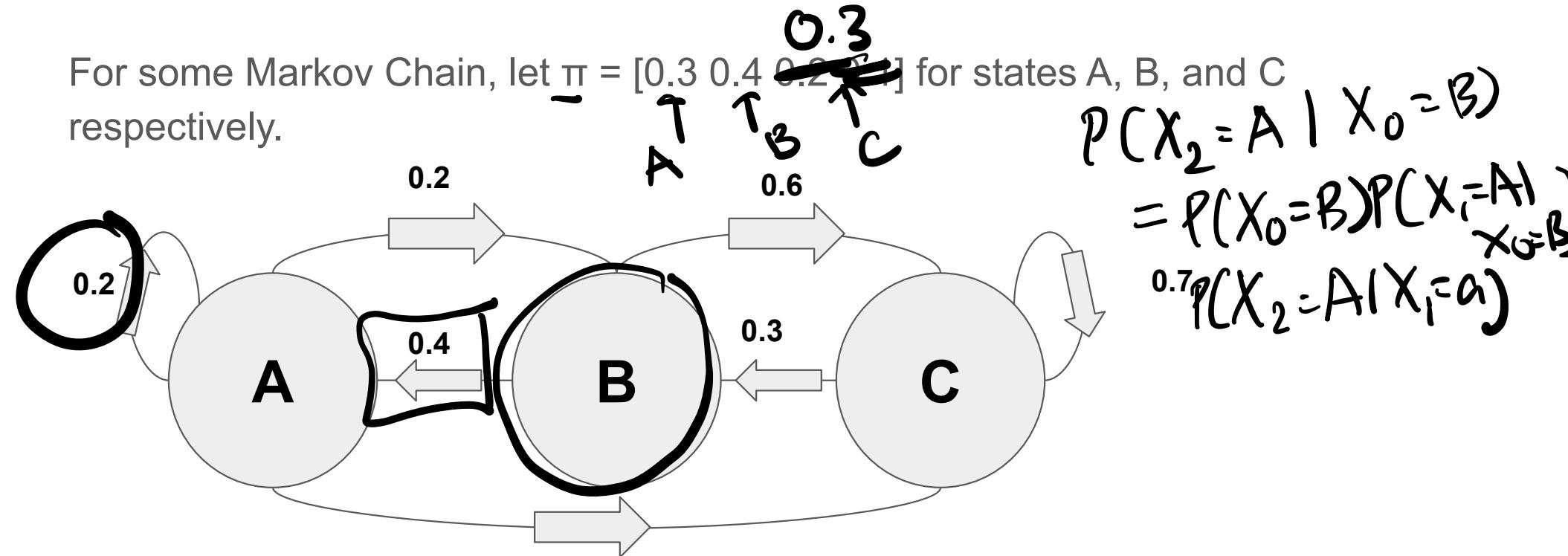
↑  
probability  
of  
starting in  
state 0

$$0 \leq \pi(i) \leq 1$$

$$\pi(0) + \dots + \pi(n) = 1$$

# Using the initial distribution

For some Markov Chain, let  $\pi = [0.3 \ 0.4 \ 0.2]$  for states A, B, and C respectively.



$$P(A) = P(A \cap B) + P(A \cap \bar{B})$$

## Using the initial distribution

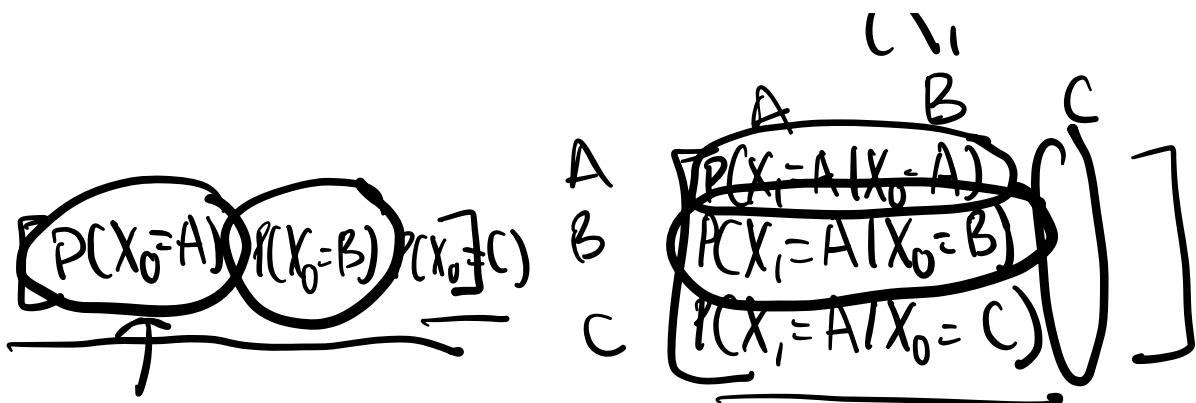
Let  $\pi = [0.3 \ 0.4 \ 0.3]$ . After one step, what is the probability of being in state A?

Initial dist :  $[0.3 \ 0.4 \ 0.3]^T$

Three states: A, B, C

Starting in B:  $P(\text{state}_A) \cdot P(B \rightarrow A) = 0.4$

$$P(X_1 = A) = P(X_1 = A | X_0 = A)P(X_0 = A) + P(X_1 = A | X_0 = B)P(X_0 = B) + P(X_1 = A | X_0 = C)P(X_0 = C)$$



$$P(X_1 = A) = P(X_0 = A)P(X_1 = A | X_0 = A) + P(X_0 = B)P(X_1 = A | X_0 = B)$$

after Step 1 vector =  $\pi P^1$

↑  
initial dist.  
probability matrix

$$\text{after step 2 vector} = \text{After step 1 vector } P = \pi P^2$$

$\begin{bmatrix} N(A) & N(B) \\ N(C) \end{bmatrix}$

after step n =  $\pi P^n$

probability of state A after n steps

1st entry of this new vector

$$\begin{aligned}
 &= 0.2 \times 0.3 + 0.4 \times 0.4 + 0. \\
 &= 0.2 \times 0.3 + 0.4 \times 0.4 \leftarrow \\
 &= 0.16 + 0.06 = 0.22
 \end{aligned}$$

$$P(X_1 = B) = 0.48$$

$$P(X_1 = C) = 0.3$$

Probability of where you are after step 1

is  $[0.22 \quad 0.48 \quad 0.3]$



new initial dist

# Generalize!

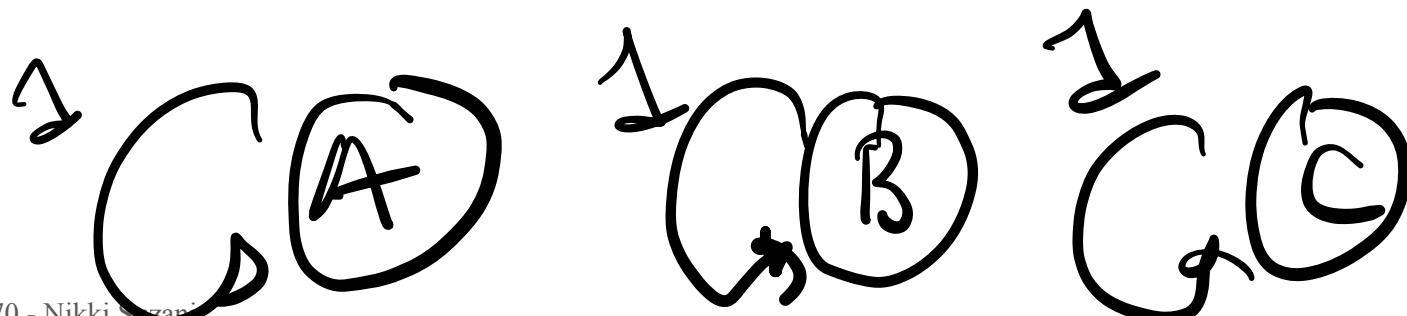
Let's look at the new matrix that we make. Now, what's the probability of being in State A after two steps?

$$P(X_2 = A) = P(X_2 = A | X_1 = A)P(X_1 = A)$$
$$+ \dots$$

# Generalize

How do we find the probability of being in a certain state after  $n$  steps?

$$\pi_n = \pi P^n \left( \text{1st entry} \right)$$



More Vocab!

$$\begin{bmatrix} 0.3 & 0.4 & 0.3 \\ 1 & 0 & 0 \end{bmatrix}$$

An invariant (or stationary) distribution  $\pi$  is a starting distribution such that:

- $\pi = \pi P$

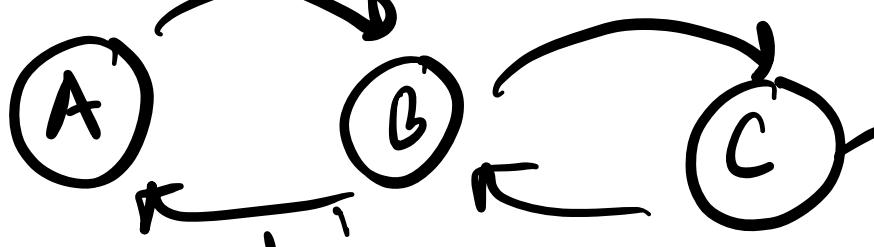
example  
invariant

when I multiply my initial dist. by  
my probability matrix, I get the  
same distribution

$$\begin{bmatrix} a & b & c \end{bmatrix} \xrightarrow{\text{A } P} \begin{bmatrix} a & b & c \end{bmatrix}$$

where  $P = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

## More Vocab!

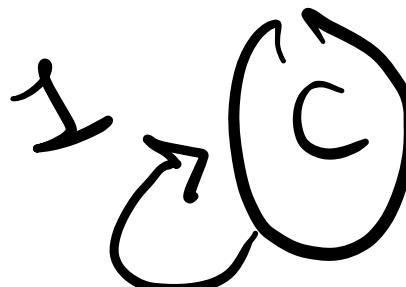
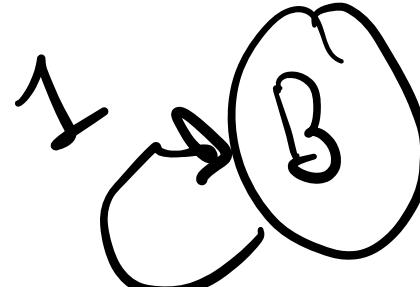
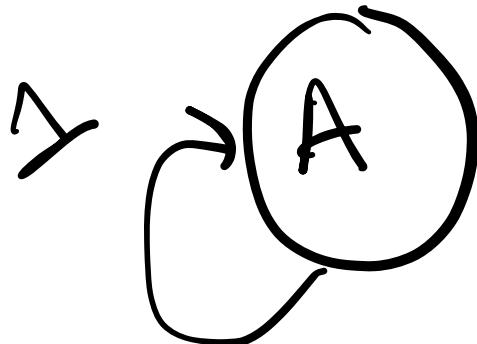


1

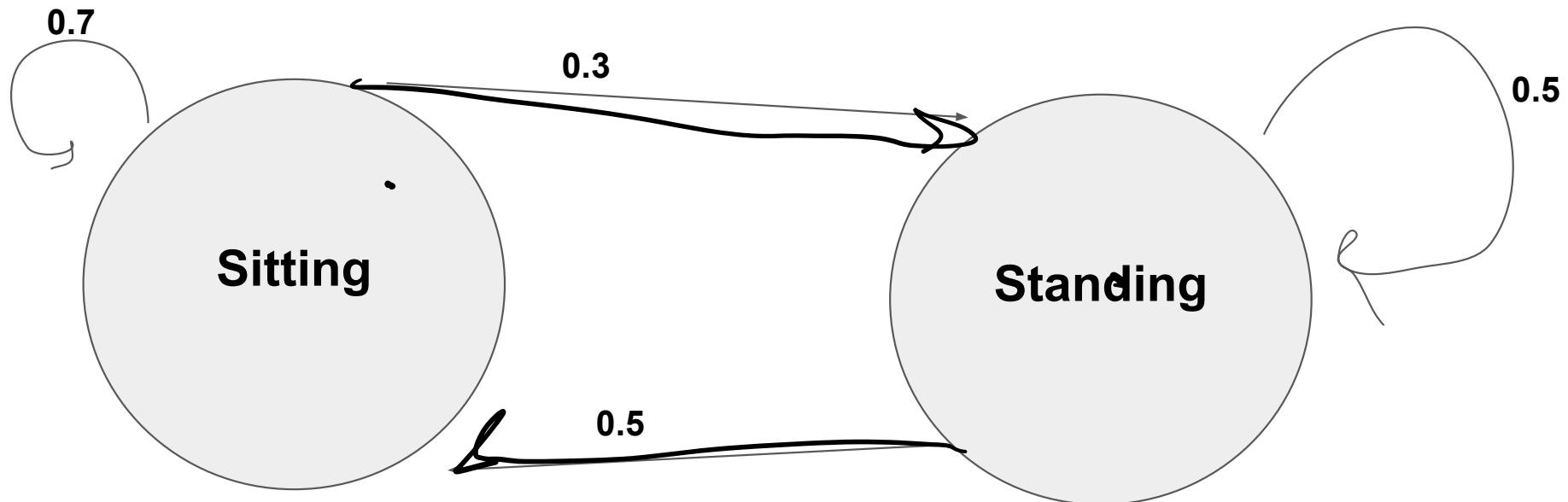
A Markov chain is said to be **irreducible** if you can go from any **starting space** to any other **ending space**.

- Specifically, there is a path of nonzero (positive) probability that goes from state i to state j for all i & j.

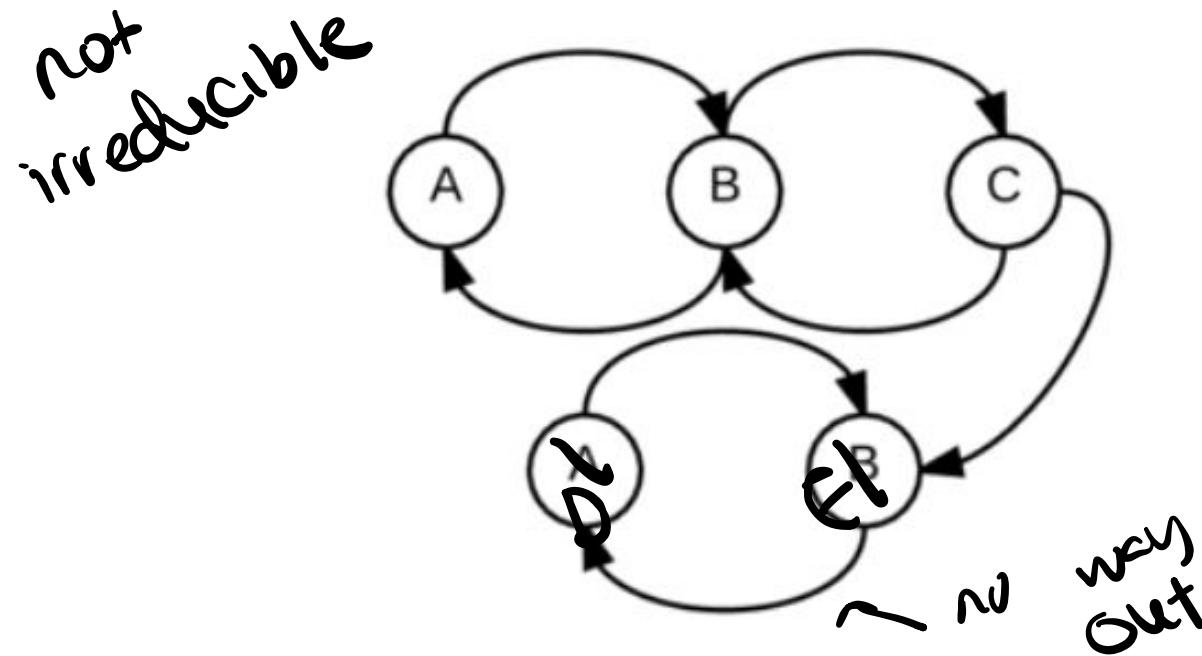
not ~~irreducible~~



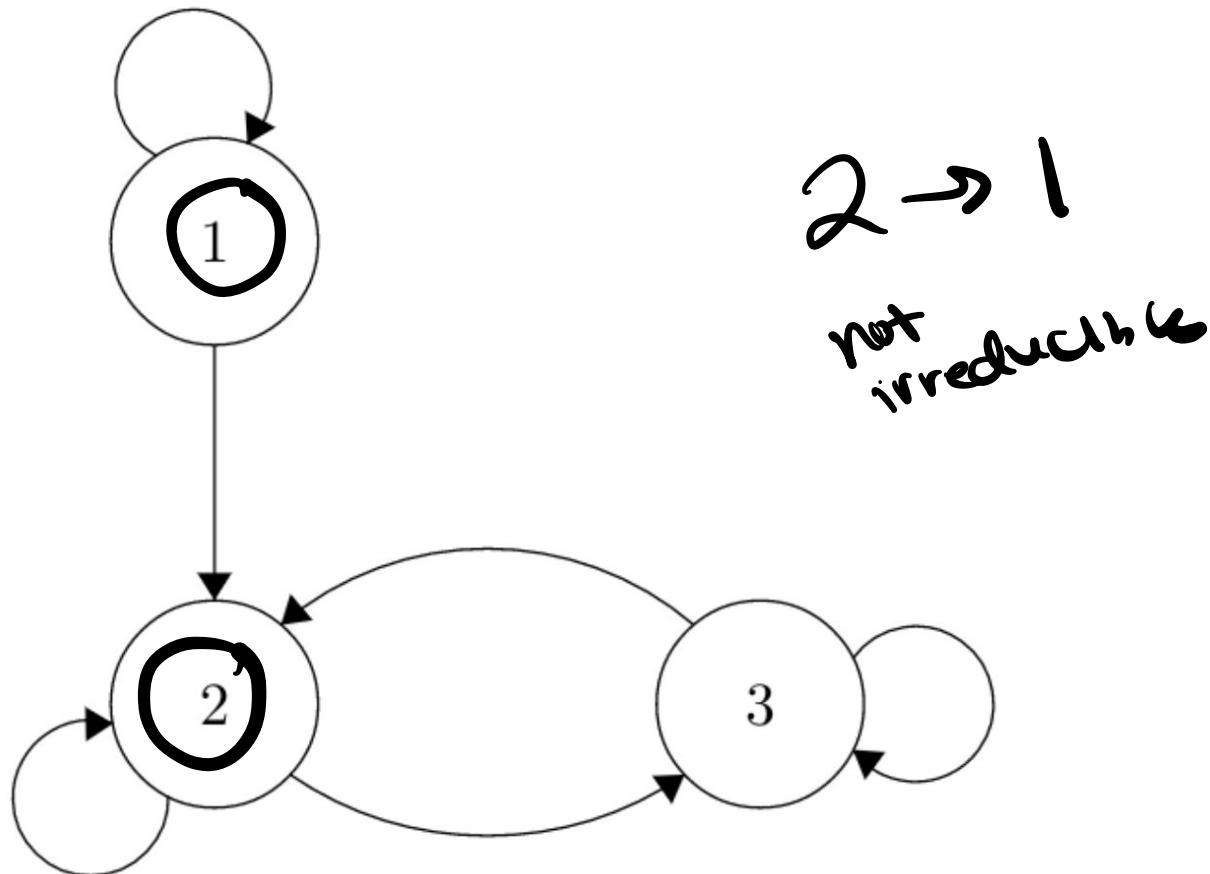
# Irreducible or Not?



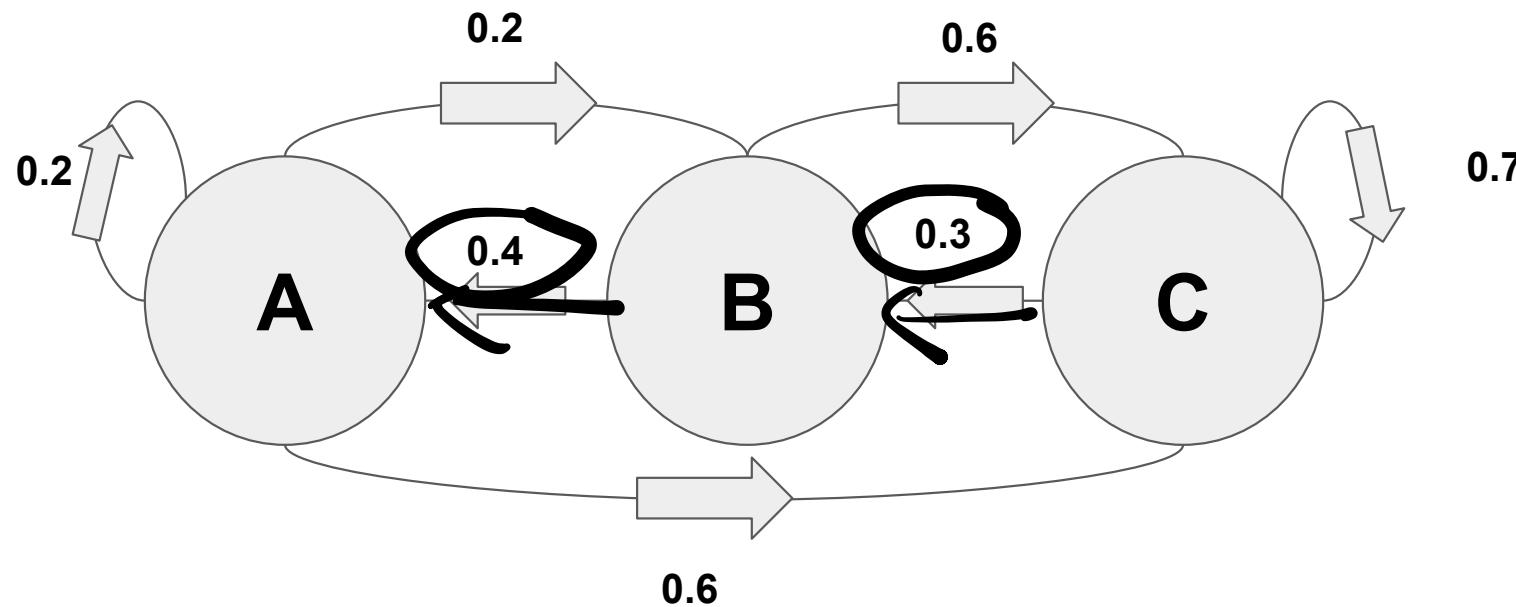
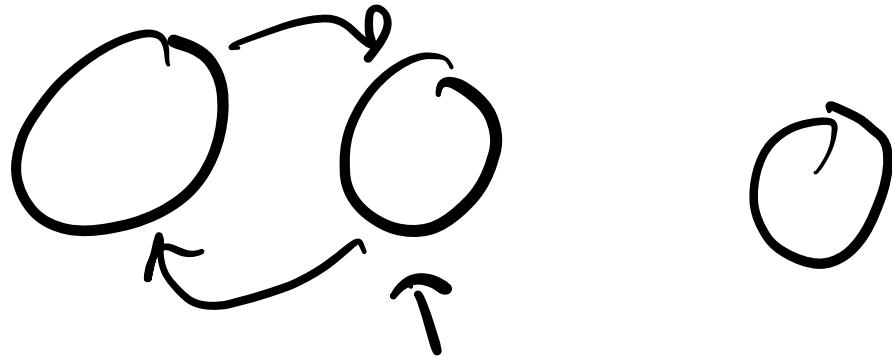
# Irreducible or Not?



# Irreducible or Not?



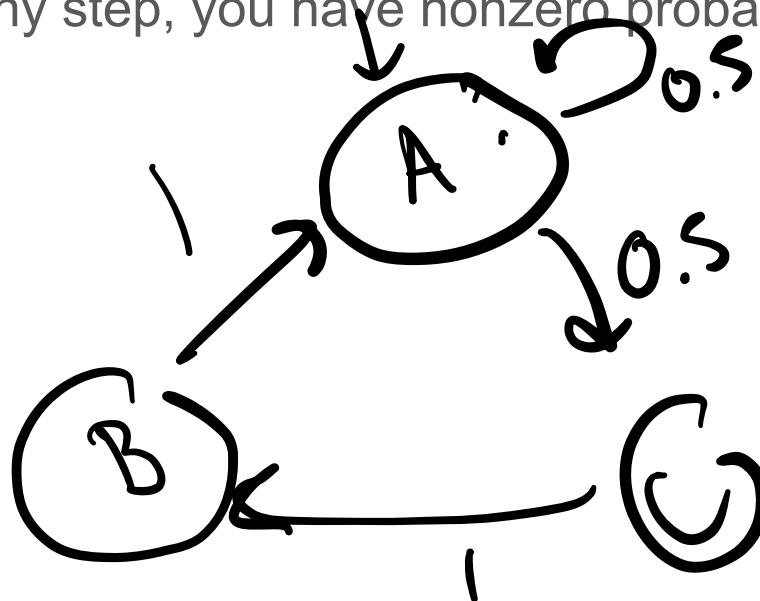
# Irreducible or Not?



# More Vocab!

A state  $i$  has **period  $d$**  if the Markov Chain can only come back to  $i$  in multiples of  $d$ .

- A Markov Chain is said to be **aperiodic** if the period of the chain is 1 – meaning at any step, you have nonzero probability of being in any state.



# Aperiodic (Formally)

**Theorem 22.4.** Consider an irreducible Markov chain on  $\mathcal{X}$  with transition probability matrix  $P$ . Define

$$d(i) := \text{g.c.d}\{n > 0 \mid P^n(i, i) = \Pr[X_n = i | X_0 = i] > 0\}, i \in \mathcal{X}. \quad (16)$$

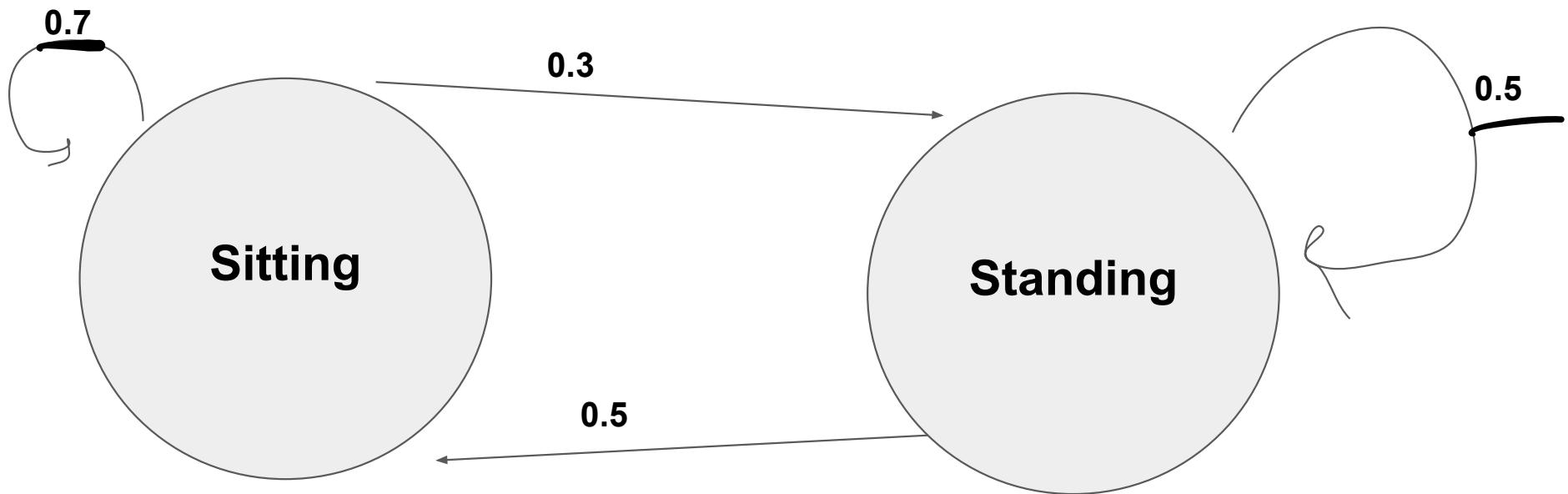
(a) Then,  $d(i)$  has the same value for all  $i \in \mathcal{X}$ . If that value is 1, the Markov chain is said to be aperiodic. Otherwise, it is said to be periodic with period  $d$ .

# Aperiodic Quick Tip!

If any state in an irreducible Markov Chain has a **self-loop with nonzero probability**, then it is **aperiodic**.

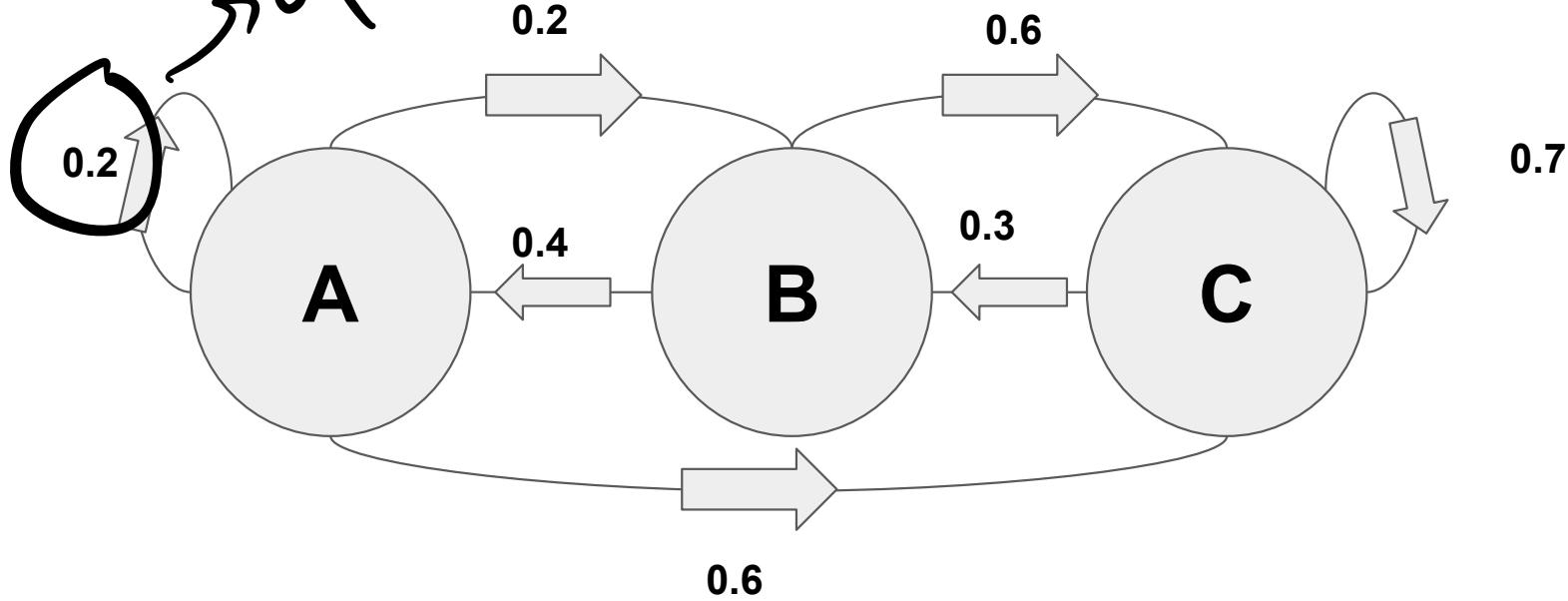
# Aperiodic or Not?

*Aperiodic*



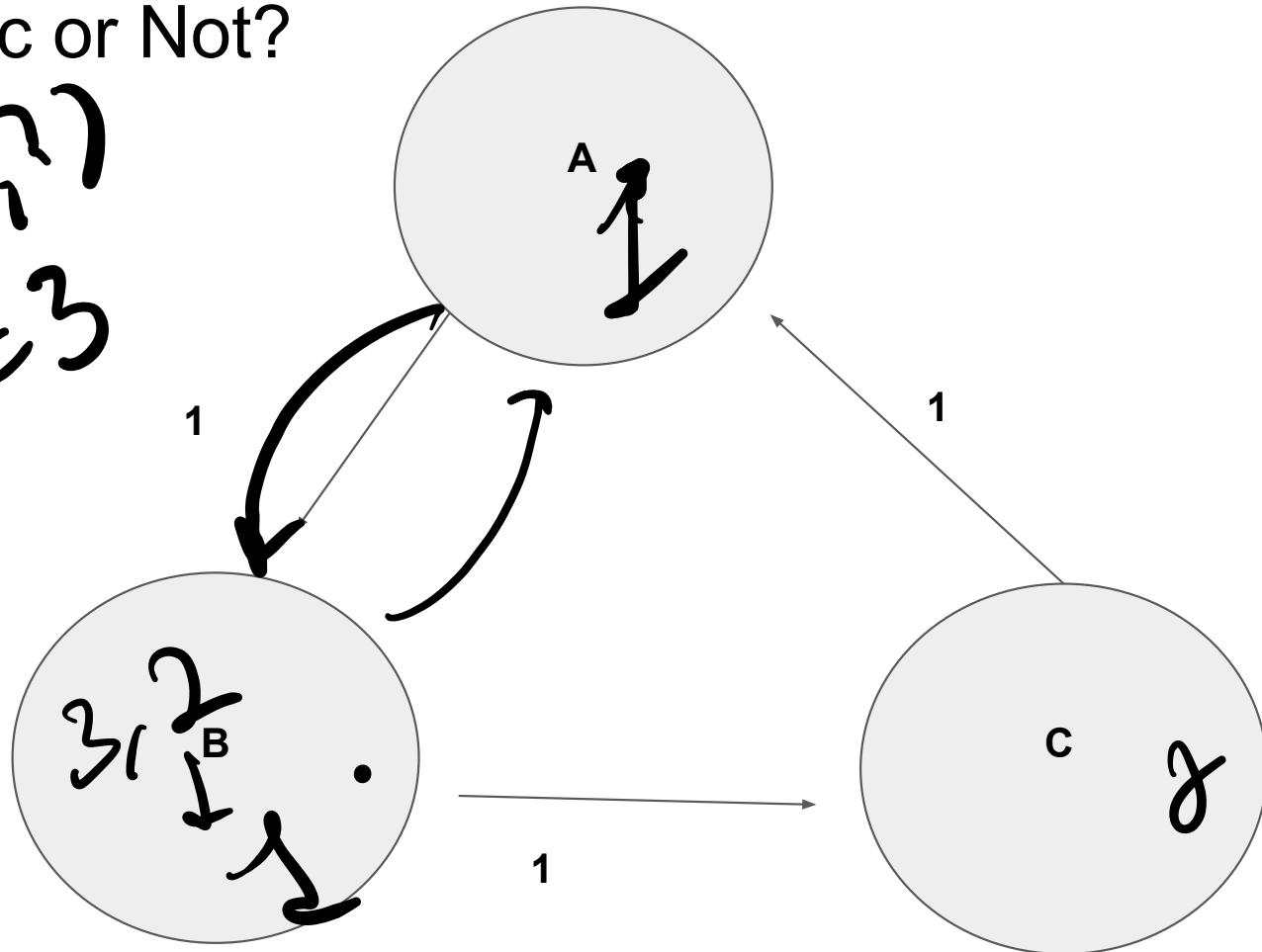
# Aperiodic or Not?

*→ aperiodic*

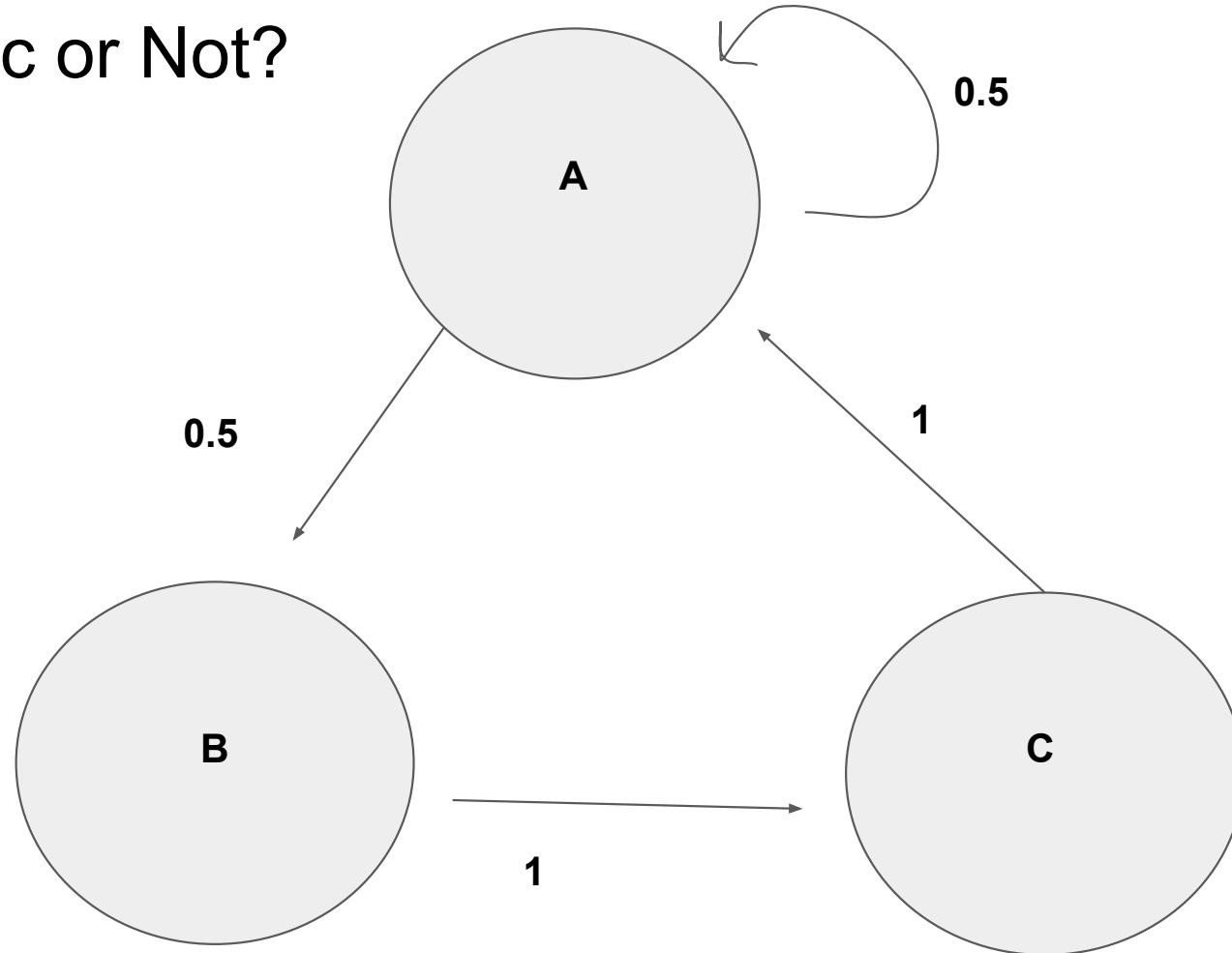


# Aperiodic or Not?

$\gcd(3, 1, 2)$



# Aperiodic or Not?



## More Vocab!

$$\pi P = \pi$$

If a Markov Chain is finite and irreducible, then its invariant distribution both exists and is unique. If it is aperiodic as well, it converges to the invariant distribution.

↓  
regardless of  $n$

$$\pi P^n \rightarrow \text{invariant}$$

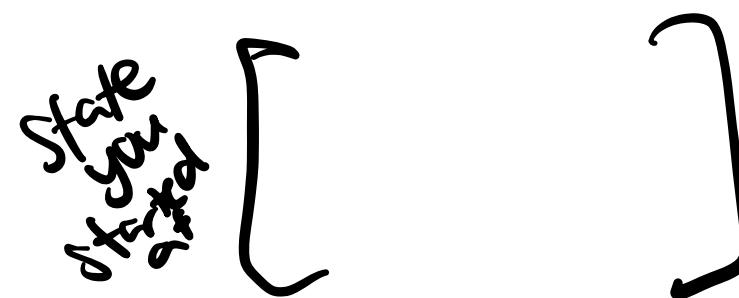
↑ more than one

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

State you  
end in

## Solving for Invariant

1. Write out transition probability matrix



2. Write out detailed balance equations – using  $\pi = \pi P$  and the fact that the starting probabilities have to add to 1.

$$\pi(1) + \pi(2) + \dots + \pi(n) = 1 \quad \pi P = \pi$$

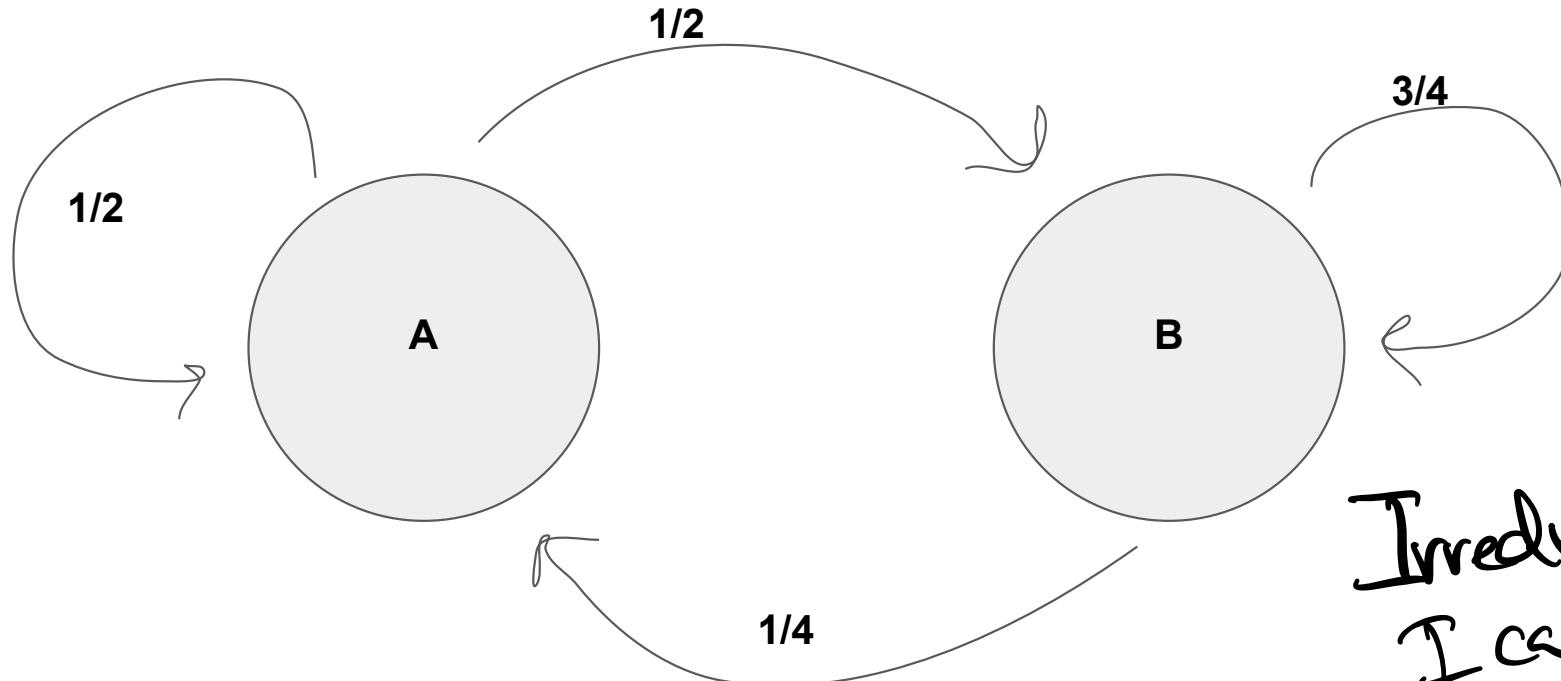
↓  
do math

$$[\pi(1) \quad \pi(2) \quad \dots \quad \pi(n)]$$

$$\begin{bmatrix} P(1,1) & \dots & \dots \\ P(2,1) \\ \vdots \\ P(n,1) \end{bmatrix}$$

$$\pi(1)P(1,1) + \pi(2)P(2,1) + \dots = \pi(1)$$

Solving for Invariant



Irreducible!  
I can get  
from A to B  
& vice-versa

Aperiodic:  
self-loop

Solving for Invariant

probabilistic  
starting  
in state A

$$\begin{matrix} & \text{A} & \text{B} \\ \text{A} & \left[ \begin{array}{c} \frac{1}{2} \\ \frac{1}{4} \end{array} \right] & \left[ \begin{array}{c} \frac{1}{2} \\ \frac{3}{4} \end{array} \right] \\ \text{B} & \left[ \begin{array}{c} \frac{1}{2} \\ \frac{3}{4} \end{array} \right] & \left[ \begin{array}{c} \frac{1}{2} \\ \frac{1}{4} \end{array} \right] \end{matrix}$$

$\pi P = \pi$

$$[\pi(A) \ \pi(B)] \left[ \begin{array}{cc} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{4} & \frac{3}{4} \end{array} \right] = [\pi(A) \ \pi(B)]$$

$\frac{1}{2} \pi(A) + \frac{3}{4} \pi(B) = \pi(A)$   
 $\frac{1}{4} \pi(A) + \frac{1}{2} \pi(B) = \pi(B)$

$$\underbrace{[\frac{1}{2}\pi(A) + \frac{1}{4}\pi(B)]}_{\frac{1}{2}\pi(A) + \frac{3}{4}\pi(B)} = \underbrace{[\pi(A)]}_{\pi(B)}$$

$$\frac{1}{2}\pi(A) + \frac{1}{4}\pi(B) = \pi(A) \rightarrow \frac{1}{2}\pi(A) = \frac{1}{4}\pi(B)$$

$$\frac{1}{2}\pi(A) + \frac{3}{4}\pi(B) = \pi(B)$$

$$\underline{\pi(A) + \pi(B) = 1}$$

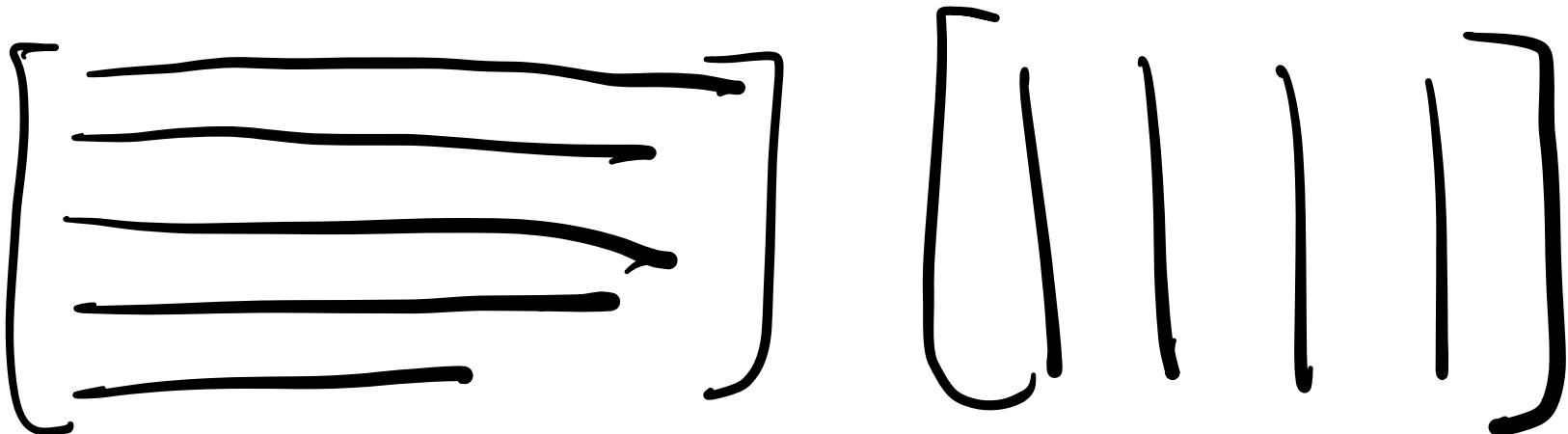
$$\frac{1}{2}\pi(B) + \pi(B) = 1$$

$$[\frac{1}{3} \quad \frac{2}{3}] \rightarrow \text{invariant dist.}$$

$$\begin{aligned}\frac{3}{2}\pi(B) &= 1 \\ \pi(B) &= \frac{2}{3} \\ \pi(A) &= \frac{1}{3}\end{aligned}$$

# Special Case: Doubly Stochastic Matrices

A matrix is doubly stochastic if all the rows and all the columns sum to 1.



*invariant  
is unique*

## Doubly Stochastic Invariant

Suppose you have an irreducible, aperiodic finite Markov Chain. Prove that the uniform distribution is the invariant distribution.

$$\left[ \frac{1}{n} \quad \frac{1}{n} \quad \dots \quad \frac{1}{n} \right]$$

$$\left[ \frac{1}{3} \quad \frac{1}{3} \quad \frac{1}{3} \right]$$

$$\begin{bmatrix} P(1,1) & \dots & P(1,n) \\ P(2,1) & \dots & P(2,n) \\ \vdots & & \vdots \\ P(n,1) & \dots & P(n,n) \end{bmatrix}$$

↑ and the prob. matrix  
↓ is doubly stochastic

if this

$$\frac{1}{n} P(1,1) + \frac{1}{n} P(2,1) + \dots + \frac{1}{n} P(n,1) = \left(\frac{1}{n}\right) \text{ is } \frac{1}{n}$$

$\frac{1}{n} (P(1,1) + P(2,1) + \dots + P(n,1))$

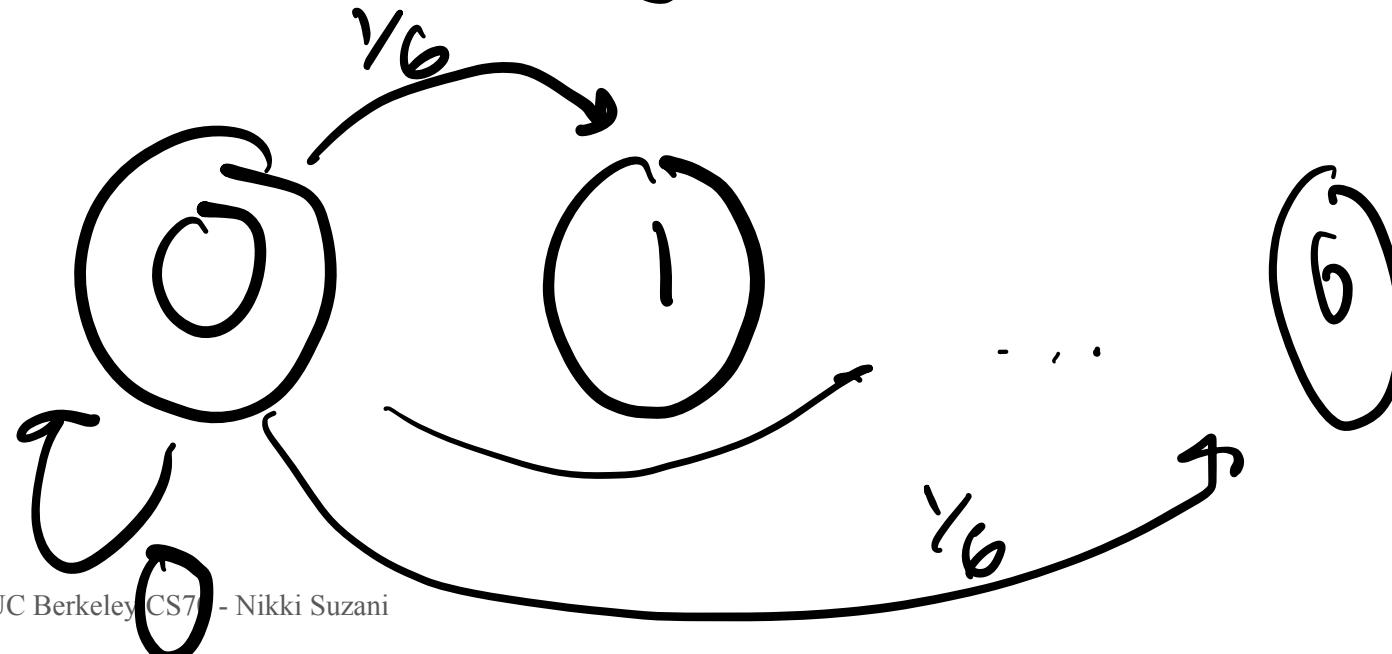
$\frac{1}{n} (1) = \frac{1}{n}$  ✓

If columns sum to 1, is the uniform dist. invariant

# Doubly Stochastic Example! data140 ☺

You roll a dice  $n$  times for some large  $n$ . What's the probability that the sum of all the dice rolls is a multiple of 7?

$X$ : sum of my dice rolls  $(\text{mod } 7)$



## Doubly Stochastic Example!

$$\begin{matrix} & 0 & 1 & 2 & 3 & 4 & 5 & 6 \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \end{matrix} & \left[ \begin{matrix} 0 & 0 & \frac{1}{6} & \frac{2}{6} & \frac{3}{6} & \frac{4}{6} & \frac{5}{6} \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ \vdots & & & & & & \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{matrix} \right] & \begin{matrix} \text{all columns} \\ \text{sum to} \\ \text{one} \end{matrix} \end{matrix}$$

Probability my sum  
is 0 (mod 7)  
 $= \frac{1}{7}$

$$[\gamma_1 \dots \gamma_7]$$

# Recap

Learned about Markov Chains:

- Represent states and transitions where the next state **only** depends on the previous state
- Learned about **invariant** (or stationary) distributions, and how irreducible/aperiodic relates to them
- Learned how to solve for **stationary distributions** in general, and especially in **doubly stochastic** matrices