# Class 13

Markov Chains I

#### Announcements

- HW6 due tomorrow!
- HW7 will be out next week, it's not due until the week after Thanksgiving.
- Did anyone leave a pair of headphones in my office?

#### Recap (Time homogeneous, finite) Markov Chains!

Memorylessness:  $Pr[X_t = a | X_0, ..., X_{t-1}] = Pr[X_t = a | X_{t-1}]$ 



#### e.g.,  $\varphi = (x_1 \vee x_2) \wedge (\overline{x_1} \vee x_2) \wedge \cdots \wedge (x_5 \vee \overline{x_7})$

#### Recap Randomized algorithm for 2SAT!

- Algorithm:
	- While not done:
		- Find an unsatisfied clause, flip one of the variables at random.
- Analysis: This Markov chain hits  $\binom{n}{n}$  in no more than  $100n^2$  steps whp:



### Questions?

Q1

- $X_0 = A$  with probability 1.
- Q1.1:  $Pr[X_1 = B]$ ?
- Q1.2:  $Pr[X_2 = B]$ ?
- Q1.3:  $Pr[X_{10} = B]$ ?



Q2 0 1 2 3 3 4 5 6 7 8 1 2/3 1/3 2/3 1/3 2/3 1/3 2/3 1/3 2/3 1/3 2/3 1/3 2/3 1/3 2/3 1/3 2/3 2/3 1/3

$$
\bullet r_i = E[\min_t \{t : Z_n = n\} \mid Z_0 = i]
$$

- Q2.1. What expression do the  $r_i$  satisfy?
- Q2.2. Sanity-check: prove that  $r_i = f_i + r_{i+1}$  where  $f_i = 2f_{i-1} + 3$ and  $f_0 = 1$ .
- Q2.3.  $r_0 = 2^{\Omega(n)}$

#### In the mini-lectures

• We saw one way to analyze a chain that looked like this:



• Whp, it took  $\Theta(n^2)$  steps to reach n.



- We will see another way to use the transition matrix to analyze (certain nice) Markov chains.
- We'll analyze a Markov chain that looks like this:
- What should happen if the Markov chain runs for long enough?
- What's your intuition about how long "long enough" is?



## Let's do this first group work together.

• Transition matrix?



• Pr[ 
$$
X_t = 2 | X_0 = 0
$$
 ] for t=1, 2, ..., 100?

• As  $t \to \infty$ , what do you think this prob. should go to?

## Next group work!

• Show that:

$$
P = F \cdot \begin{pmatrix} 1 & & & \\ & 1/3 & & \\ & & -1/3 & \\ & & & 1/3 \end{pmatrix} \cdot F^*.
$$

• Use this to find a nicer way of computing  $Pr[X_t = 2 | X_0 = 0]$ 

$$
F = \frac{1}{2} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & -i & -1 & i \\ 1 & -1 & 1 & -1 \\ 1 & i & -1 & -i \end{pmatrix}
$$

Show 
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 $\begin{pmatrix} 1 & 1 & 0 \\ 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ -i \\ -1 \end{pmatrix}$ . . .  $\begin{pmatrix} 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ -i \\ -1 \\ i \end{pmatrix} = \begin{pmatrix} 1 \\ -i \\ -1 \\ i \end{pmatrix}$  Eigenvector with

-1 eigenvalue uith<br>1



 $\begin{pmatrix} 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \end{pmatrix}\begin{pmatrix} 1 \\ i \\ -1 \\ -i \end{pmatrix} = \begin{pmatrix} 1 \\ i \\ -1 \\ -i \end{pmatrix}$  Eigenvector with  $\pm 1$ 

igenvector wi<br>genvalue -1 ith

Eigenvector cui<br>Eigenvector cui<br>eigenvalue 1 'm



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#### Back to group work! Do the same thing for a large cycle.

• We'll do this somewhat synchronously since the math is a bit gross.



### Part 1: Decomposing the adjacency matrix



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# Part 2:  $Pr[X_t = 0 | X_0 = 0]$

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## Part 3: What happens as t gets big?

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$$
t
$$
 gets big?  
\n
$$
\mathbb{P}[\chi_{t=0} | \chi_{0}=0] = \frac{1}{h} + \frac{1}{h} \sum_{j=1}^{n-1} \underbrace{\left(\frac{1+2cos(2\pi j_{n})}{3}\right)^{t}}_{\text{this} \to 0 \text{ as } t \to \infty}
$$
\n
$$
\frac{1}{h} \times \frac{1}{h} \times \frac{1}{h} \times \frac{1}{h} \times \frac{1}{h}
$$
\n
$$
\frac{1}{h} \times \frac{1}{h} \times \frac{1}{h} \times \frac{1}{h} \times \frac{1}{h} \times \frac{1}{h}
$$

## Part 4: How big does t need to be?

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### Take-aways

- If we can diagonalize the transition matrix, it can make analyzing a Markov chain easier.
	- This is called "spectral analysis."
- If the second eigenvalue of a (symmetric) transition matrix is bounded away from 1, then the Markov chain "mixes" quickly.
	- We'll see what it means to "mix quickly" more formally next week.