

## LECTURE 18

- **Readings:** Section 7.4

## Lecture outline

- Review
- Multiple recurrent classes
- Absorption probability
- Expected time to absorption
- Mean first passage and recurrence times

## Review

- Markov chain with a **single recurrent class**, which is **aperiodic**, has convergence of  $n$ -step transition probabilities

$$\lim_{n \rightarrow \infty} r_{ij}(n) = \pi_j \quad (\text{with no dependence on } i)$$

to values that give a **steady-state PMF** on the states

$$\pi_j = \lim_{n \rightarrow \infty} \mathbf{P}(X_n = j), \quad j = 1, 2, \dots, m.$$

- $\pi_1, \pi_2, \dots, \pi_m$  can be found as unique solution to:

$$\pi_j = \sum_{k=1}^m \pi_k p_{kj}, \quad j = 1, 2, \dots, m \quad (\text{balance equations})$$

$$\sum_{j=1}^m \pi_j = 1 \quad (\text{normalization})$$

## Multiple recurrent classes



- Is there convergence to a steady-state distribution?
- $\lim_{n \rightarrow \infty} \mathbf{P}(X_n = j | X_0 = 2)$

$$= \begin{cases} \quad, & \text{for } j = 1; \\ \quad, & \text{for } j = 2; \\ \quad, & \text{for } j = 3; \\ \quad, & \text{for } j = 4. \end{cases}$$

## Absorption probability

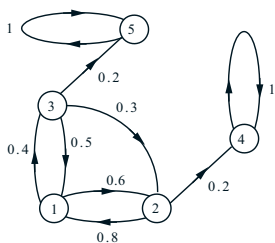
- A state  $k$  is **absorbing** when  $p_{kk} = 1$
- Fix an absorbing state  $s$ . The **absorption probability** (to  $s$ ) starting from state  $i$  is defined as

$$a_i = \mathbf{P}(\text{state } s \text{ is eventually reached} | X_0 = i)$$

- When a Markov chain has only transient and absorbing states [each recurrent class has only a single state], absorption probabilities are the unique solution to

$$\begin{aligned} a_s &= 1 \\ a_i &= 0 \quad \text{for all absorbing } i \neq s \\ a_i &= \sum_{j=1}^m p_{ij} a_j \quad \text{for all transient } i \end{aligned}$$

## Absorption probability: Example



- What are the probabilities of absorption to state 5?

$$a_1 =$$

$$a_2 =$$

$$a_3 =$$

$$a_4 =$$

$$a_5 =$$

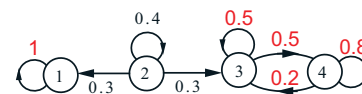
## Absorption probability: Slight generalization

- Fix a **recurrent class**  $S$ . The **absorption probability** (to  $S$ ) starting from state  $i$  is defined as

$$a_i = \mathbf{P}(\text{class } S \text{ is eventually reached} | X_0 = i)$$

- Absorption probabilities are the unique solution to

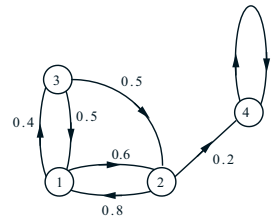
$$\begin{aligned} a_i &= 1 \quad \text{for all } i \in S \\ a_i &= 0 \quad \text{for all recurrent } i \notin S \\ a_i &= \sum_{j=1}^m p_{ij} a_j \quad \text{for all transient } i \end{aligned}$$



**Expected time to absorption**

- Entering a recurrent state is called **absorption**
- Expected time to absorption** starting from state  $i$ :  

$$\mu_i = \mathbb{E}[\min\{n \geq 0 \text{ such that } X_n \text{ is recurrent}\} \mid X_0 = i]$$
- $\mu_1, \mu_2, \dots, \mu_m$  are the unique solution to
 
$$\begin{aligned} \mu_i &= 0 && \text{for all recurrent states } i \\ \mu_i &= 1 + \sum_{j=1}^m p_{ij} \mu_j && \text{for all transient states } i \end{aligned}$$

**Expected time to absorption: Example**

- What are the expected times to absorption?

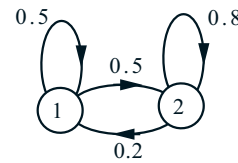
$$\begin{aligned} \mu_1 &= \\ \mu_2 &= \\ \mu_3 &= \\ \mu_4 &= \\ \mu_5 &= \end{aligned}$$

**Mean first passage and recurrence times**

- Consider an MC with one recurrent class  $S$  and fix  $s \in S$
- Mean first passage time from  $i$  to  $s$**  is defined as  

$$t_i = \mathbb{E}[\min\{n \geq 0 \text{ such that } X_n = s\} \mid X_0 = i]$$
- Mean recurrence time of  $s$**  is defined as  

$$t_s^* = \mathbb{E}[\min\{n \geq 1 \text{ such that } X_n = s\} \mid X_0 = s]$$
- $t_1, t_2, \dots, t_m$  are the unique solution to
 
$$\begin{aligned} t_s &= 0 \\ t_i &= 1 + \sum_{j=1}^m p_{ij} t_j && \text{for all } i \neq s \end{aligned}$$
- Mean recurrence time is  $t_s^* = 1 + \sum_{j=1}^m p_{sj} t_j$

**Mean first passage and recurrence times: Example**

- What are the mean first passage times to 1?

$$\begin{aligned} t_1 &= \\ t_2 &= \end{aligned}$$

- What is the mean recurrence time of 1?

$$t_1^* =$$

**Generality of Markov chain models**

- Most discrete-time, finite-valued processes can be approximated well by a Markov chain, with a suitable state
  - Memoryless:  $p_{ij} = \mathbb{P}(X_n = j)$  (no dependence on  $i$ )
  - “basic case”:  $X_{n+1}$  and  $X_{n-1}$  are conditionally independent given  $X_n$
  - Longer memory: handled by increasing  $m$  (size of the state space)

**Example**

- $X_0, X_1, X_2, \dots$  are Bernoulli random variables with

$$p_{X_{n+1}|X_n, X_{n-1}}(1 \mid x_n, x_{n-1}) = \begin{cases} q_{00}, & \text{when } (x_n, x_{n-1}) = (0, 0); \\ q_{01}, & \text{when } (x_n, x_{n-1}) = (0, 1); \\ q_{10}, & \text{when } (x_n, x_{n-1}) = (1, 0); \\ q_{11}, & \text{when } (x_n, x_{n-1}) = (1, 1). \end{cases}$$

- $X_0, X_1, X_2, \dots$  is not a Markov chain, but we can define one over a larger set  $\{1, 2, \dots, m\}$