

# MATH 285: Stochastic Processes

[math-old.ucsd.edu/~ynemish/teaching/285](http://math-old.ucsd.edu/~ynemish/teaching/285)

Today: Reducible Markov chains with  
finite state space  
Markov chains with infinite state  
space

- Homework 2 is due on Friday, January 21 11:59 PM

# General form of transition matrix with finite $S$

$$P = \left[ \begin{array}{ccc|c} P_1 & & & 0 \\ & P_2 & & 0 \\ & & P_3 & \\ & & & \ddots \\ 0 & & & P_r \\ \hline & & S & Q \end{array} \right]$$

$P_e$  submatrix for the recurrent class  $R_e$

$P_e$  is a stochastic matrix, we can consider it as a Markov chain on  $R_e$

$[SIQ]$  transition probabilities starting from transient states.

- If  $P_e$  is aperiodic, then  $P_e^n \rightarrow \begin{bmatrix} \pi^{(e)} \\ \vdots \\ \pi^{(e)} \end{bmatrix}$ ,  $n \rightarrow \infty$
- What about transient states?
- What if  $P_e$  is not aperiodic?

# Transient states

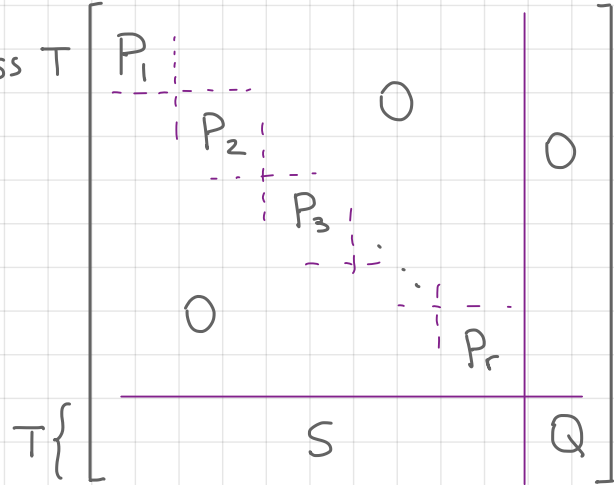
Suppose there exists one transient class  $T$

- $S \neq \emptyset$

If  $S = \emptyset$  then  $T$  is recurrent

- If  $S \neq \emptyset$ , then  $Q$  is substochastic,

i.e.,  $\exists i \in T$  s.t.  $\sum_{j \in T} Q_{ij} < 1$



- If  $Q$  is substochastic, then for all eigenvalues  $\lambda$  of  $Q$   $|\lambda| < 1$

$\Rightarrow Q^n \rightarrow 0, n \rightarrow \infty$ , i.e. for  $i, j \in T$   $P_i[X_n = j] \rightarrow 0, n \rightarrow \infty$

- $I + Q + Q^2 + \dots = I + V D V^{-1} + V D^2 V^{-1} + \dots = V (I + D + D^2 + \dots) V^{-1}$  converges

For  $i, j \in T$ ,  $E_i \left[ \sum_{k=0}^{\infty} \mathbb{1}_{X_k = j} \right] =$

=

# Transient states

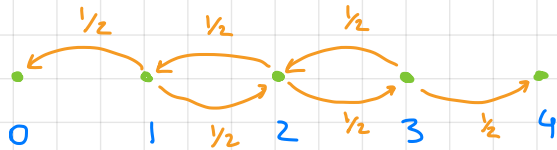
Conclusion: if TCS is a transient class, then  $\forall i, j \in T$

$$\lim_{n \rightarrow \infty} \mathbb{P}_i [X_n = j] =$$

$$\mathbb{E}_i \left[ \sum_{k=0}^{\infty} \mathbb{1}_{\{X_k = j\}} \right] =$$

expected number of visits to  $j$  starting from  $i$

## Example 8.1



$$Q = \begin{bmatrix} 0 & \frac{1}{2} & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & \frac{1}{2} & 0 \end{bmatrix}$$

$$(I - Q)^{-1} = \begin{bmatrix} \frac{3}{2} & 1 & \frac{1}{2} \\ 1 & 2 & 1 \\ \frac{1}{2} & 1 & \frac{3}{2} \end{bmatrix}$$

$$P = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \end{matrix} & \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 \\ 0 & \frac{1}{2} & 0 & \frac{1}{2} \end{bmatrix} \end{matrix}$$

Expected number of visits to ② starting from ① is 1

Expected number of steps before absorption starting from ① is  $\frac{3}{2} + 1 + \frac{1}{2} = 3$

## Transient states

Recall, First step analysis for the mean hitting time

$$g_i = \mathbb{E}_i[\tau_A] = \begin{cases} 0, & i \in A \\ 1 + \sum_{j \in S} P(i,j) g_j, & i \notin A \end{cases}$$

$$\tau_A = \sum_{n=0}^{\infty} \mathbb{1}_{\{X_n \notin A\}}$$

Instead of adding 1 for each step, add 1 only when  $X_n$  visits  $j$ :

Denote  $S \setminus A =: T$ , and for  $i, j \in T$   $g_{ij} =$

Then FSA  $g_{ij} =$  if  $i \in A$

$$g_{ij} =$$

$G = [g_{ij}]$ , then

# Transient states

Starting from  $T$ , in which class will  $(X_n)$  end up?

Collapse each  $R_e$  into one state  $r_e$ , keep transient states  $t_e$ ,  $T = \{t_e\}$

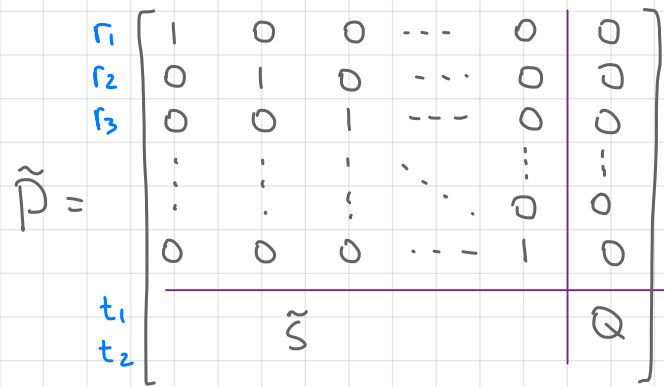
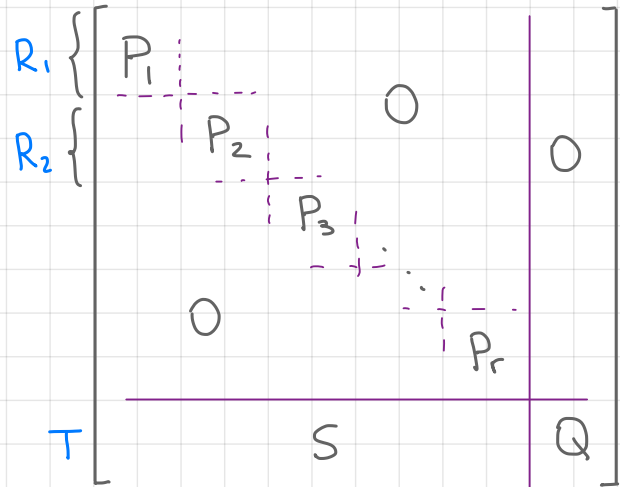
$(\tilde{X}_n)$  new MC on the reduced state space, and transition matrix  $\tilde{P}$ ,

with  $\tilde{s}(t_i, r_j) =$

Denote  $\tilde{A} = [a(t_i, r_j)]$  with

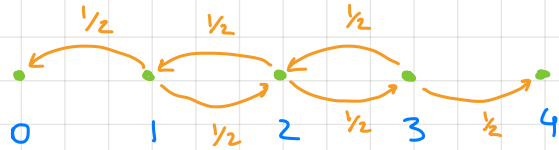
$a(t_i, r_j) :=$

Then  $\tilde{A} =$



# Transient states

## Example 8.2



$$P = \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \end{array} \left[ \begin{array}{cc|ccc} 0 & 4 & 1 & 2 & 3 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ \hline \frac{1}{2} & 0 & 0 & \frac{1}{2} & 0 \\ 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & \frac{1}{2} & 0 & \frac{1}{2} & 0 \end{array} \right]$$

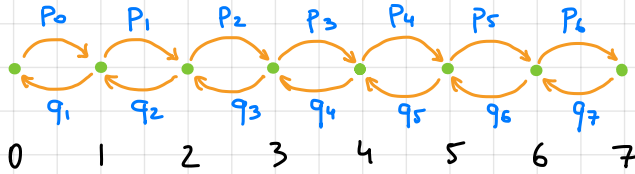
What is the probability that starting from a transient state  $i$  we end up in a recurrent state  $j$ ?

Use  $\tilde{A} =$  (nothing to collapse in this case)

$$\tilde{A} = \begin{bmatrix} \frac{3}{2} & 1 & \frac{1}{2} \\ 1 & 2 & 1 \\ \frac{1}{2} & 1 & \frac{3}{2} \end{bmatrix} \begin{bmatrix} \frac{1}{2} & 0 \\ 0 & 0 \\ 0 & \frac{1}{2} \end{bmatrix} = \begin{bmatrix} \frac{3}{4} & \frac{1}{4} \\ \frac{1}{2} & \frac{1}{2} \\ \frac{1}{4} & \frac{3}{4} \end{bmatrix}$$

- Expected transit times from  $i$  to  $j$  (think about  $j$  as absorbing)...

# Birth and death processes (infinite state space)



$$S = \{0, 1, 2, 3, \dots\}$$

$$p(i, i+1) = p_i, \quad p(i, i-1) = 1 - p_i \quad \text{if } q_i$$

$$p(0, 1) = p_0, \quad p(0, 0) = 1 - p_0$$

$p_0 \in [0, 1]$ ,  $p_0 = 0$  absorbing,  $p_0 = 1$  reflecting

Model of population growth:  $X_n =$  size of the population at time  $n$

$\mathbb{P}_i[\exists n \geq 0 : X_n = 0]$  - extinction probability

$\mathbb{P}_i[X_n \rightarrow \infty \text{ as } n \rightarrow \infty]$  - probability that population explodes

Denote  $h(i) := \mathbb{P}_i[\exists n \geq 0 : X_n = 0] =$

First step analysis:

Theorem 7.0  $(h(0), h(1), \dots)$  is the minimal solution to

$$\begin{cases} h(0) = 1 \\ h(i) = \sum_{j=0}^{\infty} p(i, j) h(j) \end{cases}$$



# Birth and death processes

$$(*) \begin{cases} h(i) = \sum_{j \geq 0} p(i,j) h(j) \\ h(0) = 1 \end{cases}$$

$$(*) \begin{cases} h(0) = 1 \\ h(1) = p_1 h(2) + q_1 h(0) \\ h(2) = p_2 h(3) + q_2 h(1) \\ \vdots \\ h(i) = p_i h(i+1) + q_i h(i-1) \\ \vdots \end{cases}$$

$$p(i,j) = \begin{cases} p_i, & j = i+1 \\ q_i, & j = i-1 \\ 0, & \text{otherwise} \end{cases}$$

$$\begin{cases} u(1) = h(1) - h(0) = h(1) - 1 \\ u(2) = \frac{q_1}{p_1} u(1) \\ u(3) = \frac{q_2}{p_2} u(2) = \frac{q_2 q_1}{p_2 p_1} u(1) \\ \vdots \\ u(i+1) = \frac{q_i}{p_i} u(i) = \frac{q_i \dots q_1}{p_i \dots p_1} u(1) \\ \vdots \end{cases}$$

Denote

## Birth and death processes

$$u(1) = u(1)$$

$$u(i) = h(i-1) - h(i)$$

$$u(2) = p_1 u(1)$$

Take the sum of the first  $i$  equations

$$u(3) = p_2 u(1)$$

$\vdots$

$$u(i+1) = p_i u(1)$$

$\vdots$

By Thm. 7.0 we need the minimal solution to (\*)

Notice that  $u(1)$  uniquely determines all  $h(i)$

$$h(i) = h(0) - (1 + p_1 + p_2 + \dots + p_i) u(1)$$

and the minimal solution corresponds to maximal  $u(1)$

- If  $1 + \sum_{i=1}^{\infty} p_i = \infty$ , then

$$\text{In this case } h(0) - h(i) = 0 \quad \forall i \Rightarrow$$

## Birth and death processes

- If  $1 + \sum_{i=1}^{\infty} p_i < \infty$ , then for any

we get a solution to (\*) by taking

$$\forall i \quad h(0) - h(i) = (1 + p_1 + p_2 + \dots + p_{i-1}) a$$

If  $u(1) > \frac{1}{1 + \sum_{i=1}^{\infty} p_i}$ , then for some  $n$  large enough

Therefore,

value of  $u(1)$ , and the corresponding minimal

solution is  $h(j) =$

## Positive and null recurrence

Let  $(X_n)$  be a Markov chain, and let  $i$  be a recurrent state. Starting from  $i$ ,  $(X_n)$  revisits  $i$  infinitely many times,  $\mathbb{P}_i[X_n = i \text{ for infinitely many } n] = 1$

How often does  $(X_n)$  revisit state  $i$ ?

(i) After  $n$  steps,  $(X_n)$  revisits  $i \approx \frac{n}{2}$  times, spends half of the time at  $i$

(ii) After  $n$  steps,  $(X_n)$  revisits  $i \approx \sqrt{n}$  times, the fraction of time spent at  $i$  tend to 0 as  $n \rightarrow \infty$ ,  $\frac{\sqrt{n}}{n} \rightarrow 0, n \rightarrow \infty$

Def 9.2 Let  $i$  be a recurrent state for MC  $(X_n)$ .

Denote  $T_i = \min \{n \geq 1 : X_n = i\}$ . If  $\mathbb{E}_i T_i < \infty$ , then we call  $i$

positive recurrent, the we call  $i$

## Positive and null recurrence

Remark If  $i$  is recurrent, then  $\mathbb{P}_i[T_i] < \infty$ . But it is still possible that  $\mathbb{E}[T_i] = \infty$  or that  $\mathbb{E}[T_i] < \infty$ .

Example:  $Y_1, Y_2 \in \mathbb{N}$ ,  $\mathbb{P}[Y_1 = k] = \frac{1}{2^k}$ ,  $Y_2 = \sum_{k=1}^{\infty} 2^k \mathbb{1}_{\{Y_1 \geq k\}}$ ,  $\mathbb{P}[Y_2 = 2^k] = \frac{1}{2^k}$ .

$$\mathbb{P}[Y_1 < \infty] = \mathbb{P}[Y_2 < \infty] = 1, \quad \mathbb{E}[Y_1] = \infty, \quad \mathbb{E}[Y_2] = \infty$$

Prop 9.4 In a finite-state irreducible Markov chain all states are

Proof. Fix state  $j \in S$

(1) There exist  $N \in \mathbb{N}$  and  $q \in (0, 1)$  such that for any  $i \in S$   
(probability of reaching  $j$  from  $i$  in the next  $N$  steps)

Since  $(X_n)$  is irreducible,

Take

## Positive and null recurrence

(2) For any  $i \in S$   $\mathbb{P}_i[T_j > N] \leq$  . | follows from (1)

(3) For any  $k \in \mathbb{N}$ ,  $\mathbb{P}_j[T_j > (k+1)N] \leq$

For any  $i \in S$   $\mathbb{P}_j[T_j > (k+1)N \mid T_j > kN, X_{kN} = i] \stackrel{\text{(SMP)}}{=}$

$$\mathbb{P}_j[T_j > (k+1)N] =$$

=

=

$\leq$

Now repeat  $k$  times.

## Positive and null recurrence

$$(4) \quad \mathbb{E}_j[T_j] = \sum_{n=1}^{\infty} \mathbb{P}_j[T_j \geq n] =$$

$$(5) \quad \mathbb{P}_j[T_j \geq n] \text{ is}$$

Therefore  $\forall n \in \{kN+1, \dots, (k+1)N\}$

$$\mathbb{P}_j[T_j \geq n] \leq$$

$$(6) \quad \sum_{n=kN+1}^{(k+1)N} \mathbb{P}_j[T_j \geq n] \leq$$

Finally,  $\mathbb{E}_j[T_j] \leq$

Conclusion: All states of an irreducible MC with finite state space are positive recurrent.

## Positive recurrence and stationary distributions

Thm 9.6 Let  $(X_n)$  be a Markov chain with a state space that is countable (but not necessarily finite).

Suppose there exists a positive recurrent state  $i \in S$ ,  $\mathbb{E}_i[T_i] < \infty$ .

For each state  $j \in S$  define

$$\gamma(i,j) =$$

(the expected number of visits to  $j$  before reaching  $i$ ).

Then the function  $\pi: S \rightarrow [0,1]$

$$\pi(j) =$$

is a stationary distribution for  $(X_n)$ .