

## MAT 526 – Introduction to Stochastic Processes - Fall 2017

**Course Description** This is a first course in stochastic processes. Topics to be covered include: random walks, branching processes, Markov chains, the Poisson process and queuing theory.

**Prerequisite** Solid backgrounds in calculus (MAT 397) and probability (MAT 521), and some familiarity with linear algebra (MAT 331).

**Instructor** Prof. JT Cox, 311B Carnegie, 443-1488, [jtcox@syr.edu](mailto:jtcox@syr.edu)

**Class Time and Location** Tu/Thur 2:00-3:20, Carnegie 115

**Office Hours Held in Carnegie 311B**

- ~~TBA~~ Tu Th 03:45 - 05:00pm
- and at other times by appointment

**Texts**

- A comprehensive calculus book
- Introduction to Stochastic Processes with R, by Robert Dobrow

**Course Web page** Some use of BlackBoard and/or WebWork may be made.

**Calculator policy** A calculator is useful for homework problems, but the statistical freeware package “R” is recommended instead. Calculators are not allowed on exams.

**Cell phone policy**

- Cell phones should be turned off and put away during class.
- Cell phones are not allowed on exams. Specifically, using or having available for use any calculator, cell phone or other electronic device during any exam will be considered a violation of the Academic Integrity Policy. During exams, cell phones and other electronic devices must be stowed out of reach, either in a closed backpack or at the front of the room.
- Violations of this policy will be considered Academic Integrity Violations.

**Attendance** You are expected to attend every class and every exam. You are expected to arrive on time for every class. *Please do not take this course if you cannot arrive on time every day.* If you do miss a class, it is your responsibility to obtain a copy of the lecture notes for that class from another student. You are also responsible for any announcements about changes to the course schedule, the exam schedule or the course requirements made during a missed class.

**Homework/Reading** There will be daily required reading assignments and weekly homework assignments. You are expected to keep up with both, as both are essential for learning the course material. Homework will be collected weekly.

**Exams/Quizzes** There will be 2 midterm exams and a final exam. The tentative dates are

- Midterm 1: Thur Sep 28
- Midterm 2: Tues Oct 30
- Final: Friday Dec 15, 8:00–10:00am (This date is NOT tentative.)

Exams will be based on class notes and examples, text readings and examples, and homework assignments. In addition to problems, definitions and theorem statements, short proofs will be asked on exams. There will be no “make up” exams given. The final exam will be given only at the scheduled time, it **will not be offered at any other time!** Do not make travel plans that conflict with any exam date.

- There may be short quizzes.

**Grading** The course grade weighting scheme is as follows:

- homework/quizz 20%
- each midterm exam 25%
- final exam 30%

**Student Learning Outcomes of BS degree mapped to this course**

- Demonstrate facility with the techniques of single and multivariable calculus and linear algebra
- Effectively communicate mathematical ideas orally and in writing
- Make accurate calculations by hand and with technological assistance
- Reproduce essential assumptions, definitions, examples, and statements of important theorems
- Describe the logical structure of the standard proof formats, reproduce the underlying ideas of the proofs of basic theorems, and create simple original proofs

**Specific Course Goals**

- understand the role of stochastic modeling
- gain practice developing and analyzing simple stochastic models
- learn and master some of the basic mathematical tools and techniques of stochastic modeling
- understand the relevant mathematical concepts and methods

**Disability-Related Accommodations** If you believe that you need accommodations for a disability, please contact the Office of Disability Services (ODS), <http://disabilityservices.syr.edu>, located in Room 309 of 804 University Avenue, or call (315) 443-4498, TDD: (315) 443-1371 for an appointment to discuss your needs and the process for requesting accommodations. ODS is responsible for coordinating disability-

related accommodations and will issue students with documented Disabilities Accommodation Authorization Letters, #as appropriate. Since accommodations may require early planning and generally are not provided retroactively, **please contact ODS as soon as possible.**

**Academic Integrity.** Syracuse University's academic integrity policy reflects the high value that we, as a university community, place on honesty in academic work. The policy defines our expectations for academic honesty and holds students accountable for the integrity of all work they submit. Students should understand that it is their responsibility to learn about course-specific expectations, as well as about university-wide academic integrity expectations. The university policy governs appropriate citation and use of sources, the integrity of work submitted in exams and assignments, and the veracity of signatures on attendance sheets and other verification of participation in class activities. The policy also prohibits students from submitting the same written work in more than one class without receiving written authorization in advance from both instructors. The presumptive penalty for a first instance of academic dishonesty by an undergraduate student is course failure, accompanied by a transcript notation indicating that the failure resulted from a violation of academic integrity policy. The presumptive penalty for a first instance of academic dishonesty by a graduate student is suspension or expulsion. SU students are required to read an online summary of the university's academic integrity expectations and provide an electronic signature agreeing to abide by them twice a year during pre-term check-in on MySlice. For more information and the complete policy, see <http://academicintegrity.syr.edu/>. For more precise details, see

- [One page guide: AI at SU](#)
- [10 things all students need to know about AI](#)

**Religious observances policy** SU religious observances policy recognizes the diversity of faiths represented among the campus community and protects the rights of students, faculty, and staff to observe religious holidays according to their tradition. Under the policy, students are provided an opportunity to make up any examination, study, or work requirements that may be missed due to are religious observance provided they notify their instructors before the end of the second week of classes. For fall and spring semesters, an online notification process is available through MySlice (Student Services -> Enrollment -> My Religious Observances) **from the first day of class until the end of the second week of class.**

MAT 526 - Intro to Stoch. Processes

Stochastic process

Discrete time  
 • a sequence or finitely family of random variables indexed by a parameter (is usually time), say  $X_0, X_1, X_2, \dots = (X_n)$  ← the whole sequence  
 $X_n$  will be the "state" of some "system" at "time"  $n$ ,  
 $n=0, 1, 2, \dots$

Continuous time  
 $(X_t, t \geq 0)$   
 ↑ ↑  
 system at time  $t$ ,  $t$  is a "continuous" variable

$0 \leq p \leq 1$  is a parameter

Example 1.6 Random walk, Gambler's Ruin

A gambler places a sequence of independent bets with win probability  $p$ . (given)

• On each bet the gambler's "fortune" ← amount of money the gambler has at a given time goes up \$1 or down \$1

with prob.  $p$  with probability  $q=1-p$  - after  $n^{\text{th}}$  gamble

• Notation:  $S_n$  = gambler's fortune at "time"  $n$ ,  $n=0, 1, 2, 3, \dots$   
 $S_0$  = --- initial fortune (given)

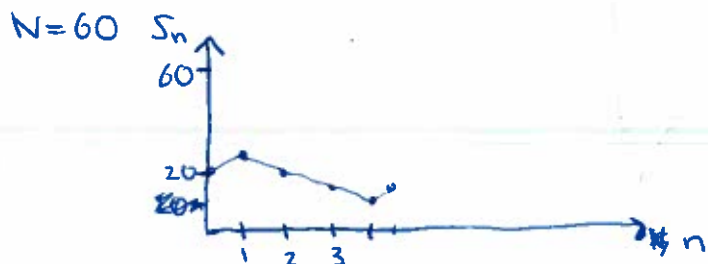
- the gambler is "ruined" if his fortune reaches 0.
- there is a "target" level  $N$  (given) and the gambler quits (wins the game) if his fortune reaches  $N$  before it reaches 0.

• Think of  $p = \frac{2}{3}$ ,  $N=10$ ,  $S_0=2$

Natural problems:

① Given the initial fortune  $S_0=k$ , what is the probability the gambler is ruined (or wins the game)

② On average, how long does it take to play the game (reach either 0 or  $N$ )?



Suppose outcome of the first bets are (win, loose, loose, loose, win, ...)

possible outcomes ( $n \in 1000$ ) in simulation: ruin, success, not yet resolved

The answers to these questions cannot be decided by looking at 1, or 2, or any finite nr of random variables.

Given  $p, N$ , consider start with  $S=k$  for  $k=0, 1, 2, \dots, N$ .

Let  $x_k = P(\text{ruin} | S_0 = k)$ .

We want to find the numbers  $x_0, x_1, \dots, x_N$  or  $(x_k)_{0 \leq k \leq N}$ .

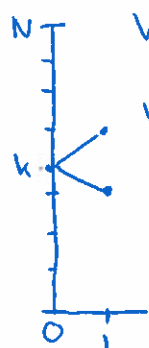
(Think of  $N=10, p = \frac{2}{3}$ , we want to find  $x_0, x_1, \dots, x_{10}$ .)

We already know:  $x_0 = 1$   
 $x_N = 0$

We want to find  $x_1, x_2, \dots, x_{N-1}$ .

Derive a difference equation (system of equations) for  $(x_k)$ ,  $1 \leq k \leq N-1$ .

Say  $S_0 = k$ , we have  $k$  dollars,  $x_k = P(\text{ruin} | S_0 = k)$



We go up to  $k+1$  with probability  $p$ , ruin/success have not happened.

Starting at  $k+1$ , we want  $x_{k+1}$ .

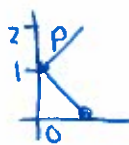
We go down to  $k-1$  with prob.  $q$ .

Starting at  $k-1$ , we want  $x_{k-1}$ .

So we should have  $x_k = p x_{k+1} + q x_{k-1}$

Is this correct if  $k=1$ ?

Eqn is  $x_1 = p x_2 + q x_0 = p x_2 + q \cdot 1 = p x_2 + q$



Prob. we go up to 2 is  $p$ , start at 2

Prob. we go down to 0 (hence are ruined) is prob  $q$

$x_1 = p x_2 + q$  (ruined)

can check for  $k=N$  as well

We get

$x_0 = 1, x_N = 0$

$x_k = p x_{k+1} + q x_{k-1}$  for all  $1 \leq k \leq N-1$

has "nothing" to do with probability

general form is  $0 = p x_{k+1} - x_k + q x_{k-1}$   
 $= a x_{k+1} + b x_k + c x_{k-1}$

$(a=p, b=-1, c=q)$

is a difference equation (system)

Want  $(x_k), 0 \leq k \leq N$  with  $\uparrow$

DE handout

→ how to solve such eqns

1.4 Conditional Probability

→ MAT 521

Def  $P(A|B) = \frac{P(A \cap B)}{P(B)}$  (if  $P(B) \neq 0$ )

Multiplication formulas:  $P(A \cap B) = P(A|B) P(B)$

In some problems,  $P(A|B)$  is easy to find and  $P(A \cap B)$  is not.

$P(A \cap B) = P(B \cap A) = P(B|A) P(A)$

Law of Total Probability (LOTP)

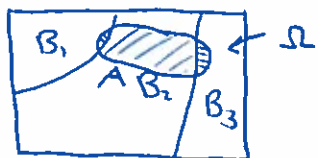
$P(A) = ?$ ,  $B_1, B_2, \dots$

If  $B_1, B_2, \dots$  is a sequence of disjoint events such that

$\bigcup_i B_i = \Omega$  ← this is the entire sample space

then  $P(A) = \sum_i P(A \cap B_i) = \sum_i P(A|B_i) P(B_i)$

The sets  $(B_1, B_2, \dots)$  form a partition of the sample space  $\Omega$



$B_1, B_2, B_3$  form a partition

Reason is: ①  $A = (A \cap B_1) \cup (A \cap B_2) \cup (A \cap B_3)$  (property (2))

and these are disjoint (property (1))

②  $P(A) = P(A \cap B_1) + P(A \cap B_2) + P(A \cap B_3)$

(additivity of axiom of probab.)

Value of this?

Useful when we want  $P(A)$  and for some partition  $(B_i)$ , we know  $P(A|B_i)$ ,  $P(B_i)$

Example: We have 2 boxes,

- Box #1 has 4 red chips, 8 green chips
- Box #2 has 9 red chips, 6 " " "

We select Box #1 with probability  $\frac{1}{6}$   
 " " #2 " " " "  $\frac{5}{6}$

Then draw a chip from the selected box. Find the probab. the chip is red

Let  $A = \{ \text{selected chip is red} \}$ . We want  $P(A)$ .

Let  $B_1 = \{ \text{select box \#1} \}$   
 $B_2 = \{ \text{"-" " \#2} \}$

Then  $B_1, B_2$  form a partition.  $B_1 \cap B_2 = \emptyset$   
 $B_1 \cup B_2 = \Omega$

We know  $P(B_1) = \frac{1}{6}, P(B_2) = \frac{5}{6}$   
 $P(A|B_1) = \frac{4}{12}, P(A|B_2) = \frac{9}{15}$

Then  $P(A) = P(A|B_1)P(B_1) + P(A|B_2)P(B_2)$   
 $= \frac{4}{12} \cdot \frac{1}{6} + \frac{9}{15} \cdot \frac{5}{6} (= \frac{1}{18} + \frac{3}{6} = \frac{10}{18})$

Aug 31

Chapter 2 - Markov chains

(think of  $X_n$  as the state of some "system" at time  $n$ )

$\Omega$  = the sample space = the set of all outcomes

Def: Let  $S$  be a discrete set, call this the state space.  
(either finite or countable)  
 $\{x_0, x_1, \dots, x_N\}$  or  $\{x_0, x_1, x_2, \dots\}$   
but not the interval  $[a, b]$

A discrete time Markov chain taking values in  $S$  is a stochastic process  $(X_n) = (X_0, X_1, X_2, \dots)$  with the

Markov property:  
$$P(X_{n+1} = j \mid X_n = i, \overset{\text{future}}{X_{n-1} = x_{n-1}}, \overset{\text{present}}{X_{n-2} = x_{n-2}}, \dots, X_0 = x_0, X_1 = x_1, \dots, X_{n-1} = x_{n-1})$$
  
$$= P(X_{n+1} = j \mid X_n = i)$$
  
"past"  
 $i, j, x_0, x_1, \dots, x_{n-1} \in S$

Remarks • The time index set is  $\{0, 1, 2, \dots\}$

- If we change the  $(x_j)$  and keep  $i, j$  the same, the probability doesn't change.
- The Gambler's Ruin process is a Markov chain.

Let  $X_n$  = gambler's fortune at time  $n$ .

The sequence of bets are independent with  $P(\text{win}) = p$ ,  
 $P(\text{lose}) = q (= 1-p)$

What is  $X_{n+1}$  equal to given  $X_n, X_{n-1}, \dots, X_1, X_0$ ?

$$X_{n+1} = \begin{cases} X_n + 1 & \text{with prob } p \\ X_n - 1 & \text{with prob } q \end{cases}$$

Does not depend on  $X_{n-1}, X_{n-2}, \dots, X_0$ .

Def: A Markov-chain is "time-homogeneous" if for all states  $i, j$ ,

$P(X_{n+1} = j | X_n = i)$  does not depend on  $n$ . (don't change with time)

(For example,  $P(X_5 = j | X_4 = i) = P(X_4 = j | X_3 = i) = P(X_3 = j | X_2 = i) = P(X_2 = j | X_1 = i) = P(X_1 = j | X_0 = i)$ .)

We will always have this property.

Ex: Gambler's Ruin process. Time homogeneous?

$P(X_{n+1} = k+1 | X_n = k) = p$  for all  $n$ .

We can now define the (probability) transition matrix  $\underline{P}$  of the chain  $(P_{ij})_{i,j \in S}$  and  $P_{ij} = P(X_1 = j | X_0 = i)$  (also  $P(X_{n+1} = j | X_n = i)$ )  
(always square matrix)  $\uparrow$  all basic parameters of the model.   
transition from  $i$  to  $j$

Example:  $S = \{0, 1, 2\}$ .  $\underline{P}$  is a  $3 \times 3$  matrix.

$$\underline{P} = \begin{matrix} & \begin{matrix} 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} P_{00} & P_{01} & P_{02} \\ P_{10} & P_{11} & P_{12} \\ P_{20} & P_{21} & P_{22} \end{bmatrix} \end{matrix}$$

$P(X_1 = 1 | X_0 = 0)$    
transition from 0 to 1

$P_{ij}$ :  $i$  is the row number  
 $j$  is the column "

Gambler's Ruin Target level  $N$ , with prob.  $p$ ,  $(X_n)$

What is  $\underline{P}$ ?

transition matrix of Markov Chain

$$P_{ij} = \begin{cases} 1 = P_{00} & \text{if } i=j=0 \\ p & \text{if } j=i+1 \\ q & \text{if } j=i-1 \\ 1 = P_{NN} & \text{if } i=j=N \end{cases}$$

and all other  $P_{ij}$  equal 0.

$$\underline{P} = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & \dots & N-1 & N \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ \vdots \\ N-1 \end{matrix} & \begin{bmatrix} 1 & 0 & 0 & 0 & \dots & 0 & 0 \\ q & p & 0 & 0 & \dots & 0 & 0 \\ 0 & q & p & 0 & \dots & 0 & 0 \\ 0 & 0 & q & p & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 1 & 0 \end{bmatrix} \end{matrix}$$

$q = 1 - p$



Def: A stochastic matrix is a square matrix with

- (1) all entries are non-negative
- (2) each row sum equals 1.

Fact: A transition matrix is a stochastic matrix.  $\neq$

Check Gambler's Ruin P.

Proof:  $(P_{ij})$ ,  $i^{\text{th}}$  row sum

$$\sum_{j \in S} P_{ij} = \sum_{j \in S} P(X_1 = j | X_0 = i)$$

$$= \sum_{j \in S} \frac{P(X_0 = i, X_1 = j)}{P(X_0 = i)}$$

(def of P)

(def of cond. prob.)

$$= \frac{1}{P(X_0 = i)} \underbrace{\sum_{j \in S} P(X_0 = i, X_1 = j)}_{P(X_0 = i)}$$

(algebra)

(LOTP, or additivity axiom)

$$= \frac{1}{P(X_0 = i)} P(X_0 = i)$$

$$= 1 \quad \checkmark$$

The events  $\{X_1 = j\}_{j \in S}$  form a partition of  $\Omega$



$$\{X_0 = i\} = \bigcup_{j \in S} \{X_0 = i, X_1 = j\}$$

(disjoint union)

$$P(X_0 = i) = P(\bigcup_{j \in S} \{X_0 = i, X_1 = j\})$$

$$= \sum_{j \in S} P(X_0 = i, X_1 = j)$$

□

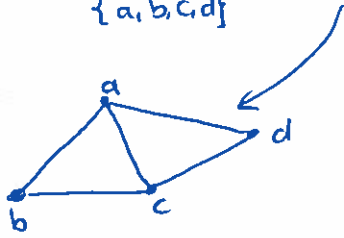
### General Goals

- (1) Given a "system",
  - (a) determine if  $(X_n)$  is a M.C.
  - (b) find P.
- (2) Given P, determine various properties of the system.

Examples

2.8 Random walk on graphs network

A graph has vertices and edges.  
 $\{a, b, c, d\}$



We say  $i, j$  are "neighbors" and write  $i \sim j$  if there is an edge joining  $i$  and  $j$ .

[Large example: World Wide Web]

The degree of vertex  $i$ ,  $\text{deg}(i)$  is the number of edges connected to  $i$

$[\text{deg}(a)=3, \text{deg}(b)=2, \text{deg}(c)=3, \text{deg}(d)=2]$

A random walk  $(X_n)$  jumps from one vertex to another at each time step, it jumps "uniformly at random" according to the number of edges at current side.   
independently

$$\text{If } X_n = b, X_{n+1} = \begin{cases} a & \text{with prob } \frac{1}{2} \\ c & \text{with prob } \frac{1}{2} \end{cases}$$

$$\text{If } X_n = c, X_{n+1} = \begin{cases} a & \text{with prob } \frac{1}{3} \\ b & \text{with prob } \frac{1}{3} \\ d & \text{with prob } \frac{1}{3} \end{cases}$$

So in general  $P_{ij} = \begin{cases} \frac{1}{\text{deg}(i)} & \text{if } i \sim j \\ 0 & \text{otherwise} \end{cases}$

$$P = \begin{matrix} & \begin{matrix} a & b & c & d \end{matrix} \\ \begin{matrix} a \\ b \\ c \\ d \end{matrix} & \begin{bmatrix} 0 & 1/3 & 1/3 & 1/3 \\ 1/2 & 0 & 1/2 & 0 \\ 1/3 & 1/3 & 0 & 1/3 \\ 1/2 & 0 & 1/2 & 0 \end{bmatrix} \end{matrix}$$

Example (3.6) Ehrenfest urn model for diffusion of a gas across a membrane (dog - flea model)



We have 2 urns (containers),  $N$  distinct (labeled balls) (like  $N=10$ ) in the urns.

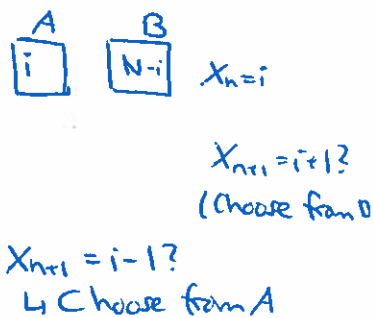
"Dynamics": at time step, pick a "ball" <sup>equal prob for all balls</sup> "uniformly at random", and move it from the urn it is in to the other urn.

Let  $X_n = \#$  of balls in urn A after  $n^{\text{th}}$  move.

Then  $(X_n)$  is a Markov chain, state space is  $S = \{0, 1, 2, \dots, N\}$ .

② If  $X_n = i$  then there are  $N-i$  balls in urn B.

③ 
$$P_{ij} = \begin{cases} \frac{N-i}{N} & j = i+1 \\ \frac{i}{N} & j = i-1 \\ 0 & \text{otherwise} \end{cases}$$



Questions

① If  $X_0 = N$  (all balls in A), what happens as  $n \rightarrow \infty$ .

② Is there an equilibrium?

③ If  $X_0 = N$ , how long on average does it take to have all balls in B.



Example Not everything is a Markov chain.

We have <sup>25¢</sup> 5 quarters, <sup>10¢</sup> 5 dimes, <sup>5¢</sup> 5 nickels.

Draw a coin at random, put it on the table.

Then draw again, etc.

$X_n =$  amount of money on the table after  $n^{\text{th}}$  draw.

$X_0 = 0$  [ $X_{15} = 2.00 = X_{16} = X_{17} = \dots$ ]

Claim:  $(X_n)$  is not a Markov chain.

Why?

① Intuitive?

② Formally, can we violate the Markov property of for any  $n$ , any sequence of states.

Claim:

$$P(X_5 = .45 \mid X_0 = 0, X_1 = .25, X_2 = .30, X_3 = .35, X_4 = .40)$$

$$\neq P(X_5 = .45 \mid X_0 = 0, X_1 = .10, X_2 = .20, X_3 = .30, X_4 = .40)$$

Calculate each by def of cond prob.

Sep 5

Markov Chain - sequence of rand. var.  $(X_n \mid n=0,1,2,-)$  taking values

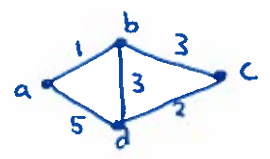
in state space  $S$  satisfying  $P(X_{n+1} = j \mid X_0 = x_0, X_1 = x_1, \dots, X_n = x_n) = P(X_{n+1} = j \mid X_n = x_n)$

$$\stackrel{(MP)}{=} P(X_{n+1} = j \mid X_n = i) \stackrel{(TH)}{=} P(X_1 = j \mid X_0 = i)$$

transition matrix  $\underline{P}$ ,  $P_{ij} = P(X_1 = j \mid X_0 = i)$   $i, j \in S$   
(the one-step probabilities)

Think of  $X_n$  = state of some "system" at time  $n$ .

Example 2.11 random walk on weighted graphs  
(see text directed weighted graphs)



vertices  
edges  $(i \sim j \text{ if there is an edge from } i \text{ to } j)$   
weights  $w_{ij} \geq 0$  on edges  $i \sim j$

Let  $w_i$  = total weight of edges containing vertex  $i$  ( $w_d = 10$ )

$$\text{Let } P_{ij} = \begin{cases} \frac{w_{ij}}{w_i} & \text{if } i \sim j \\ 0 & \text{if not} \end{cases}$$

Here,  $w_d = 10$ ,  $w_a = 6$ ,  $w_b = 7$ ,  $w_c = 5$

$$\underline{P} = \begin{matrix} & \begin{matrix} a & b & c & d \end{matrix} \\ \begin{matrix} a \\ b \\ c \\ d \end{matrix} & \begin{bmatrix} 0 & \frac{1}{6} & 0 & \frac{5}{6} \\ \frac{1}{7} & 0 & \frac{3}{7} & \frac{3}{7} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \end{matrix}$$

etc.

The n-step probabilities

are  $P(X_n = j \mid X_0 = i)$ ,  $i, j \in S$ ,  $n = 1, 2, 3, \dots$

Can we find these from P?

n=1:  $P(X_1=j | X_0=i) = P_{ij}$

n=2:  $P(X_2=j | X_0=i) = \sum_k P(X_2=j | X_1=k, X_0=i) \underbrace{P(X_1=k | X_0=i)}_{P_{ik}}$

$\{X_1=k\}_{k \in S}$  form a partition

(LOTP)  
(conditional form)  
HW1-exer(3)

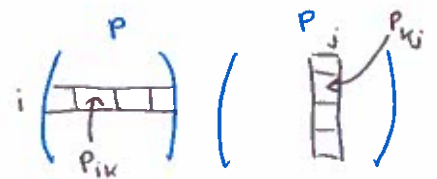
MP  $= \sum_{k \in S} \underbrace{P(X_2=j | X_1=k)}_{= P_{kj}} P_{ik}$

$= \sum_{k \in S} P_{kj} P_{ik}$

$= \sum_k P_{ik} P_{kj}$

$= (\underline{P} \times \underline{P})_{ij}$

matrix mult.  $\uparrow$   
E·E an Stelle (i,j)



$= (\underline{P}^2)_{ij}$

Notation: We write  $(\underline{P}^2)_{ij} = P_{ij}^2 \neq (P_{ij})^2$

$\Rightarrow P(X_2=j | X_0=i) = (\underline{P}^2)_{ij}$

n=3:  $P(X_3=j | X_0=i) \stackrel{\text{LOTP}}{=} \sum_{k \in S} P(X_3=j | X_2=k, X_0=i) \cdot P(X_2=k | X_0=i)$

$\{X_2=k\}_{k \in S}$  form a partition

MP  $= \sum_{k \in S} P(X_3=j | X_2=k) \cdot P_{ik}^2 \leftarrow n=2 \text{ case}$

TH  $= \sum_{k \in S} P_{kj} \cdot P_{ik}^2$

$= \sum_{k \in S} P_{ik}^2 P_{kj}$

matrix mult.  $= (\underline{P}^2 \times \underline{P})_{ij}$

$= (\underline{P} \times \underline{P}^2)_{ij}$

$= (\underline{P}^3)_{ij}$

Conclusion:

The  $n$ -step probabilities are  $P(X_n=j | X_0=i) = P_{ij}^n$ ,  $n=1,2,3, \dots$

$$\underline{P}^0 = ? = P(X_0=j | X_0=i) = \begin{cases} 1 & \text{if } j=i \\ 0 & \text{if } j \neq i \end{cases} = \text{identity matrix}$$

Example

Suppose  $S = \{0, 1, 2\}$ ,  $\underline{P} = \begin{matrix} & \begin{matrix} 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} .1 & .1 & .8 \\ .2 & .2 & .6 \\ .3 & .3 & .4 \end{bmatrix} \end{matrix}$

Find  $P(X_2=0 | X_0=0) =$

- ① Use LOTP
- ②  $P_{00}^2 = (\underline{P} \times \underline{P})_{00} = .27$

Check that  $\underline{P}^2 = \begin{matrix} & \begin{matrix} 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} .27 & .27 & .46 \\ .24 & .24 & .52 \\ .21 & .21 & .58 \end{bmatrix} \end{matrix}$   $P_{22}^2 = .58$  etc.

Chapman-Kolmogorov equations

By matrix multiplication

$$\underline{P}^{n+m} = \underline{P}^n \times \underline{P}^m = \underline{P}^m \times \underline{P}^n.$$

$$\underbrace{\underline{P} \times \underline{P} \times \dots \times \underline{P}}_{n \text{ times}}$$

So, this gives us

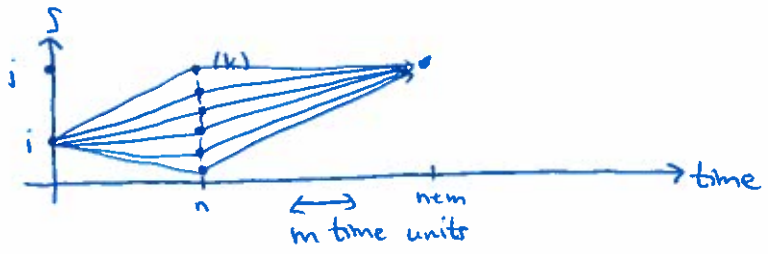
$$P(X_{n+m}=j | X_0=i) = P_{ij}^{n+m} = \sum_{k \in S} P_{ik}^n P_{kj}^m \quad (= (\underline{P}^n \times \underline{P}^m)_{ij})$$

$$= \sum_{k \in S} P(X_n=k | X_0=i) \underbrace{P(X_m=j | X_0=k)}_{m \text{ steps from } 0}$$

$$= \sum_{k \in S} P(X_n=k | X_0=i) P(X_{n+m}=j | X_n=k)_{-m \text{ steps from time } n}$$

That is,

$$P(X_{n+m}=j | X_0=i) = \sum_k P(X_n=k | X_0=i) \cdot P(X_{n+m}=j | X_n=k)$$



• A probability row vector  $\underline{\alpha} = (\alpha_i)_{i \in S}$  satisfies: each  $\alpha_i \geq 0$ ,  $\sum_{i \in S} \alpha_i = 1$ .  
 (In effect,  $\underline{\alpha}$  is a probability mass fct. of a discrete r.v.)

• A Markov chain  $(X_n)$  has initial distribution  $\underline{\alpha}$  (a probability row vector) if  $P(X_0 = i) = \alpha_i, i \in S$ . ↑  
time 0

Fact  $\forall$  The probability distribution of  $X_n$  is given by

$$P(X_n = j) = (\underline{\alpha} \underline{P}^n)_j = \sum_{i \in S} \alpha_i P_{ij}^n$$

why? LOTP

$$P(X_n = j) = \sum_{i \in S} P(X_n = j | X_0 = i) P(X_0 = i)$$

↑  
form a partition

$$= \sum_{i \in S} P_{ij}^n \cdot \alpha_i = \sum_{i \in S} \alpha_i \cdot P_{ij}^n = (\underline{\alpha} \underline{P}^n)_j$$

Previous Example:

$$\underline{P}^2 = \begin{matrix} & \begin{matrix} 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} .27 & .27 & .46 \\ .24 & .24 & .52 \\ .21 & .21 & .58 \end{bmatrix} \end{matrix}$$

Suppose  $X_0$  has distribution  $\underline{\alpha} = (.7 \ .2 \ .1)$ .

$$\text{Find } P(X_2 = 0) = (\underline{\alpha} \underline{P}^2)_0 = \left( \begin{bmatrix} .7 & .2 & .1 \end{bmatrix} \begin{bmatrix} .27 & .27 & .46 \\ .24 & .24 & .52 \\ .21 & .21 & .58 \end{bmatrix} \right)_0$$

$$= \left[ (.7)(.27) + (.2)(.24) + (.1)(.21) \right]$$

$$= \left[ \frac{129}{500} \quad \frac{121}{500} \quad \frac{121}{2500} \right]_0 = \frac{129}{500}$$

Fact:

$$P(X_1 = i_1, X_2 = i_2, X_3 = i_3, \dots, X_n = i_n | X_0 = i_0)$$

$$= P_{i_0 i_1} \cdot P_{i_1 i_2} \cdot P_{i_2 i_3} \cdot \dots \cdot P_{i_{n-1} i_n}$$

joint distr. of  $X_1 \rightarrow X_n$  given  $X_0 = i_0$

[ Given with disk.  $\alpha$ , then

$$P(X_0=i_0, X_1=i_1, \dots, X_n=i_n) = \alpha_{i_0} p_{i_0 i_1} \dots p_{i_{n-1} i_n}$$

$$[ 0 \leq n_1 < n_2 < \dots < n_k \Rightarrow P(X_{n_1}=i_1, X_{n_2}=i_2, \dots, X_{n_k}=i_k | X_0=i_0) = p_{i_0 i_1}^{n_1} \cdot p_{i_1 i_2}^{n_2-n_1} \dots p_{i_{k-1} i_k}^{n_k-n_{k-1}} ]$$

$$P(X_{(3)}=b, X_{(4)}=c, X_{(7)}=d, X_{(10)}=f | X_0=a)$$

$\begin{matrix} \swarrow & \searrow & \swarrow & \searrow \\ n_1 & \xrightarrow{\quad} & n_2 & \xrightarrow{\quad} & n_3 & \xrightarrow{\quad} & n_4 \end{matrix}$

$$= P_{ab}^3 \cdot P_{bc}^4 \cdot P_{cd}^2 \cdot P_{df}$$

Mult. Rule(s)

$$P(A_2 \cap A_1) = P(A_2 | A_1) P(A_1)$$

$$P(A_3 \cap A_2 \cap A_1) = P(A_3 | A_2 \cap A_1) P(A_2 \cap A_1)$$

$$= P(\check{A}_3 | A_2 \cap A_1) P(\check{A}_2 | A_1) P(\check{A}_1)$$

Similar  $P(A_n \cap A_{n-1} \cap \dots \cap A_1) = P(A_n | A_{n-1} \cap \dots \cap A_1) P(A_{n-1} | A_{n-2} \cap \dots \cap A_1) \dots P(A_2 | A_1) P(A_1)$

...  $P(A_n \cap A_{n-1} \cap \dots \cap A_1) = \dots$

Example MC  $\{X_n\}$  with state space  $S = \{0, 1, 2\}$

transition matrix  $\underline{P}$

$$\underline{P} = \begin{matrix} & \begin{matrix} 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} .1 & .1 & .8 \\ .2 & .2 & .6 \\ .3 & .3 & .4 \end{bmatrix} \end{matrix}$$

$$\underline{P}^2 = \begin{matrix} & \begin{matrix} 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} .22 & .22 & .56 \\ .23 & .23 & .54 \\ .24 & .24 & .53 \end{bmatrix} \end{matrix}$$

$$\underline{P}^3 = \begin{matrix} & \begin{matrix} 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} .219 & .219 & .562 \\ .228 & .228 & .544 \\ .237 & .237 & .526 \end{bmatrix} \end{matrix}$$

Ⓐ  $P(X_1=0, X_2=0, X_3=2, X_4=1 | X_0=2) = P_{20} P_{00} P_{02} P_{21} = (.3)(.1)(.8)(.3)$

Ⓑ  $P(X_{(7)}=2 | X_1=0, X_2=0, X_3=2, X_{(4)}=1) = P(X_7=2 | X_4=1) = P_{12}^3 = .544$   
3-4=3 time steps

[ formulas (J01), (J02), (MP), (J03) → pp 56-58 ]

Ⓒ  $P(X_{(2)}=1, X_{(4)}=2, X_5=1, X_8=0 | X_0=0) = P_{01}^2 P_{12}^2 P_{21} P_{10}^3 = (.22)(.54)(.3)(.228)$



Proof of

$n-m=n-1$

$m=1$  case of (MP)

$$P(X_{n+1}=j | X_0=x_0, X_1=x_1, \dots, X_{n-1}=i) \stackrel{\text{cond. form of LOTP}}{=} \sum_{k \in S} P(X_{n+1}=j | X_0=x_0, X_1=x_1, \dots, X_{n-1}=i, X_n=k) \cdot P(X_n=k | X_0=x_0, \dots, X_{n-1}=i)$$

↑ timestep  $\rightarrow$  (MP)

$$\stackrel{(MP)}{=} \sum_{k \in S} P_{X_{n+1}} P_{kj} P_{ik} = \sum_{k \in S} P_{ik} P_{kj} = P_{ij}^{n+1}$$

Proof  $n=3$

initial dot is  $\alpha$

$$P(X_1=j, X_2=k, X_3=L | X_0=i) = P(X_3=L, X_2=k, X_1=j, X_0=i)$$

$$\stackrel{\text{mult. rule}}{=} P(X_3=L | X_2=k, X_1=j, X_0=i) \cdot P(X_2=k | X_1=j, X_0=i) \cdot P(X_1=j | X_0=i) \cdot P(X_0=i)$$

$$\stackrel{(MP)}{=} P(X_3=L | X_2=k) \cdot P(X_2=k | X_1=j) \cdot P(X_1=j | X_0=i) \cdot \alpha_i$$

$$= P_{kL} P_{jk} P_{ij} \alpha_i = \alpha_i P_{ij} P_{jk} P_{kL}$$

Ex from books: What happens to  $P_{ij}^n$  as  $n \rightarrow \infty$ ?

We appear see

(0) 0 entries are absent  $P_{ij}^n$  for large  $n$

(1) for each  $\begin{matrix} i,j \\ (0,1,2) \end{matrix}$   $\lim_{n \rightarrow \infty} P_{ij}^n$  exist

same  $\downarrow$

(2) There is a limiting matrix.  $\lim_{n \rightarrow \infty} P^n$  exists.

(3) The rows in the limiting matrix are identical.

$$P_{00}^{100} = P_{10}^{100} = P_{20}^{100} \text{ (approximately)}$$

That is,  $\lim_{n \rightarrow \infty} P_{ij}^n$  does not depend on  $i$ .

$$P(X_n=j | X_i=i)$$

"the chain forgets its starting point"

Another ex: limit does not exist

Def: A MC  $(X_n)$  has a Limiting distribution  $\lambda$

with transition matrix  $\underline{P}$

if for all  $i$  and  $j$ ,  $\lim_{n \rightarrow \infty} P_{ij}^n = \lambda_j$  (Think more than just  $\lim_{n \rightarrow \infty} P_{ij}^n$  exists.)  
only depends on  $j$

$$\lim_{n \rightarrow \infty} P(X_n = j | X_0 = i)$$

Notes: ① A chain cannot have 2 different limiting distributions.

② It is usually impossible to directly compute  $\underline{P}^n$  to check if there is a limiting distribution

Example (3.2) The two state M.C.

Let  $0 \leq p \leq 1, 0 \leq q \leq 1$  ( $q \neq 1-p$ )

$$\underline{P} = \begin{matrix} & \begin{matrix} 1 & 2 \end{matrix} \\ \begin{matrix} 1 \\ 2 \end{matrix} & \begin{bmatrix} 1-p & p \\ q & 1-q \end{bmatrix} \end{matrix}$$

Special Cases:

①  $p=q=0$ ,

$$\underline{P} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \underline{P}^n = \underline{P} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \forall n$$

②  $p=q=1$ ,

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

Note that  $\lim_{n \rightarrow \infty} P_{ij}^n = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$  exists for all  $i, j$ , but depends on both  $i, j$ , so no limiting distribution for  $\underline{P}$

$$\underline{P}^2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \underline{P}^3 = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad \underline{P}^4 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\underline{P}^2 = \underline{I}, \quad \underline{P}^2 \times \underline{P} = \underline{I} \times \underline{P} = \underline{P}, \quad \underline{P}^2 \times \underline{P}^2 = \underline{I} \times \underline{I} = \underline{I}$$

$$\Rightarrow \underline{P}^n = \begin{cases} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, & \text{if } n \text{ is odd} \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} & \text{if } n \text{ is even} \end{cases}$$

$P_{00}^n = (0, 1, 0, 1, 0, 1, \dots)$ , does not have a limit

General Case of interest

$$\underline{P} = \begin{bmatrix} 1-p & p \\ q & 1-q \end{bmatrix} \quad \text{where } 0 < p+q < 2$$

Let  $r = 1-p-q$ , note  $-1 < r < 1$

$$\text{Then } \textcircled{*} \underline{P}^n = \frac{1}{p+q} \begin{bmatrix} q+pr^n & p-pr^n \\ q-qr^n & p+qr^n \end{bmatrix}$$

(The first row sum is  $\frac{1}{p+q} (q+pr^n + p-pr^n) = 1$  ✓)

$$\text{and } \lim_{n \rightarrow \infty} \underline{P}^n = \frac{1}{p+q} \begin{bmatrix} q & p \\ q & p \end{bmatrix} \quad \text{since } \lim_{n \rightarrow \infty} r^n = 0. \quad (|r| < 1)$$

$$= \begin{bmatrix} \frac{q}{p+q} & \frac{p}{p+q} \\ \frac{q}{p+q} & \frac{p}{p+q} \end{bmatrix}$$

We get a limiting distribution

$$\underline{\lambda} = (\lambda_1, \lambda_2)$$

$$\lambda_1 = \lim_{n \rightarrow \infty} P_{11}^n = \frac{q}{p+q} = \lim_{n \rightarrow \infty} P_{21}^n$$

$$\lambda_2 = \lim_{n \rightarrow \infty} P_{12}^n = \frac{p}{p+q} = \lim_{n \rightarrow \infty} P_{22}^n$$

Proof of  $\textcircled{*}$ 

I. Check by induction  $\textcircled{*}$  is correct.

- Check  $n=1$
- $\underline{P}^{n+1} = \underline{P} \times \underline{P}^n$

II. See text for a derivation.

Find a formula for  $P_{ii}^n$  in terms of  $P_{ii}^{n-1}$ .

III. Use difference eqn's.

What happens if the initial distribution is chosen to be  $\underline{\lambda}$  the limiting dist.?

$$\text{ie. } P(X_0=1) = \frac{q}{p+q}, \quad P(X_0=2) = \frac{p}{p+q}.$$

What is the dist. of  $X_1$ .

$$P(X_1=1) \stackrel{\text{LOTP}}{=} \underbrace{P(X_1=1 | X_0=1)}_{= P_{11}} P(X_0=1) + \underbrace{P(X_1=1 | X_0=2)}_{= P_{21}} P(X_0=2)$$

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$$= (1-p) \cdot \frac{q}{p+q} + q \cdot \frac{p}{p+q} = \frac{q-pq+pq}{p+q} = \frac{q}{p+q} = P(X_0=1).$$

$$P(X_1=1) = P(X_0=1)$$

$$P(X_1=2) = P(X_0=2)$$

→ dist of MC does not change from time 0 to time 1  
→ stationary dist

$$\underline{P} = \frac{1}{2} \begin{bmatrix} 1-p & p \\ q & 1-q \end{bmatrix}$$

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Claim: If  $0 < p, q < 1$ , and  $r = 1-p-q$ , then

$$\underline{P}^n = \frac{1}{p+q} \begin{bmatrix} q+p r^n & p-p r^n \\ q-q r^n & p+q r^n \end{bmatrix}$$

$$\lim_{n \rightarrow \infty} \underline{P}^n = \frac{1}{p+q} \begin{bmatrix} q & p \\ q & p \end{bmatrix} = \begin{bmatrix} \frac{q}{p+q} & \frac{p}{p+q} \\ \frac{q}{p+q} & \frac{p}{p+q} \end{bmatrix}$$

so  $\lambda$  is the limiting distribution.  
 $\lambda = \begin{bmatrix} \frac{q}{p+q} & \frac{p}{p+q} \end{bmatrix}$

$$\underline{P}^n \stackrel{?}{=} \frac{q+p r^n}{p+q}$$

Proof via DE's

$$\text{Let } x_n = \underline{P}^n_{11} = (\underline{P} \times \underline{P}^{n-1})_{11} = (\underline{P}^{n-1} \times \underline{P})_{11}$$

$$\underline{P}^{n-1} \times \underline{P} = \begin{bmatrix} p_{11}^{n-1} & p_{12}^{n-1} \\ p_{21}^{n-1} & p_{22}^{n-1} \end{bmatrix} \begin{bmatrix} 1-p & p \\ q & 1-q \end{bmatrix} = \begin{bmatrix} (1-p)p_{11}^{n-1} + q p_{12}^{n-1} & \dots \\ \dots & \dots \end{bmatrix}$$

$$\Rightarrow x_n = (1-p)p_{11}^{n-1} + q \left( p_{12}^{n-1} \right) = 1 - p_{11}^{n-1}$$

$$= (1-p)x_{n-1} + q(1-x_{n-1}) = q + x_{n-1}(1-p-q) = q + r x_{n-1}$$

$$\Rightarrow x_n - r x_{n-1} = q \quad \text{1st order difference equation}$$

Characteristic eqn in  $t$  is  $t-r=0$

$$ax_{n+1} + bx_n + c = z_n$$

Char. eqn  $ar^2 + br + c = 0$

solution is  $t=r$

(1) Solution to  $x_n - rx_{n-1} = 0$  is  $x_n = Ar^n$

(2) For a particular solution, guess const., so  $x_n = c$

[  $x_n - rx_{n-1} = q = z_n$  guess sth like  $z_n = q$  (const) ]

[ 2<sup>nd</sup> order linear, const. coeff. differential eqns  
 $ay'' + by' + cy = f(x)$   $\rightarrow$  guess const.  $f(x)$  ]

Plug in,  $x_n - rx_{n-1} = c - rc = q$ , solve for  $c$ ,  $c(1-r) = q$ ,  $c = \frac{q}{1-r} = \frac{q}{p+q}$

General soln is  $x_n = Ar^n + \frac{q}{p+q}$  gen + particular soln (OE handout)

[  $P^0 =$  identity matrix ]  
 $x_0 = P_{11}^0 = 1 = Ar^0 + \frac{q}{p+q} \Rightarrow A = 1 - \frac{q}{p+q} = \frac{p+q-q}{p+q} = \frac{p}{p+q}$

so  $x_n = Ar^n + \frac{pq}{p+q} = \frac{p}{p+q} r^n + \frac{pq}{p+q} = \frac{1}{p+q} (q + pr^n)$ .

Limiting Distributions ✓

Def: A stationary distribution for a transition matrix  $P$  is a

① probability row vector  $\underline{\lambda}$  such that ②  $\underline{\lambda} P = \underline{\lambda}$  ( $= 1 \cdot \underline{\lambda}$ )

$\rightarrow \underline{\lambda}$  is a left eigenvalue of  $P$

② = Same as:  $(\underline{\lambda} P)_j = \lambda_j$  for each  $j$ ,  $\sum_{i \in S} \lambda_i P_{ij} = \lambda_j$  for each  $j$ .

We will usually use  $\underline{\pi}$  for a stationary distribution.

1)  $\underline{\pi}$  is a probability row vector

2)  $\pi_j = \sum_i \pi_i P_{ij}$  for each  $j$

Ex:  $P = \begin{bmatrix} 1-p & p \\ q & 1-q \end{bmatrix}$ , we found  $\underline{\lambda} = \begin{bmatrix} \frac{q}{p+q} & \frac{p}{p+q} \end{bmatrix}$

is a stationary distribution.

check!

Fact: If  $\underline{\pi} = \underline{\pi} \underline{P}$ , then  $\underline{\pi} = \underline{\pi} \underline{P}^2 = \underline{\pi} \underline{P}^3 = \dots$

In terms of the MC  $(X_n)$ , if  $X_0$  has distribution  $\underline{\pi}$  then

$X_n$  has distr.  $\underline{\pi}$  for  $n=1, 2, 3, \dots$  i.e.  $P(X_n=j) = P(X_0=j) = \pi_j$  for all  $n, j$   
↑  
stationary

Check:  $\underline{\pi} \underline{P}^2 = \underline{\pi} \underline{P} \underline{P} = (\underline{\pi} \underline{P}) \underline{P} = \underline{\pi} \underline{P} = \underline{\pi} \checkmark$   
 $\underline{\pi} \underline{P}^3 = (\underline{\pi} \underline{P}^2) \underline{P} = \underline{\pi} \underline{P} = \underline{\pi} \checkmark$

If  $X_0$  has distribution  $\underline{\pi}$  then  $P(X_n=j) \stackrel{\text{LOTP}}{=} \sum_i P(X_n=j | X_0=i) P(X_0=i)$   
 $= \sum_i P_{ij}^n \pi_i = \sum_i \pi_i P_{ij}^n = \pi_j = P(X_0=j) \checkmark$

Can we find stationary distributions  $\underline{\pi}$  for a given  $\underline{P}$ ?

Yes,

Solve linear eqns for  $(\pi_j)$

- ①  $\sum_{i \in S} \pi_i = 1$
- ②  $\sum_{i \in S} \pi_i P_{ij} = \pi_j$  for all  $j \in S$

Example:  $\underline{P} = \frac{1}{2} \begin{bmatrix} 1-p & p \\ q & 1-q \end{bmatrix}$

① If  $p$  and  $q$  are not both 0, then there is a single solution to

$$\begin{cases} \pi_1 + \pi_2 = 1 & \textcircled{1} \\ \pi_1 = \pi_1 P_{11} + \pi_2 P_{21} = \pi_1 (1-p) + \pi_2 q & \textcircled{2} \ j=1 \\ \pi_2 = \pi_1 P_{12} + \pi_2 P_{22} = \pi_1 p + \pi_2 (1-q) & \textcircled{2} \ j=2 \end{cases}$$

$\Rightarrow \begin{cases} \pi_1 + \pi_2 = 1 \\ p\pi_1 - q\pi_2 = 0 \\ p\pi_1 - q\pi_2 = 0 \end{cases}$  same eqn  $\rightarrow$  one eqn is redundant  
is always like this  $\rightarrow$   $\Rightarrow$  have to use ① as well

$$p\pi_1 = q\pi_2$$

$$\Leftrightarrow \pi_1 = \frac{q\pi_2}{p}$$

plug in:  $\frac{q\pi_2}{p} + \pi_2 = 1$

$$\Leftrightarrow \pi_2 \left(\frac{q}{p} + 1\right) = 1 \Leftrightarrow \pi_2 \left(\frac{q+p}{p}\right) = 1 \Leftrightarrow \pi_2 = \frac{p}{q+p}$$

$$\pi_1 = \frac{q}{q+p}$$

(the limiting distribution)

② If  $p=q=0$ ,  $\underline{P} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

$$\underline{\pi} \underline{P} = \underline{\pi} \quad \left[ \pi_1, \pi_2 \right] \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \left[ \pi_1, \pi_2 \right]$$

$$\left. \begin{array}{l} \textcircled{2} \pi_1 = \pi_1 \\ \pi_2 = \pi_2 \\ \textcircled{1} \pi_1 + \pi_2 = 1 \end{array} \right\} \Rightarrow \begin{array}{l} \pi_1 = \cancel{c} \\ \pi_2 = 1 - \cancel{c} \end{array}$$

For any number  $c$ ,  $0 \leq c \leq 1$ ,  $\underline{\pi} = [c \ 1-c]$  is a stationary distribution

This shows there can be more than one stationary distribution.

③ Take  $p=q=1$ ,  $\underline{P} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$ , then  $\underline{\pi} = \left[ \frac{1}{2} \ \frac{1}{2} \right]$  is the unique stationary distribution.

However,  $\lim_{n \rightarrow \infty} \underline{P}^n$  does not exist. Recall:  $\underline{P}^n = \begin{cases} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} & \text{if } n \text{ is odd} \\ \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} & \text{if } n \text{ is even} \end{cases}$

Lemma 3.1 If  $(X_n)$  is a MC with transition matrix  $\underline{P}$  and  $\underline{\lambda}$  which has a limiting distribution  $\underline{\lambda}$ , then  $\underline{\lambda}$  is a stationary distribution. The converse is false by the last example.

Proof: Assume  $\lim_{n \rightarrow \infty} P_{ij}^n = \lambda_j$  for all  $i, j$ .

Consider  $P_{ij}^{n+1} = (\underline{P}^n \times \underline{P})_{ij} = \sum_k P_{ik}^n P_{kj}$

As  $n \rightarrow \infty$ ,  $P_{ij}^{n+1} \rightarrow \lambda_j$ , also  $P_{ik}^n \rightarrow \lambda_k$  Plug this into

$$P_{ij}^{n+1} = \sum_k P_{ik}^n P_{kj}$$

 $n \rightarrow \infty \downarrow$ 
 $\downarrow n \rightarrow \infty$ 

$$\lambda_j = \sum_k \lambda_k P_{kj}$$

$$= (\underline{\lambda} \underline{P})_j$$

 $\Rightarrow \lambda$  is a stationary distribution.

### "Regular" transition matrices

A matrix  $\underline{M}$  is called positive if all entries  $M_{ij} > 0$ .

Def: A transition matrix  $\underline{P}$  is called regular if there is some  $n \geq 1$  such that  $\underline{P}^n$  is a positive matrix. from both

### Examples

①  $\underline{P} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ , not regular

②  $\underline{P} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$ , not regular

③  $\underline{P} = \begin{bmatrix} .2 & .8 \\ 0 & 1 \end{bmatrix}$  (Check  $\underline{P}^n$  from our formula, we see  $P_{21}^n = 0$  for all  $n$ )  
not regular

④  $\underline{P} = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & \frac{1}{3} & \frac{2}{3} \end{bmatrix}$  (i) can find  $\underline{P}^2, \underline{P}^3, \underline{P}^4$  and see  $\underline{P}^4$  is positive, so  $\underline{P}$  is regular.

(ii) Use +/0 method.

$$\underline{P}^2 = \begin{bmatrix} 0 & 0 & + \\ + & 0 & 0 \\ 0 & + & + \end{bmatrix} \begin{bmatrix} 0 & 0 & + \\ + & 0 & 0 \\ 0 & + & + \end{bmatrix} = \begin{bmatrix} 0 & + & + \\ 0 & 0 & + \\ + & + & + \end{bmatrix}$$

$$\underline{P}^4 = \underline{P}^2 \cdot \underline{P}^2 = \begin{bmatrix} 0 & ++ & + \\ 0 & 0 & + \\ + & ++ & + \end{bmatrix} \cdot \begin{bmatrix} 0 & ++ & + \\ 0 & 0 & + \\ + & ++ & + \end{bmatrix} = \begin{bmatrix} + & ++ & + \\ + & ++ & + \\ + & ++ & + \end{bmatrix}$$

So all entries of  $\underline{P}^4$  are positive, so  $\underline{P}$  is regular.



Fact (p.85): If for some  $n > 1$ ,  $\underline{P}^n$  has at least one zero, and all the zero entries in  $\underline{P}^{n+1}$  occur in the same places as all the zero entries in  $\underline{P}^{n+2}$ , then  $\underline{P}$  is not regular.

HW solutions: on reserve in the library

Def.  $\underline{P}$  is regular if for some  $n$ ,  $\underline{P}^n$  is positive. (all entries are positive)

Exercise 3.33 If  $\underline{P}^n$  is positive for some  $n$ , then  $\underline{P}^k$  is positive  $\forall k > n$ .

Thm 3.2: A MC whose transition matrix is regular has a limiting distribution, and this lim. dist. is the unique stationary distribution.

[recall: A prob. row vector  $\underline{\lambda}$  is the limiting distribution for  $\underline{P}$  if

$\lim_{n \rightarrow \infty} P_{ij}^n = \lambda_j$  for all states  $i, j$ . It is not enough to have  $\lim_{n \rightarrow \infty} P_{ij}^n$  existing.

That is, there is a unique probability vector  $\underline{\pi}$  such that

(a)  $\lim_{n \rightarrow \infty} P_{ij}^n = \pi_j$  for all states  $i, j$ .

and (b)  $\underline{\pi} \underline{P} = \underline{\pi}$ .

(a) is the same as  $\lim_{n \rightarrow \infty} \underline{P}^n = \underline{\underline{1}}$ , where each row of  $\underline{\underline{1}}$  is  $\underline{\pi}$

Furthermore,  $\underline{\pi}$  is positive ( $\pi_i > 0$  for each  $i \in S$ ).

Example: Let  $0 < p < 1$ , define

$$\underline{P} = \begin{matrix} & \begin{matrix} 1 & 2 & 3 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \end{matrix} & \begin{bmatrix} 0 & 1-p & p \\ p & 0 & 1-p \\ 1-p & p & 0 \end{bmatrix} \end{matrix} \leftarrow \text{an example of a doubly stochastic matrix}$$

(a)  $\underline{P}$  is regular because

$$\underline{P}^2 = \begin{bmatrix} 0 & + & + \\ + & 0 & + \\ + & + & 0 \end{bmatrix} \begin{bmatrix} 0 & + & + \\ + & 0 & + \\ + & + & 0 \end{bmatrix} = \begin{bmatrix} + & + & + \\ + & + & + \\ + & + & + \end{bmatrix}$$
 is positive.

(b) Find stationary dist.  $\underline{\pi} = [\pi_1, \pi_2, \pi_3]$

The Thm says  $\underline{\pi}$  is unique

Def: A doubly stochastic matrix is a stoch. matrix where all the column sums are 1.

Fact: Every finite doubly stochastic matrix  $\underline{P}$  has a stationary distribution which is uniform over the states. If there are  $k$  states, then  $\underline{\pi}, \pi_i = \frac{1}{k}$  for all  $i$  is a stationary distribution.

The Thm says  $\underline{\pi}$  is unique. Since  $\underline{P}$  is doubly stochastic,  $\underline{\pi}$  is uniform.  $\underline{\pi} = [\frac{1}{3} \ \frac{1}{3} \ \frac{1}{3}]$

(c) Furthermore,  $\lim_{n \rightarrow \infty} p_{ij}^n = \frac{1}{3}$  for each  $i, j \in \{1, 2, 3\}$ .

We did not have to compute powers  $\underline{P}^n$ .

Proof of fact: Let  $\pi_i = \frac{1}{k}$

$$\begin{aligned} (\underline{\pi} \underline{P})_j &= \sum_{i \in S} \pi_i P_{ij} = \sum_{i \in S} \frac{1}{k} P_{ij} = \frac{1}{k} \left( \sum_{i \in S} P_{ij} \right) \\ &= \frac{1}{k} \cdot 1 = \frac{1}{k}. \end{aligned}$$

Sum over entries in column  $j$  of  $\underline{P}$

Note: Unique stationary dist. does not imply existence of a limiting dist.

$$\underline{P} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad \text{not regular}$$

$$\text{Set } \underline{\pi} \stackrel{?}{=} \underline{\pi} \underline{P} = [\pi_1 \ \pi_2] \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = [\pi_2 \ \pi_1] \stackrel{?}{=} [\pi_1 \ \pi_2]$$

Must have  $\pi_1 = \pi_2$ . Since  $\pi_1 + \pi_2 = 1$ ,  $\pi_1 = \pi_2 = \frac{1}{2}$ .

So,  $[\frac{1}{2} \ \frac{1}{2}]$  is the unique stationary distribution.

But  $\lim_{n \rightarrow \infty} p_{ij}^n$  does not exist.

### 3.3 Classification of states

Notation: For a transition matrix  $\underline{P}$ , states  $i, j$ , write

- $i \mapsto j$  means  $P_{ij} > 0$  (single step)
- $i \rightarrow j$  (  $i$  leads to  $j$ , or  $j$  is accessible from  $i$  ) means  $P_{ij}^{(n)} > 0$ , some  $n \geq 0$  (allows  $n=0$ ) ( $\underline{P}^{(0)} = \underline{I}$ )
- $i \leftrightarrow j$  ( $i$  and  $j$  communicate) means  $i \rightarrow j$  and  $j \rightarrow i$

$$\underline{P} = \begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix} \quad \begin{matrix} 0 \mapsto 1 \\ 1 \mapsto 0 \end{matrix}$$

#### Remarks

- ① If  $i \mapsto j$  then  $i \rightarrow j$
- ②  $i \rightarrow i$   $P_{ii}^{(0)} = 1 \forall i$
- ③ If  $i \rightarrow j$  and  $j \rightarrow k$  then  $i \rightarrow k$ .

Proof of ③: By assumption, there are  $m, n$  such that  $P_{ij}^{(m)} > 0$  and  $P_{jk}^{(n)} > 0$ .

Consider  $L = m+n$ , check  $P_{ik}^{(L)} > 0$ ?

$$\underline{P}^{(L)} = \underline{P}^{(m)} \times \underline{P}^{(n)}, \quad P_{ik}^{(L)} = \sum_{\alpha \in S} P_{i\alpha}^{(m)} P_{\alpha k}^{(n)} \geq P_{ij}^{(m)} P_{jk}^{(n)} > 0.$$

each term is  $\geq 0$   
keep  $\alpha = j$

Fact: (p. 94)

Communication ( $\leftrightarrow$ ) is an equivalence relation on  $S$  (set of states)

- That is
- (i)  $i \leftrightarrow i$  for all  $i \in S$  ( $i \rightarrow i \Rightarrow i \leftrightarrow i$ )
  - (ii) If  $i \leftrightarrow j$  then  $j \leftrightarrow i$  ( $i \leftrightarrow j$  means  $i \rightarrow j$  &  $j \rightarrow i \Rightarrow j \leftrightarrow i$ )
  - (iii) If  $i \leftrightarrow j$  and  $j \leftrightarrow k$  then  $i \leftrightarrow k$ .

(iii) We need to check that  $i \rightarrow k$  and  $k \rightarrow i$ .  
We know  $i \rightarrow i$  and  $i \rightarrow k$  thus  $i \rightarrow k$ . Same arg. gives  $k \rightarrow i$ .  $\square$

(17) As a consequence, we can ~~say~~ break the state space  $S$  into disjoint equivalence (communication) classes (sets), say  $C_1, C_2, C_3, \dots$

These have the properties

(i)  $S = C_1 \cup C_2 \cup \dots$  (every state belongs to some class  $C_i$ )

(ii) The  $C_i$  are disjoint.

(iii) For  $\forall$  given class  $C$ , if  $i \in C$  and  $i \leftrightarrow j$ , then  $j \in C$ .

Also, if  $i$  and  $j$  belong to different classes, then  $i \not\leftrightarrow j$ .

Example:

$$P = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \end{matrix} & \begin{bmatrix} 1 & 0 & 0 & 0 \\ \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{2} \\ \frac{1}{5} & \frac{2}{5} & \frac{1}{5} & \frac{1}{5} \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{matrix}$$

Find the equivalence classes for  $P$ .

state 0:  $0 \nleftrightarrow j$  for  $j \neq 0$ ,  $C_1 = \{0\}$  is a communicating class.

state 3:  $3 \nleftrightarrow j$  for  $j \neq 3$ ,  $C_2 = \{3\}$  --- --- ---

states 1, 2:  $1 \rightarrow j$  for all  $j$  so  $1 \leftrightarrow 2$   
 $2 \rightarrow j$  for all  $j$

$1 \rightarrow 0$  but  $0 \nleftrightarrow 1$  so  $0 \nleftrightarrow 1$ , etc.  $\Rightarrow C_3 = \{1, 2\}$ .

$\Rightarrow$  equivalence classes:  $\{0\}, \{3\}, \{1, 2\}$ .

Why bother?

We will see that certain properties of states are class properties.

That is, if some  $i \in C$  has a property, then all states in  $C$  have this property.  
a communicating class

Proposition: Let  $i, j$  be distinct states.

(i)  $i \rightarrow j$  iff there is some  $k \geq 1$  and sequence of states

$$a_0 \xrightarrow{a_1} a_2 \xrightarrow{a_3} \dots \xrightarrow{a_k} a_k \quad \text{with} \quad a_0 = i, a_k = j \quad \text{and} \quad P_{a_0 a_1} \cdot P_{a_1 a_2} \cdot \dots \cdot P_{a_{k-1} a_k} > 0$$

$\Rightarrow P_{i, a_1} > 0, P_{a_1, a_2} > 0, \dots$

Same as  $a_0^i \rightarrow a_1 \rightarrow a_2 \rightarrow \dots \rightarrow a_k^j$

or  $P(X_1 = a_1, X_2 = a_2, \dots, X_k = a_k \mid X_0 = a_0^i) > 0$

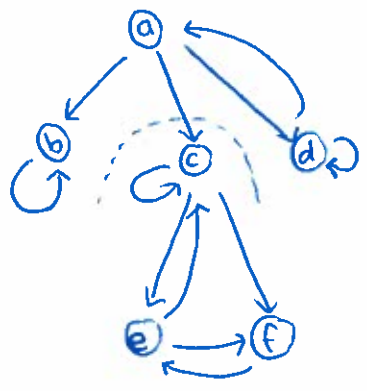
Example:

$$P = \begin{matrix} & \begin{matrix} a & b & c & d & e & f \end{matrix} \\ \begin{matrix} a \\ b \\ c \\ d \\ e \\ f \end{matrix} & \begin{bmatrix} 0 & \frac{1}{8} & \frac{3}{4} & \frac{1}{8} & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{3} & 0 & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & 0 & 0 & \frac{2}{3} & 0 & 0 \\ 0 & 0 & \frac{1}{4} & 0 & 0 & \frac{3}{4} \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \end{matrix}$$

Find communicating classes: Determine  $i \rightarrow j (\exists)$  for all  $i, j$

$i \rightarrow j$

(see p. 95)



$$a \rightarrow \begin{cases} b \rightarrow b \\ c \rightarrow \begin{matrix} c \\ e \\ f \end{matrix} \\ d \rightarrow a \end{cases} \Rightarrow \begin{matrix} a \rightarrow b \checkmark & b \rightarrow b \\ a \rightarrow c \checkmark & c \rightarrow c \\ a \rightarrow d \checkmark & c \rightarrow e \\ a \rightarrow e \checkmark & c \rightarrow f \\ a \rightarrow f \checkmark & \dots \end{matrix}$$

$C_1 = \{c, e, f\}$  one class       $C_2 = \{b\}$  one class       $C_3 = \{a, d\}$  one class.

Note that  $a \rightarrow c$ , so the class  $\{a,d\} \rightarrow \{c,e,f\}$

but  $\{c,e,f\} \not\rightarrow \{a,d\}$ .

$i, j$  states,  $\underline{P}$

$i \rightarrow j$  if  $P_{ij}^n > 0$  for some  $n \geq 0$   
can depend on  $i, j$

"i leads to j"

$i \leftrightarrow j$  if  $i \rightarrow j$  and  $j \rightarrow i$

"i and j communicate"

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$\leftrightarrow$  is an equiv. relation, so there are disjoint sets (classes)  $C_1, C_2, \dots$

s.t.

• every state is in some  $C_k$

•  $i \leftrightarrow j$  if  $i, j \in$  same class

•  $i \not\leftrightarrow j$  if  $i$  and  $j$  belong to different classes

write  $C_k \rightarrow C_l$  ( $C_k$  leads to  $C_l$ )

to mean for some  $i, j, i \in C_k, j \in C_l, i \rightarrow j$ , and necessarily  $j \rightarrow i$



Def: A class  $C$  is closed if  $C$  leads to no other class, and is

Open if  $C$  does lead to a different class.

Example:

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

$1 \rightarrow 2, 2 \rightarrow 1$  so  $1 \leftrightarrow 2$

But  $1 \not\leftrightarrow 1, 2 \not\leftrightarrow 2$ , so classes are  $C_1 = \{1, 2\}$  (open),  $C_2 = \{1\}$  (closed),  $C_3 = \{2\}$  (closed)

Def: A MC is called irreducible if it has a single communicating class.

Proposition (p. 95): Let  $i, j$  be distinct states. Then

1.  $i \rightarrow j$  if and only if for some  $k$  there are states  $a_0, a_1, \dots, a_k$  with

$a_0 = i, a_k = j$  and

$$\underbrace{P_{a_0, a_1} \cdot P_{a_1, a_2} \cdot \dots \cdot P_{a_{k-1}, a_k}}_{\text{equivalent to } P^k} > 0.$$

2. The chain is irreducible iff there is some  $k$ , some state  $a_0$ , and states  $a_1, a_2, \dots, a_k = a_0$  such that every state appears at least once in this list, and  $P_{a_0 a_1} \cdot P_{a_1 a_2} \cdot \dots \cdot P_{a_{k-1} a_k} > 0$ .

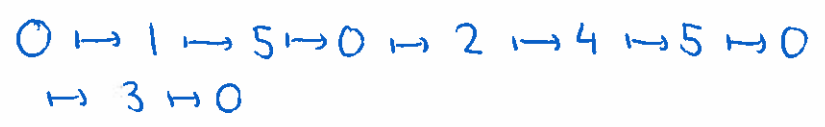
Example:

$$P = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & 4 & 5 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{matrix} & \left[ \begin{array}{cccccc} 0 & 0 & 1/8 & 3/4 & 1/8 & 0 \\ 0 & 0 & 9/10 & 0 & 0 & 1/10 \\ 0 & 0 & 0 & 1/3 & 0 & 0 \\ 1/3 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{array} \right] \end{matrix}$$

Is  $P$  irreducible?

$$P = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & 4 & 5 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{matrix} & \left[ \begin{array}{cccccc} 0 & 1/8 & 3/4 & 1/8 & 0 & 0 \\ 0 & 9/10 & 0 & 0 & 0 & 1/10 \\ 0 & 0 & 1/3 & 0 & 1/3 & 1/3 \\ 1/3 & 0 & 0 & 2/3 & 0 & 0 \\ 0 & 0 & 1/4 & 0 & 0 & 3/4 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{array} \right] \end{matrix}$$

Write  $i \mapsto j$  if  $P_{ij} > 0$



$a_0 \ a_1 \ a_2 \ a_3 \ a_4 \ a_5 \ a_6 \ a_7 \ a_8 \ a_9$   
 $0, 1, 5, 0, 2, 4, 5, 0, 3, 0$

All states appear at least once above

$\stackrel{\text{prop}}{\Rightarrow} P$  irreducible.  
 "  $i \mapsto j$  for every  $i, j$

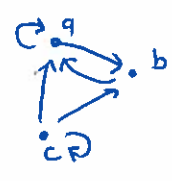
- Why:
- $0 \rightarrow$  every state  $\checkmark$
  - $1 \rightarrow$  every state  $\checkmark$
  - $2 \rightarrow$  " " "  $\checkmark$
  - $3 \rightarrow$  " " "  $\checkmark$
  - $4 \rightarrow$  " " "  $\checkmark$
  - $5 \rightarrow$  " " "  $\checkmark$

# Recurrence & Transience

Example:

$$P = \begin{matrix} & \begin{matrix} a & b & c \end{matrix} \\ \begin{matrix} a \\ b \\ c \end{matrix} & \begin{bmatrix} 1/3 & 2/3 & 0 \\ 1 & 0 & 0 \\ 1/4 & 2/4 & 1/4 \end{bmatrix} \end{matrix}$$

$\sum = 3/4$        $\sigma_c$



$a \leftrightarrow b, a \nleftrightarrow c, b \nleftrightarrow c$

$c \rightarrow a, c \rightarrow b$

Classes are  $\{a, b\}$  and  $\{c\}$ .  
closed                  open

(1) Starting at either  $a$ , or  $b$ , the chain is certain to return to  $a$  or  $b$                   recurrent

(2) Starting at  $c$ , there is prob.  $\frac{3}{4}$  of never returning to  $c$ .  
transient

Def: Let  $(X_n)$  be a MC with state space  $S$ .

For each state  $a \in S$ , define the random variables

$$H_a = \begin{cases} \min \{n \geq 0: X_n = a\} \\ +\infty \quad \text{if } X_n \neq a \quad \forall n \geq 0 \end{cases} \quad \text{hitting time of } a$$

$$R_a = \begin{cases} \min \{n \geq 1: X_n = a\} \\ +\infty \quad \text{if } X_n \neq a \quad \forall n \geq 1 \end{cases} \quad \begin{matrix} \text{return time} \\ \text{if } X_0 = a \end{matrix}$$

State  $a$  is called recurrent if  $P(R_a < \infty | X_0 = a) = 1$ .

--- --- --- transient if  $P(R_a < \infty | X_0 = a) < 1$ .

Ex:  $P(R_c < \infty | X_0 = c) = \frac{1}{4}$                    $c$  is transient

$P(R_a < \infty | X_0 = a) = \frac{1}{3} + \frac{2}{3} \cdot 1 = 1$                    $a$  is recurrent  
[ $R_a = 1$  or  $R_a = 2$ ]                  ( $b$  is too)

Ex: For some MC, we see the "realization" of the experiment  
 $X_0 = 1, X_1 = 1, X_2 = 3, \forall X_4 = 2, X_5 = 3, X_6 = 1, X_7 = 2, \dots$



For this realization

$$R_1 = ?$$

$$\{n \geq 1 : X_n = 1\} = \{1, 6, \dots\} \Rightarrow R_1 = 1, H_1 = 0$$

$$\{n \geq 0 : X_n = 1\} = \{0, 1, 6, \dots\}$$

$$R_2 = \min \{n \geq 1 : X_n = 2\} = \min \{4, 7, \dots\} = 4$$

$$H_2 = \min \{n \geq 0 : X_n = 2\} = \min \{4, 7, \dots\} = 4, H_2 = R_2$$

Def: Let  $f_a = P(R_a < \infty | X_0 = a)$ .

$a$  is recurrent if  $f_a = 1$   $\rightarrow$  you come back to  $a$  infinitely times  
 $\leftarrow$  transient if  $f_a < 1$   $\rightarrow$  only finitely many times

Goal: Classify each state in a given chain as recurrent or transient.

How do we do this?

$$f_a = P(R_a < \infty | X_0 = a)$$

$\leftarrow$  r.v., can be 1, 2, 3, ...  $\rightarrow$

$$= P(R_a = 1 | X_0 = a) + P(R_a = 2 | X_0 = a) + P(R_a = 3 | X_0 = a) + \dots$$

$$= \sum_{n=1}^{\infty} P(R_a = n | X_0 = a) \quad (\text{there is no } n = \infty \text{ term})$$

(Sum does not include  $R_a = \infty$  term)

$$\lim_{N \rightarrow \infty} \sum_{n=1}^N P(R_a = n | X_0 = a)$$

If we could find these  $P(R_a = n | X_0 = a)$ , we could add them up and check if the sum is 1 or  $< 1$ . (Usually impossible.)

Thm: (p. 98)

State  $a$  is ~~recurrent~~ recurrent iff  $\sum_{n=1}^{\infty} P_{aa}^n = +\infty$ .

State  $a$  is transient iff  $\sum_{n=1}^{\infty} P_{aa}^n < \infty$ .

Example

$$P = \begin{matrix} & \begin{matrix} 0 & 1 \end{matrix} \\ \begin{matrix} 0 \\ 1 \end{matrix} & \begin{bmatrix} .4 & .6 \\ 0 & 1 \end{bmatrix} \end{matrix} \quad P^n = ?$$

$$P_{00}^n = P(X_n=0 | X_0=0)$$

$$= P(X_1=0, X_2=0, \dots, X_n=0 | X_0=0)$$

if one goes to 1, one never comes back to 0

$$= \underbrace{P_{00} P_{00} P_{00} \dots P_{00}}_{n \text{ times}} = (0.4)^n \quad \Rightarrow P_{01}^n = 1 - (0.4)^n$$

$$P^n = \begin{bmatrix} (0.4)^n & 1 - (0.4)^n \\ 0 & 1 \end{bmatrix}$$

$$P_{11}^n = P(X_n=1 | X_0=1) = P(X_1=1, X_2=1, \dots, X_n=1 | X_0=1)$$

only possible state after 1 is 1 (1 to 0)

$$= P_{11} \cdot P_{11} \cdot \dots \cdot P_{11} = 1^n = 1$$

Check  $\sum_{n=1}^{\infty} P_{aa}^n$  for  $a = 0, 1$ .

$$a=0, \sum_{n=1}^{\infty} (0.4)^n < \infty \quad \text{geometric series} \quad \Rightarrow \text{So, } 0 \text{ is transient.}$$

$$a=1, \sum_{n=1}^{\infty} 1 = \infty \quad \Rightarrow 1 \text{ is recurrent.}$$

Thm 3.3

If  $i \leftrightarrow j$  then either both  $i$  and  $j$  are recurrent or both  $i, j$  are transient.

[ Recurrence (transience) are class properties. ]

[ If one state in a communicating class is recurrent then all states are. ]

Note: If the chain is irreducible, then either all states are recurrent or are transient.

Ex.  $P = \begin{bmatrix} 0 & 1 \\ 0.4 & 0.6 \\ 0 & 1 \end{bmatrix}$       0 transient      0, 1 are in different classes  
1 recurrent      or  $P$  is not irreducible.

Proof: Suppose  $i$  is recurrent and  $i \leftrightarrow j$  ( $i, j$  communicate).

We know:  $\sum_{n=1}^{\infty} P_{ii}^n = +\infty$  by Thm (p. 98).

- There is some  $k$  such that  $P_{ij}^k > 0$  ( $i \rightarrow j$ )
- There is some  $m$  s.t.  $P_{ji}^m > 0$  ( $j \rightarrow i$ )

We want to show that  $\sum_{l=1}^{\infty} P_{jj}^l = +\infty$ , imply  $j$  is recurrent.

$$\begin{aligned}
 \text{Consider } P_{jj}^{m+k+l} &= (P_{ji}^m \times P_{ij}^k \times P_{jj}^l)_{jj} \\
 &= \sum_x P(X_{m+k+l} = j \mid X_0 = j) \\
 &\geq P(X_m = i, X_{m+k} = i, X_{m+k+l} = j \mid X_0 = j) \\
 &= P_{ji}^m P_{ij}^k P_{jj}^l = B \cdot P_{ii}^l \cdot A = AB P_{ii}^l \\
 \sum_{l=0}^{\infty} P_{jj}^l &\geq \sum_{l=m+n}^{\infty} P_{jj}^l = \sum_{\tilde{l}=0}^{\infty} P_{jj}^{\tilde{l}+m+n} = \sum_{\tilde{l}=0}^{\infty} AB P_{ii}^{\tilde{l}} = AB \sum_{\tilde{l}=0}^{\infty} P_{ii}^{\tilde{l}} = +\infty
 \end{aligned}$$

- Exam #1 date moved to Tue Oct 3 Sep 21
- sol's Hw #3 → Library

Prop: (Irreducibility and regularity)

Assume a MC has a finite nr of states.

- Then
- ① If  $\underline{P}$  is regular then  $\underline{P}$  is irreducible.
  - ② If  $\underline{P}$  is irreducible, and there is a  $t$  least one state  $i$  such that  $P_{ii}^t > 0$ , then  $\underline{P}$  is regular.

$\underline{P}$  regular implies there exists some  $n$  with  $\underline{P}^n > 0$ . For this  $n$ ,  $P_{ij}^n > 0$ , so  $i \rightarrow j$  for all states  $i, j$ .

Example:

	a	b	c	d	e	f
a	0	0	0	0	0	0
b	0	0	0	0	0	0
c	0	0	0	0	0	0
d	0	0	0	0	0	0
e	0	0	0	0	0	0
f	0	0	0	0	0	0

1) Irreducible? Yes, because  $a \rightarrow b \rightarrow c \rightarrow d \rightarrow e \rightarrow f \rightarrow a$

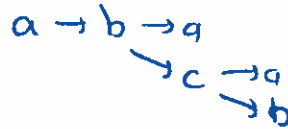
2)  $P_{ff} > 0$

By the prop.,  $\underline{P}$  is regular.

Note that  $\underline{P}^9$  is not positive, but  $\underline{P}^{10}$  is positive.

Example:  $\underline{P} = \begin{matrix} & \begin{matrix} a & b \end{matrix} \\ \begin{matrix} a \\ b \end{matrix} & \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \end{matrix}$ , then  $\underline{P}$  is irreducible, but not regular.

Example:  $\underline{P} = \begin{matrix} & \begin{matrix} a & b & c \end{matrix} \\ \begin{matrix} a \\ b \\ c \end{matrix} & \begin{bmatrix} 0 & 1 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & 0 \end{bmatrix} \end{matrix}$



- 1) Irreducible ✓
- 2)  $P_{ii} = 0$  for each  $i$

But  $\underline{P}$  is regular.

Recall:  $R_a = \begin{cases} \min \{n \geq 1 : X_n = a\} \\ +\infty \text{ if } X_n \neq a \text{ for all } n = 1, 2, \dots \end{cases}$

State  $a$  is called recurrent if  $P(R_a < \infty | X_0 = a) = 1$ .

(same as  $P(R_a = +\infty | X_0 = a) = 0$ )

State  $a$  is called transient if  $P(R_a < \infty | X_0 = a) < 1$

(same as  $P(R_a = +\infty | X_0 = a) < 1$ ).

Thm: • State  $a$  is recurrent iff  $\sum_{n=1}^{\infty} P_{aa}^n = +\infty$ .

equiv. to state  $a$  is transient iff  $\sum_{n=1}^{\infty} P_{aa}^n < \infty$ .

• If state  $a$  is transient, and  $b$  is any state,

then  $\sum_{n=1}^{\infty} P_{ba}^n < \infty$ . In particular,  $\lim_{n \rightarrow \infty} P_{ba}^n = 0$ . } pf like trans  $\Rightarrow \Sigma < \infty$

Thm 3.3: If  $i \leftrightarrow j$  then either both  $i$  and  $j$  are recurrent or both  $i$  and  $j$  are transient.

Proof: Suppose  $i \neq j$ ,  $i \leftrightarrow j$ , and  $i$  is recurrent.

Since  $i \rightarrow j$  and  $j \rightarrow i$  there are positive  $m, n$  such that

$$A = P_{ij}^n > 0 \quad \text{and} \quad B = P_{ji}^m > 0.$$

For any positive  $k$ ,  $P_{jj}^{k+m+n} = P(X_{k+m+n} = j \mid X_0 = j)$

$$\geq P(X_m = i, X_{k+m} = i, X_{k+m+n} = j \mid X_0 = j)$$

$$\stackrel{MP}{=} \underbrace{P_{ji}^m}_B \underbrace{P_{ii}^k}_{P_{ii}^k} \underbrace{P_{ij}^n}_A = AB P_{ii}^k$$

$$\sum_{L=1}^{\infty} P_{jj}^L \geq \sum_{L=m+n+1}^{\infty} P_{jj}^L = \sum_{k=1}^{\infty} P_{jj}^{k+m+n} \geq \sum_{k=1}^{\infty} AB P_{ii}^k = AB \sum_{k=1}^{\infty} P_{ii}^k = +\infty$$

$$\begin{aligned} \text{Let } k &= L - m - n \\ L &= k + m + n \end{aligned}$$

Since  $i$  is recurrent by Thm.

This shows  $j$  is recurrent.  $\square$

Sketch of Proof: [Thm a rec.  $\Leftrightarrow \sum_{n=1}^{\infty} P_{aa}^n = \infty$ ]

① For state  $a$ , let  $V_a$  be the nr of times the chain "visits" (is at) state  $a$ .

Let  $I_n = \begin{cases} 1 & \text{if } X_n = a \\ 0 & \text{if } X_n \neq a \end{cases}$  Then  $V_a = \sum_{n=1}^{\infty} I_n$ , a random variable.

$$\begin{aligned} \text{Then } E[V_a \mid X_0 = a] &= E\left(\sum_{n=1}^{\infty} I_n \mid X_0 = a\right) = \sum_{n=1}^{\infty} E(I_n \mid X_0 = a) \\ E(I_n \mid X_0 = a) &= 1 \cdot P(X_n = a \mid X_0 = a) + 0 \cdot P(X_n \neq a \mid X_0 = a) = P_{aa}^n \\ &\Rightarrow E[V_a \mid X_0 = a] = \sum_{n=1}^{\infty} P_{aa}^n \end{aligned}$$

② Suppose  $a$  is recurrent. Then starting at  $a$ , the MC comes back to  $a$  w/ prob. 1 at some time. Now, starting at  $a$ , the MC comes back to  $a$  w/ prob. 1 some further time. Again, starting at  $a$ , ...

some further time.  $\Rightarrow V_a = +\infty$  w/ prob. 1. This implies

$$E[V_a \mid X_0 = a] = +\infty \stackrel{\text{①}}{\Rightarrow} \sum_{n=1}^{\infty} P_{aa}^n = +\infty. \quad \text{See text for the rest. } \square$$

Corollary 3.4:

If a MC has a finite state space and is irreducible, then all states are recurrent.

[This is false in general for MC's with infinite state space.]

Proof: Let  $S = \{1, 2, \dots, k\}$ .

① For any state  $i$ , since  $\underline{P}^n$  is a stochastic matrix,

$$1 = \sum_{j=1}^k p_{ij}^n \text{ for all } n$$

② Suppose all states  $j$  are transient.

Then, for every state  $i$  and  $j$ ,  $\lim_{n \rightarrow \infty} p_{ij}^n = 0$ .

$$1 = \lim_{n \rightarrow \infty} 1 = \lim_{n \rightarrow \infty} \sum_{j=1}^k p_{ij}^n = \sum_{j=1}^k \lim_{n \rightarrow \infty} p_{ij}^n = \sum_{j=1}^k 0 = 0. \text{ A contradiction!}$$

so all states must be recurrent.

Lemma 3.5: Let  $C$  be a communicating class for a MC.

Suppose  $C$  is closed. finite. ① Then  $C$  is closed iff all states in  $C$  are recurrent.

⇒ All states in a closed communicating class are recurrent.

② iff  $C$  is open, then all states in  $C$  are transient.

Example: Suppose a MC has communicating classes  $C_1 = \{0, 1\}$ ,  $C_2 = \{2, 3\}$ ,  $C_3 = \{4, 5\}$ . Suppose also that  $C_1 \rightarrow C_2$  and  $C_2 \rightarrow C_3$ .

What are the recurrent and transient states?

$C_1 \rightarrow C_2$  means  $i \rightarrow j$  for some  $i \in C_1, j \in C_2$ . So  $C_1$  is open.

So is  $C_2$  open. How about  $C_3$ ?

Suppose  $C_3$  is open. Then either  $C_3 \rightarrow C_1$  or  $C_3 \rightarrow C_2$ .

Contradicts  $C_3 \rightarrow C_2$   
(all states in  $C_2, C_3$  would communicate)

(otherwise we have  $i \leftrightarrow j$  for all  $i \in C_2, j \in C_3$  : impossible)

Also,  $C_3 \nrightarrow C_1$ , since  $C_1 \rightarrow C_3$  b/c  $C_1 \rightarrow C_2$  and  $C_2 \rightarrow C_3$ .

So,  $C_3$  is closed.

states 0, 1, 2, 3 are transient  
4, 5 are recurrent

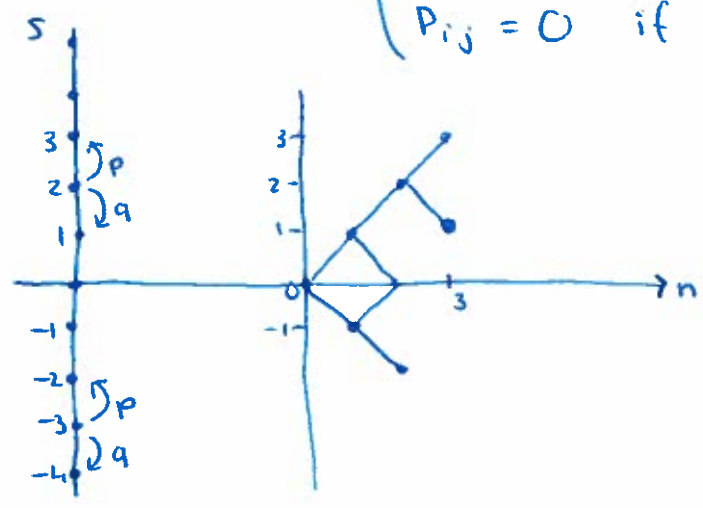
Fact: Every finite <sup>MC</sup> state must have at least one closed ~~recurrent~~ communicating class.

Example 3.3 Simple one-dimensional random walk  
→ jumps are either +1 or -1

The state space is {all integers} =  $\{0, \pm 1, \pm 2, \dots\}$

$0 < p < 1$  is a fixed parameter,  $q = 1 - p$ .

p is defined by 
$$\begin{cases} P_{i,i+1} = p & \forall i \\ P_{i,i-1} = q & \forall i \\ P_{ij} = 0 & \text{if } j \neq i \pm 1 \end{cases}$$



Thm: This MC is irreducible and

1) if  $p = \frac{1}{2}$  then all states are recurrent (check  $\sum_{n=1}^{\infty} P_{00}^n = +\infty$ )

2) if  $p \neq \frac{1}{2}$  then all states are transient (check  $\sum_{n=1}^{\infty} P_{00}^n < \infty$ )

Proof sketch: (see text for more details)

(0)  $P_{00}^n = 0$  if  $n$  is odd (starting with  $X_0 = 0$  (even))

"  
 $P(X_n = 0 | X_0 = 0)$

$X_1 = \text{odd}$

$X_2 = \text{even}$

⋮

$X_n = \text{odd if } n \text{ is odd}$ )

(1)  $P_{00}^{2n} = \binom{2n}{n} (pq)^n$  for  $n = 1, 2, 3, \dots$

(2)  $\lim_{n \rightarrow \infty} \frac{P_{00}^{2n}}{C_n} = 1$ , where  $C_n = \frac{(4pq)^n}{\sqrt{\pi n}}$

we often write:  $P_{00}^{2n} \sim \frac{(4pq)^n}{\sqrt{\pi n}}$  as  $n \rightarrow \infty$   
 ↑  
 asymptotically

(3) By comparison test for infinite series,  $\sum_{n=1}^{\infty} P_{00}^{2n}$  converges

if and only if  $\sum_{n=1}^{\infty} \frac{(4pq)^n}{\sqrt{\pi n}}$  converges.

(4) If  $p = \frac{1}{2}$ ,  $4pq = 1$ , so  $\sum_{n=1}^{\infty} \frac{(4pq)^n}{\sqrt{\pi n}} = \sum_{n=1}^{\infty} \frac{1}{\sqrt{\pi n}} = +\infty$

$\Rightarrow$  chain is recurrent

If  $p \neq \frac{1}{2}$ ,  $4pq = 4p(1-p)$ , parabola



(maximize  $4p(1-p)$   
 strict local max at  $p = \frac{1}{2}$ )

In this case,  $\sum_{n=1}^{\infty} \frac{(4pq)^n}{\sqrt{\pi n}} < \sum_{n=1}^{\infty} (4pq)^n$ , geometric series,  $4pq < 1$ ,

converges, so  $\sum_{n=1}^{\infty} \frac{(4pq)^n}{\sqrt{\pi n}} < \infty \Rightarrow$  chain is transient.

$P_{00}^{2n} \stackrel{?}{=} \binom{2n}{n} (pq)^n$ ,  $P_{00}^{2n} = P(X_{2n} = 0 | X_0 = 0)$ .



Fact:  $\underline{p}$  is irreducible

Thm: All states are recurrent if  $p = \frac{1}{2}$ .

All states are transient if  $p \neq \frac{1}{2}$ .

Intuitive argument for  $p = \frac{2}{3}$ : there is a drift upwards, so starting at a state the MC may never return.

We will show this using the  $\sum_{n=1}^{\infty} p_{ii}^n$  criteria.

It suffices to check if  $\sum_{n=1}^{\infty} p_{00}^n$  converges or diverges.

We want a formula for  $p_{00}^n$ .

$p_{00}^n = 0$  for all odd  $n$ .

We want to find  $p_{00}^{2n}$ .

$$p_{00}^{2n} = P(X_{2n} = 0 \mid X_0 = 0) = \binom{2n}{n} p^n q^n.$$

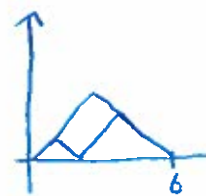
the no. of up<sup>↑</sup> steps

must equal the no. of down steps

must equal  $n$  ( $2n$  steps in total)

→  $n$  up steps  
 $n$  down steps

Any such "path" has probability  $p^n q^n$   
We must multiply by the no. of such paths =  $\binom{2n}{n}$



Read 3.5 ; BB → HW#4 hint

Sep 26

Thursday → problem / review ; next Tuesday - Exam #1

Example 3.3 p.p. 99-160

Simple random walk,  $S = \{0, \pm 1, \pm 2, \dots\}$ ,  $0 < p < 1$  fixed,  $q = 1 - p$

$P_{i,i+1} = p$ ,  $P_{i,i-1} = q$ ,  $P_{ij} = 0$  otherwise

For a path with  $X_0=0, X_{2n}=0$ , must have  $n$   $+$ -steps and

$n$   $-$ -steps, this prob. is  $(pq)^n (=p^n q^n)$ .

$$\Rightarrow P_{00}^{2n} = (pq)^n \cdot \# \text{ "paths" from } 0 \text{ to } 0 \text{ with } 2n \text{ steps}$$

↳ sequence of  $+$ 's,  $-$ 's,  $n$  of each.

$$= (pq)^n \binom{2n}{n}$$

↳ choose  $n$  positions for  $+$ 's  $\rightarrow \binom{2n}{n}$  ways to do this  
choose pos. for  $-$ 's  $\rightarrow 1$  way (positions not yet filled)

$$= \frac{(2n)!}{n!n!} (pq)^n. \quad (*)$$

Need Stirling's Formula:  $n! \sim n^n e^{-n} \sqrt{2\pi n}$  as  $n \rightarrow \infty$

$$\text{or } \frac{n!}{n^n e^{-n} \sqrt{2\pi n}} \rightarrow 1 \text{ as } n \rightarrow \infty.$$

(For  $n=10$ , this ratio is 1.0084...)

To get  $P_{00}^{2n} \sim \frac{(pq)^n}{\sqrt{\pi n}}$ , plug into (\*) with Stirling's formula,

simplify. ( $n! \sim n^n e^{-n} \sqrt{2\pi n}$ ,  $(2n)! \sim (2n)^{2n} e^{-2n} \sqrt{2\pi(2n)}$ )

• Recall that a finite irreducible MC has all states recurrent.

• This simple random walk example is irreducible but all states are transient if  $p \neq \frac{1}{2}$ .

Thm 3.6: (Basic limit thm for finite irreducible MC's)

Assume  $(X_n)$  is a finite irreducible MC. For every state  $j$  define

$$\mu_j = E(R_j | X_0 = j).$$

$$R_j \stackrel{\text{def}}{=} \min \{n \geq 1 \mid X_n = j\}$$

= first return time to  $j$  (starting at  $j$ ).

Then

$$(a) \mu_j < \infty \text{ for all } j$$

[ Note: random variables can have infinite mean. ]

Example:  $X$  has pdf  $f(x) = \begin{cases} 0 & \text{if } x < 1 \\ \frac{1}{x^2} & \text{if } x \geq 1 \end{cases}$

Check:  $\int_1^{\infty} f(x) dx = 1$  (kernel pdf)

$$EX = \int_1^{\infty} x f(x) = \int_1^{\infty} x \cdot \frac{1}{x^2} dx = \int_1^{\infty} \frac{1}{x} dx = +\infty$$

(b) There is a unique stationary dist.  $\pi$  given by  $\pi_j = \frac{1}{M_j}$  for all states  $j$ .

(c) For all states  $i, j$ ,  $\frac{1}{n} \sum_{m=1}^n P_{ij}^m = \frac{P_{ij}^1 + P_{ij}^2 + \dots + P_{ij}^n}{n}$   
 = average of  $P_{ij}^k$  up to time  $n$   
 $\xrightarrow{n \rightarrow \infty} \pi_j$

Remark:

① Does this apply to regular chains? Yes (reg  $\Rightarrow$  irred. (MC finite))

② (c) is a weaker statement than  $\lim_{n \rightarrow \infty} P_{ij}^n = \pi_j$ . Also, if  $\lim_{n \rightarrow \infty} P_{ij}^n = \pi_j$ , then (c) holds.

Example: Take  $\underline{P} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$ ,  $P_{01}^n = \begin{cases} 1 & \text{if } n \text{ is odd} \\ 0 & \text{if } n \text{ is even} \end{cases}$

$\underline{P}^2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ .  $\lim_{n \rightarrow \infty} P_{01}^n$  does not exist.

$$\frac{1}{n} \sum_{k=1}^n P_{01}^k = \frac{1}{n} (1+0+1+0+\dots+0+1) = \frac{1}{n} \left( \frac{n-1}{2} + 1 \right) = \frac{1}{n} \left( \frac{n-1+2}{2} \right) = \frac{1}{n} \left( \frac{n+1}{2} \right) = \frac{1}{2} \left( 1 + \frac{1}{n} \right) \rightarrow \frac{1}{2} \text{ as } n \rightarrow \infty$$

[Thm: If  $\lim_{n \rightarrow \infty} c_n = L$ , then  $\lim_{n \rightarrow \infty} \frac{c_1 + c_2 + \dots + c_n}{n} = L$ ]

③ This gives us a way to compute  $M_j$ :

Find  $\sum \pi_j$ ,  $M_j = \frac{1}{\pi_j}$ .

Example: If in addition  $\underline{P}$  is doubly stochastic, then

$M_j = \frac{1}{\text{\# of states}}$ , every state  $j$   $\rightarrow$  uniform stat. distr.



$$S = \{1, 2, 3, 4, 5\}$$

$$P = \begin{matrix} & \begin{matrix} \emptyset & 2 & 3 & 4 & 5 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{matrix} & \begin{bmatrix} 0 & \frac{1}{2} & 0 & 0 & \frac{1}{2} \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{2} & 0 & \frac{1}{2} & 0 \\ 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ \frac{1}{2} & 0 & 0 & \frac{1}{2} & 0 \end{bmatrix} \end{matrix}$$

Doubly stoch. matrix  $\Rightarrow \pi_j = \frac{1}{5}, \mu_j = 5.$

$j$  recurrent  $P(R_j < \infty | X_0 = j) = 1$

$j$  transient  $P(R_j < \infty | X_0 = j) < 1.$

Def: A recurrent state is positive recurrent if  $\mu_j = E(R_j | X_0 = j) < \infty$   
 null recurrent if  $\mu_j = E(R_j | X_0 = j) = \infty.$

Thm 3.6  $\Rightarrow$  a finite irred. MC has all states positive recurrent.

First-step analysis (p. 105) - ask what happens with the first step

Example (3.17)

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

irreducible, (regular)

Thm 3.6  $\Rightarrow E[R_j | X_0 = j] < \infty$  for each  $j.$

Let  $e_x = E[R_a | X_0 = x], \quad [R_a = \min \{n \geq 1 | X_n = a\}]$   
 $x = a, b, c.$

(e.a., e.b., e.c.)

$e_a = 1 + e_b$  additional amount of time depending on 1st step

$$e_b = 1 + (P_{ba} \cdot 0 + P_{bb} \cdot e_b + P_{bc} \cdot e_c) = 1 + \frac{1}{2} e_c.$$

$$e_c = 1 + (P_{ca} \cdot 0 + P_{cb} e_b + P_{cc} e_c) = 1 + \frac{1}{3} e_b + \frac{1}{3} e_c. \quad (= 1 + \sum_{y \neq a} P_{cy} e_y)$$

$$\Rightarrow \begin{cases} e_a = 1 + e_b, \\ e_b = 1 + \frac{1}{2} e_c \\ e_c = 1 + \frac{1}{3} e_b + \frac{1}{3} e_c \end{cases} \quad \begin{array}{l} 3 \text{ linear eqns,} \\ 3 \text{ unknowns,} \\ \text{a unique sol'n} \end{array}$$

$$e_a = \frac{10}{3}, e_b = \frac{7}{3}, e_c = \frac{8}{3}.$$

General Formula

For a fixed state  $a$ ,  $e_x = E[R_a | X_0 = x]$ , then

$$e_x = 1 + \sum_{y \neq a} P_{xy} e_y.$$

Consistency check:

For the example  $\pi = \begin{bmatrix} \frac{3}{10} & \frac{2}{5} & \frac{3}{10} \end{bmatrix}$

Thm 3.6:  $\mu_a = E[R_a | X_0 = a] = \frac{1}{\pi_a} = \frac{1}{3/10} = \frac{10}{3}.$

1st Step Analysis

$$R_a = \min \{n \geq 1 : X_n = a\}, \quad H_a = \min \{n \geq 0 : X_n = a\}.$$

Example:

$$P = \begin{matrix} & \begin{matrix} a & b & c \end{matrix} \\ \begin{matrix} a \\ b \\ c \end{matrix} & \begin{bmatrix} 0 & 1 & 0 \\ 1/2 & 0 & 1/2 \\ 1/3 & 1/3 & 1/3 \end{bmatrix} \end{matrix}$$

$$e_x = E[R_a | X_0 = x]$$

= an expected return time value

1st-step analysis:

$$\begin{aligned} e_a &= 1 + e_b \\ e_b &= 1 + \frac{1}{2} e_c \\ e_c &= 1 + \frac{1}{3} e_b + \frac{1}{3} e_c \end{aligned}$$

$$e_a = 1 + \sum_{j \neq a} P_{aj} e_j$$

$$e_b = 1 + \sum_{j \neq a} P_{bj} e_j$$

$$e_c = 1 + \sum_{j \neq a} P_{cj} e_j$$

Example: Run probability

$N > 0$  is fixed (target for quitting),  $S = \{0, 1, \dots, N\}$



$$P_{i,i+1} = p, \quad P_{i,i-1} = q, \quad P_{0,0} = 1, \quad P_{N,N} = 1$$

Ruin event is  $\{ \text{hit } 0 \text{ before } N \}$

$$= \{ H_0 < H_N \} = \{ H_0 < \infty \} \\ [H_N = \infty]$$

Let  $x_k = P(H_0 < \infty | X_0 = k)$ ,  $k = 0, 1, 2, \dots, N$ .

$$x_0 = 1, x_N = 0$$

Claim: For  $1 \leq k \leq N-1$ ,  $x_k = p x_{k+1} + q x_{k-1}$

Sketch: Restrict to  $X_0 = k$ ,  $2 \leq k \leq N-2$  (in this case,  $X_i$  cannot be 0 or N)

$$x_k = P(H_0 < \infty | X_0 = k) = \sum_{j \in S} P(H_0 < \infty | X_1 = j | X_0 = k) \quad (\text{LOTP})$$

$$= P(H_0 < \infty, X_1 = k+1 | X_0 = k) + P(H_0 < \infty, X_1 = k-1 | X_0 = k)$$

$$\stackrel{P(A|B) = P(A \cap B) / P(B)}{=} P(H_0 < \infty | X_1 = k+1, X_0 = k) \underbrace{P(X_1 = k+1 | X_0 = k)}_{= P_{k,k+1} = p}$$

$P(A|B) = P(A \cap B) / P(B)$

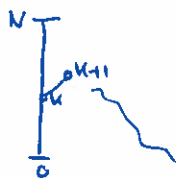
$$+ P(H_0 < \infty | X_1 = k-1, X_0 = k) \underbrace{P(X_1 = k-1 | X_0 = k)}_{= P_{k,k-1} = q}$$

$$= p P(H_0 < \infty | X_1 = k+1) + q P(H_0 < \infty | X_1 = k-1)$$

time-homog.

$$= p P(H_0 < \infty | X_0 = k+1) + q P(H_0 < \infty | X_0 = k-1)$$

"0"



Fact: In general,  $P(H_0 < \infty | X_0 = x) = u_x$

$$\text{Then } \begin{cases} u_x = \sum_{y \in S} P_{xy} u_y, & x \neq a \\ u_a = 1 \end{cases}$$

**Exam**

Next Tues

also on topics from 3.4-... in text

• Topics - lectures, text sections 2.1-2.3, 3.1-3.3, difference eqns, HW

• know - def's, theorems (props, lemmas, facts, ...) standard notation

eg.  $P_{ij}^n \neq (P_{ij})^n$ ;  $i \rightarrow j$  means for some  $n$ ,  $P_{ij}^n > 0$   
can depend on  $i, j$

• closed books, notes, no calc's, cell phones

• Types of question

1) True/false . no justification

T or F if  $i \rightarrow j$  then  $P_{ij} > 0$

[ consider  $a \begin{bmatrix} a & b & c \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix} ]$

$P_{ac} = 0$  but  $P_{ac}^2 > 0$ .

T or F if  $\underline{P}$  is regular then  $\underline{P}$  is med.

regular: there is some  $(n) \in \mathbb{N}$  s.t.  $P_{ij}^n > 0 \forall i, j$

irreducible:  $i \leftrightarrow j$  for all  $i, j$  or  $i \rightarrow j$  for all  $i, j$

2) Give an <sup>simplest possible</sup> example of (no justification)

Give a trans. matrix  $\underline{P}$  s.t.  $\underline{P}$  has more than one stationary dist.

$\underline{P} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ ,  $\underline{\pi} = [a \ 1-a]$  is a stat. dist. for all  $0 \leq a \leq 1$ .

$\underline{P}$  always has  $0/1/1 \leftrightarrow$  stat. dist.

3) "standard" calculation problem

For  $\underline{P} = \begin{bmatrix} 1/2 & 1/4 & 1/4 \\ 1/4 & 0 & 3/4 \\ 0 & 1/2 & 1/2 \end{bmatrix}$  find the stationary distribution.

4) Proof

Example

-  $\underline{P}$  is a stoch. matrix

Show: If  $\underline{P}^N > 0$  then  $\underline{P}^{N+m} > 0$  for all  $m = 1, 2, 3, \dots$

It suffices to show: if  $\underline{p}^k > 0$  then  $\underline{p}^{k+1} > 0$  for all  $k$ .

We are given  $\underline{p}_{ij}^k$  for all  $i, j$ . Want to show  $\underline{p}_{ij}^{k+1} > 0$  for all  $i, j$ .

$$\underline{p}^{k+1} = \underline{p}^k \times \underline{p} = \underline{p} \times \underline{p}^k$$

$$\underline{p}_{ij}^{k+1} = (\underline{p} \times \underline{p}^k)_{ij} = \sum_{L \in S} p_{iL} \underbrace{p_{Lj}^k}_{\text{all } > 0}$$

Given  $i$ , not all  $p_{iL}$  can be zero because  $\sum_{L \in S} p_{iL} = 1$

so given  $i$  there must be some  $L$  s.t.  $p_{iL} > 0$ .

Then 
$$\underline{p}_{ij}^{k+1} \geq \underbrace{p_{iL_0}}_{> 0} \underbrace{p_{L_0j}^k}_{> 0} > 0.$$

HW 4, 3.28

Show  $\{1, 2, 3\}$  is a closed class and  $\{4, 5, 6, 7\}$  is an open class

← all recurrent

← all transient

↳  $\lim_{n \rightarrow \infty} p_{ij}^n = 0$  if  $j$  is transient, any  $i$

implies  $\underline{p}_{ij}^n = 0$  for all  $n$ , all  $i \in \{1, 2, 3\}$ , all  $j \in \{4, 5, 6, 7\}$ .

so  $\lim_{n \rightarrow \infty} p_{ij}^n = 0$  in this case.

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

If we let  $\underline{Q} =$

1)  $\underline{P}_{12}^n = \underline{Q}_{12}^n$

2)  $\underline{Q}$  is doubly stochastic, regular, so  $\lim_{n \rightarrow \infty} \underline{Q}_{ij}^n = \pi_j = \frac{1}{3}$

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

So,  $\lim_{n \rightarrow \infty} p_{ij}^n = \frac{1}{3}$  for all  $i, j \in \{1, 2, 3\}$ .



3) How about  $\lim_{n \rightarrow \infty} p_{ij}^n$  if  $i \in \{4, 5, 6, 7\}$ ,  $j \in \{1, 2, 3\}$ .

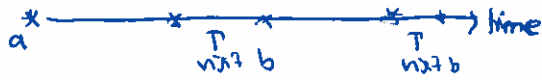
Roughly speaking, starting at ray  $4 = X_0$ ,  
eventually, for some random  $k$ ,  $X_k \in \{1, 2, 3\}$ .

$$\lim_{n \rightarrow \infty} P_{ij}^n = \pi_j = \frac{1}{3} \quad (\text{if first get to } \{1, 2, 3\})$$

$$\lim_{n \rightarrow \infty} p_{ij}^n = \frac{1}{3} \quad \text{if } i \in \{4, 5, 6, 7\}, j \in \{1, 2, 3\}.$$

T If  $a, b$  are distinct states,  $a \rightarrow b$ ,  $a$  is recurrent then  $b$  is recurrent.

We know if  $a \leftrightarrow b$  and  $a$  is recurrent, then  $B$  is recurrent.



$$H_a = \begin{cases} \min \{n \geq 0 : X_n = a\} \\ +\infty \text{ if } X_n \neq a \text{ all } n=0, 1, 2, \dots \end{cases}$$

$$R_a = \begin{cases} \min \{n \geq 1 : X_n = a\} \\ +\infty \text{ if } X_n \neq a \text{ all } n=1, 2, \dots \end{cases}$$

Note: If  $X_0 \neq a$ ,  $H_a = R_a$  ✓

Let  $u(i) = P(H_a < \infty | X_0 = i)$

$v(i) = E(R_a | X_0 = i)$

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

Take  $a=0$ ,  $u(1) = P(H_0 < \infty | X_0 = 1) < 1$   
(+1)

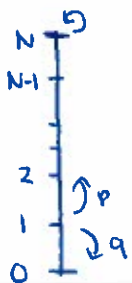
Then

$$u(i) = P_{ia} + \sum_{j \neq a} P_{ij} u(j) \quad i \neq a \quad (*)$$

$$v(i) = 1 + \sum_{j \neq a} P_{ij} v(j) \quad \text{all } i$$

### Gambler's Ruin

Fix  $p, q=1-p, N$



$$P_{00} = P_{NN} = 1$$

$$P_{i,i+1} = p, \quad 0 < i < N$$

$$P_{i,i-1} = q, \quad 0 < i < N$$

$$P_{ij} = 0 \text{ otherwise}$$

### 1<sup>st</sup> step analysis equations

$$P(\text{ruin} | X_0 = i) = P(H_0 < \infty | X_0 = i) = u(i)$$

↑  
get to 0 before N  
" ever get to 0  
" {  $H_0 < \infty$  }

Take  $2 \leq i \leq N-2$ , then  $P_{i0} = 0$

$$\begin{aligned} \Rightarrow u(i) &= \sum_{j \neq 0} P_{ij} u(j) = P_{i,i+1} u(i+1) + P_{i,i-1} u(i-1) \\ &= p u(i+1) + q u(i-1). \end{aligned}$$

$$\Rightarrow u(i) = p u(i+1) + q u(i-1), \quad 2 \leq i \leq N-2$$

Now

If we just put  $i=1$  above, using  $u(0)=1$ , we would get

$$u(1) = p u(2) + q u(0) = p u(2) + q.$$

~~Check  $u(1) = P_{11} + q$~~

Put  $i=1$  in  $\textcircled{*}$ , we get  $u(1) = P_{10} + P_{12} u(2) = q + p u(2)$ . ✓

We get  $u(0)=1, u(N)=0$

[Check  $i=N-2$ ]

$$u(i) = p u(i+1) + q u(i-1), \quad 1 \leq i \leq N.$$

Difference eqn., solved in Problem 9 on DE handout.

~~Set  $p=q=\frac{1}{2}$ , consider  $E\{\text{duration of game} \mid X_0=i\}$~~   
 $= \min\{R_0, R_N\} \stackrel{\text{def}}{=} T, \quad i \neq 0 \text{ or } N.$

Put  $w(i) = E(T \mid X_0=i)$

$$w(0) = w(N) = 0.$$

By 1<sup>st</sup>-step analysis  $w(i) = 1 + \sum_{j \neq 0, N} P_{ij} w(j) = 1 + P_{i,i+1} w(i+1) + P_{i,i-1} w(i-1)$   
 $= 1 + p w(i+1) + q w(i-1)$

Set  $p=q=\frac{1}{2}$ .  $w(i) = 1 + \frac{1}{2} w(i+1) + \frac{1}{2} w(i-1), \quad 0 < i < N$   
 $w(0) = w(N) = 0$   
 $\rightarrow$  DE, Problem 8 on DE handout

Thm 3.6

Assume  $(X_n)$  is a finite state space, irreducible MC, P. For state  $j$  define

$M_j = E(R_j | X_0 = j)$ . Then  $R_j \geq 1 \Rightarrow M_j \geq 1$

(1)  ~~$E$~~   $M_j < \infty$  for each  $j \in S$

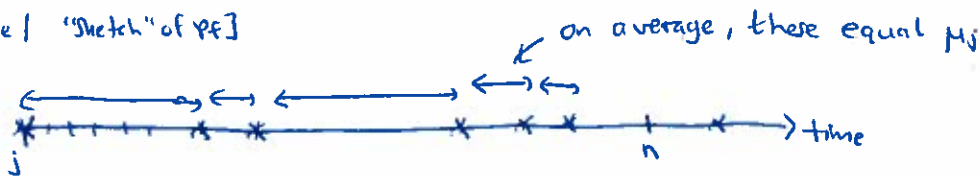
(2) There is a unique stationary distribution  $\pi$  such that  $\pi_j = \frac{1}{M_j}$  for each  $j$ .

(3) For all states  $i, j$   $\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{m=1}^n P_{ij}^m = \pi_j$ . ~~for every~~

[  $\sum_{n=1}^{\infty} P_{ii}^n < \infty \Rightarrow$  transient.  $E \left[ \begin{matrix} \text{up to time } n \\ \text{proportion of times the chain} \\ \text{is at state } j \end{matrix} \right]$  ]

Question: why is  $\pi_j = \frac{1}{M_j}$ ?

[Intuitive / "Sketch" of pf]



\* = chain is at  $j$

• # of visits to  $j$  between times 1 and  $n = x$

should have  $x \cdot M_j \approx n$ , so  $M_j \approx \frac{n}{x}$ .

reciprocals

•  $\pi_j$  is proportion of times spent at  $j$  up to time  $n = \frac{x}{n}$

$\Rightarrow \pi_j = \frac{1}{M_j}$ .

State  $i$  is recurrent if  $P(R_i < \infty | X_0 = i) = 1$ .

$i$  is called positive recurrent if  $E(R_i | X_0 = i) < \infty$

$\uparrow$   
recurrent

null recurrent if  $E(R_i | X_0 = i) = +\infty$ .

Fact: A finite state space, irred. MC has no null recurrent states.

Periodicity.

The period of state  $i$  is defined to be

$$d(i) = \underset{\substack{\uparrow \\ \text{greatest common divisor}}}{\text{g.c.d.}} \{ n \geq 1 : P_{ii}^n > 0 \}$$

If  $d(i) = 1$ , then  $i$  is called aperiodic

If all states are aperiodic, the MC is called aperiodic.

Simple examples

① Suppose state  $i$  satisfies  $P_{ii} > 0$ . Then  $d(i) = 1$ .

② Take 
$$P = \begin{matrix} & \begin{matrix} 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} 0 & 1 & 0 \\ 113 & 0 & 213 \\ 0 & 1 & 0 \end{bmatrix} \end{matrix}$$
. Find periods of each state.

$$P^2 = \begin{matrix} & \begin{matrix} 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} 0 & 1 & 0 \\ 113 & 0 & 213 \\ 113 & 0 & 213 \end{bmatrix} \end{matrix}, \quad P^3 = \begin{bmatrix} 0 & 1 & 0 \\ 113 & 0 & 213 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 113 & 0 & 213 \\ 0 & 1 & 0 \\ 113 & 0 & 213 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 113 & 0 & 213 \\ 0 & 1 & 0 \end{bmatrix} = P.$$

$$\Rightarrow P^n = \begin{cases} \begin{bmatrix} 0 & 1 & 0 \\ 113 & 0 & 213 \\ 0 & 1 & 0 \end{bmatrix} & n \text{ odd} \\ \begin{bmatrix} 113 & 0 & 213 \\ 0 & 1 & 0 \\ 113 & 0 & 213 \end{bmatrix} & n \text{ even} \end{cases}$$

Check  $d(0) = \text{g.c.d.} \{ n \geq 1 : P_{00}^n > 0 \} = \text{g.c.d.} \{ \cancel{2}, \cancel{4}, \cancel{6}, \dots \} = \text{g.c.d.} \{ 2, 4, 6, \dots \} = 2.$

$P_{00}^1 = 0$        $P_{00}^3 = 0$   
 $\downarrow$                        $\downarrow$   
 $\cancel{2}$                        $\cancel{4}$

$$d(1) = \text{g.c.d.} \{ n \geq 1 : P_{11}^n > 0 \} = \text{g.c.d.} \{ 2, 4, 6, \dots \} = 2.$$

Fact: If a state  $i$  has period  $d(i) > 1$  ( $\neq 1$ ), then  $\lim_{n \rightarrow \infty} P_{ii}^n$  does not exist.

Lemma: (see p. 108) Periodicity is a class property.

If  $i \leftrightarrow j$ , then  $d(i) = d(j)$ .

### 3.6 Ergodic MCs

#### Thm 3.8 (Extended)

Let  $(X_n)$  be an irreducible, aperiodic MC. (The state space can be infinite)

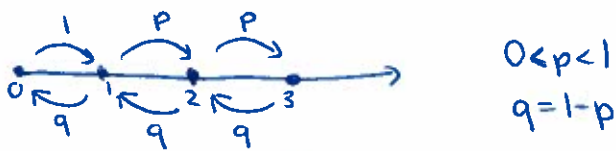
Then exactly one of the following is true.

- ① All states are transient,  $\lim_{n \rightarrow \infty} P_{ij}^n = 0$  all  $i, j$ , there is no stat. distr.
- ② All states are null recurrent, and  $\lim_{n \rightarrow \infty} P_{ij}^n = 0$  all  $i, j$ , there is no stat. distr.
- ③ All states are positive recurrent, there is a unique stationary distribution  $\pi$  s.t.
  - $\mu_j = \frac{1}{\pi_j}$  all  $j$
  - $\lim_{n \rightarrow \infty} P_{ij}^n = \pi_j$  all  $i, j$ .

(still true that  $\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n P_{ij}^k = \pi_j$ )

Fact: An irreducible MC is positive recurrent iff it has a stationary distr. Oct 10

Example - Simple Random Walk on  $S = \{0, 1, 2, \dots\}$  with reflection at 0.



Prop: This chain is irreducible, period 2, and

recurrent	{	1)	transient	if	$p > \frac{1}{2}$	If $i$ is recurrent then { pos. recurrent $E(R_i   X_0 = i) < \infty$ { null rec. $E(R_i   X_0 = i) = \infty$
	2)	null recurrent	if	$p = \frac{1}{2}$	$\Rightarrow q > \frac{1}{2}$ and $\frac{p}{q} < 1$	
	3)	positive recurrent	if	$p < \frac{1}{2}$ , and		
		$\pi$ is $\pi_0 = \frac{q-p}{2q}, \pi_j = \frac{q-p}{2q} \left(\frac{p}{q}\right)^{j-1}$ for $j \geq 1$				

recurrent:  $P(R_i < \infty | X_0 = i) = 1$

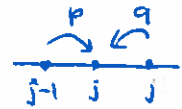
It suffices to consider state 0.

$$\begin{array}{ccc}
 P(R_0 < \infty | X_0 = 0) & = & P(H_0 < \infty | X_0 = 1) \\
 \uparrow & & \uparrow \\
 \text{1st time after time 0} & & \text{1st time including time 0}
 \end{array}$$

(Starting at 1,  $H_0 = R_0$ )

Put  $u(i) = P(H_0 < \infty | X_0 = i)$ ,  $i \geq 0$  (We really want just  $i=1$ ).

Then,  $u(i) = P_{i0} + \sum_{j \neq 0} P_{ij} u(j)$



For  $i \geq 2$ ,  $P_{i0} = 0$  and  $u(i) = pu(j+1) + qu(j-1)$

$$\text{or } pu(i+1) - u(i) + qu(i-1) = 0$$

$$u(i) = \begin{cases} A + B; & p = \frac{1}{2} \\ A + B\left(\frac{q}{p}\right)^i & p \neq \frac{1}{2}. \end{cases} \quad (\text{DE handout HW})$$

Consider  $u(1) = P_{10} + \sum P_{12} u(2)$ , with  $u(0) = 1$ ,  
 $= P_{10} u(0) + P_{12} u(2) = pu(2) + qu(0)$

$p = \frac{1}{2}$ :  $u(i) = A + B; i$

1) If  $B \neq 0$ ,  $\lim_{i \rightarrow \infty} |u(i)| = +\infty$ , impossible, all  $u(i)$  are between 0 and 1.

Now,  $u(i) = A$  for all  $i \geq 0$ .

Now, consider  $i=1$ ,  $u(1) = \frac{1}{2} + \frac{1}{2}u(2) \Rightarrow A = \frac{1}{2} + \frac{1}{2}A \Rightarrow A = 1 \Rightarrow u(i) = 1$  for all  $i \geq 1$

This means  $P(R_0 < \infty | X_0 = 0) = u(1) = 1 \Rightarrow$  recurrence.

Take  $p < \frac{1}{2}$ :  $u(i) = A + B\left(\frac{q}{p}\right)^i$ ,  $i \geq 1$

Since  $\frac{q}{p} > 1$ ,  $\left(\frac{q}{p}\right)^i \rightarrow \infty$  as  $i \rightarrow \infty$ . ~~impo~~ If  $B \neq 0$  then  $u(i) \rightarrow \infty$  as  $i \rightarrow \infty$ , impossible.  $\Rightarrow B = 0$ . Now, we have  $u(i) = A$  for all  $i \geq 1$ .

Consider  $i=1$ .  $u(1) = q + pu(2)$   
 $A = q + pA \rightarrow A(1-p) = q \rightarrow Aq = q \Rightarrow A = 1$

$\Rightarrow u(i) = 1$  for all  $i \geq 1 \Rightarrow P(R_0 < \infty | X_0 = 0) = u(1) = 1 \Rightarrow$  recurrence.

$\Rightarrow p \leq \frac{1}{2} \Rightarrow$  recurrence

Take  $p > \frac{1}{2}$ : In analogy with random walk on  $\{0, \pm 1, \pm 2, \dots\}$ , which is transient for  $p > \frac{1}{2}$ , we get transience.

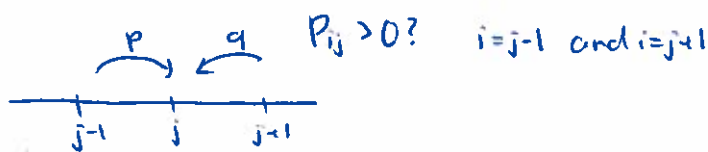
[ We got this by showing  $\sum_{n=0}^{\infty} p^{2n} < \infty$  ]

We know  $p > \frac{1}{2}$ : transient  
 $p \leq \frac{1}{2}$ : recurrent case.

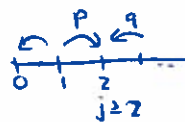
Positive vs. null recurrence?

↑ if there is a stat. dist.  $\pi$   
 ↑ if there is no stat. dist.

$\pi_j = \sum_{i=0}^{\infty} \pi_i P_{ij}$  can be solved or not with  $\sum_{j=0}^{\infty} \pi_j = 1$ .



$\pi_j = \pi_{j-1} p + \pi_{j+1} q$  for  $j \geq 2$



$j=0: \pi_0 = \sum_{i=0}^{\infty} \pi_i P_{i0} = \pi_1 P_{10} = q \pi_1$

$\pi_1 = \frac{1}{q} \pi_0$

$j=1: \pi_1 = \sum_{i=0}^{\infty} \pi_i P_{i1} = \pi_0 P_{01} + \pi_2 P_{21} = \pi_0 + \pi_2 q$

$\Rightarrow q \pi_2 = \pi_1 - \pi_0 = \frac{1}{q} \pi_0 - \pi_0 = \pi_0 (\frac{1}{q} - 1) \Rightarrow \pi_2 = \frac{\frac{1}{q} - 1}{q} \cdot \frac{1}{q} \pi_0 = \pi_0 \cdot \frac{1-q}{q^2} = \frac{p}{q^2} \pi_0$

$\Rightarrow \pi_1 = \frac{1}{q} \pi_0$   
 $\pi_2 = \frac{p}{q^2} \pi_0$

$\pi_j = q \pi_{j+1} + p \pi_{j-1}, j \geq 2$

general sol'n is  $\pi_j = \begin{cases} A + B_j & \text{if } p = \frac{1}{2} \\ A + B(\frac{p}{q})^j & \text{if } p < \frac{1}{2}. \end{cases}$

$p = \frac{1}{2}$  case: We need  $\sum_{j=0}^{\infty} \pi_j = 1 < \infty$

This requires  $\lim_{j \rightarrow \infty} \pi_j = 0$ .

$\pi_j = A + B_j$ . In order to have a stat. distr., we need  $\lim_{j \rightarrow \infty} (A + B_j) = C$

This is false if  $B \neq 0$ .



Now, given this,  $\pi_j = A, j \geq 2$ ,  $\lim_{j \rightarrow \infty} \pi_j = A = 0$  iff  $A = 0$ .

$\pi_j = 0, j \geq 2$ . [ $0 = \pi_2 = \frac{p}{q} \pi_0$ , so  $\pi_0 = 0$  and  $\pi_1 = 0$ ]

This forces  $\pi_j = 0$  for all  $j \geq 0$ , and  $\sum_{j=0}^{\infty} \pi_j = 0$ .

$\Rightarrow$  There is no stat. dist. in the case  $p = \frac{1}{2}$ .  $\Rightarrow$  null recurrent case.

Take  $p < \frac{1}{2}$ .  $\pi_j = A + B \left(\frac{p}{q}\right)^j, j \geq \frac{1}{2}$ .

( $p < q$ )

Now  $\frac{p}{q} < 1$  and  $\left(\frac{p}{q}\right)^j \rightarrow 0$  as  $j \rightarrow \infty$ . So  $\lim_{j \rightarrow \infty} \pi_j = \lim_{j \rightarrow \infty} (A + B \left(\frac{p}{q}\right)^j) = A + 0 = A$

(no matter what  $B$  is.)

If  $\sum_{j=0}^{\infty} \pi_j < \infty$ , this forces  $A = 0$ .

Now have  $\pi_j = \left(\frac{p}{q}\right)^j, j \geq 2 \Rightarrow \sum_{j=0}^{\infty} \pi_j = \pi_0 + \pi_1 + B \sum_{j=2}^{\infty} \left(\frac{p}{q}\right)^j$

$\uparrow$   
geometric series,  $\frac{p}{q} < 1$ ,  
so it converges.

We now must choose  $\pi_0, \pi_1, B$  to get  $\sum_{j=0}^{\infty} \pi_j = 1$ .

### 3.7 Time reversibility

A transition matrix  $\underline{P}$  is called time reversible with respect to a stationary distribution  $\underline{\pi}$  if the detailed balance equations are

satisfied:  $\pi_i P_{ij} = \pi_j P_{ji}$  for all  $i, j$

This is a fairly "common" property.

Example:

$$\underline{P} = \begin{matrix} & \begin{matrix} 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} \frac{1}{4} & \frac{3}{4} & 0 \\ \frac{1}{2} & \frac{1}{4} & \frac{1}{4} \\ 0 & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \end{matrix}$$

regular (since irred,  $P_{ii} > 0$ )  
 $\Rightarrow$  unique stat. dist.

$$\text{Check: } \underline{\pi} = \left[ \frac{4}{13} \quad \frac{6}{13} \quad \frac{3}{13} \right]$$

$$\pi_0 P_{01} = \pi_1 P_{10} \quad ?$$

$$\frac{4}{13} \cdot \frac{3}{4} = \frac{6}{13} \cdot \frac{1}{2} \quad \checkmark$$

$$\pi_0 P_{02} = \pi_2 P_{20} \quad \checkmark (0=0)$$

$$\pi_1 P_{12} = \pi_2 P_{21}$$

$$\frac{6}{13} \cdot \frac{1}{4} = \frac{3}{13} \cdot \frac{1}{2} \quad \checkmark$$

Prop: Suppose  $\underline{P}$  is <sup>time</sup> reversible, stat. dist  $\pi$ , and assume the

initial measure is  $\pi$ . Then for all  $n \geq 1$ , states  $i_0, \dots, i_n$

$$P(X_0 = i_0, X_1 = i_1, \dots, X_n = i_n) = P(X_0 = i_n, X_1 = i_{n-1}, \dots, X_n = i_0) \\ = P(X_n = i_0, X_{n-1} = i_1, \dots, X_0 = i_n)$$

This means the MC "looks the same" forward and backward in time.

$$n=1: P(X_0 = i, X_1 = j) = \underbrace{P(X_1 = j | X_0 = i)}_{P_{ij}} \underbrace{P(X_0 = i)}_{\pi_i} \stackrel{\text{time rev.}}{=} \pi_j P_{ji} \\ = P(X_0 = j) P(X_1 = i | X_0 = j) = P(X_1 = i, X_0 = j) = P(X_0 = j, X_1 = i)$$

Prop: If  $\underline{P}$  and a prob. vector  $\underline{x}$  satisfy  $x_i P_{ij} = x_j P_{ji}$  all  $i, j$  then  $\underline{x}$  must be a stationary distribution.

↑  
Sometimes easier to solve than  $\underline{\pi} = \underline{\pi} \underline{P}$

HW: read 4.3 prob. gen. fctrs.

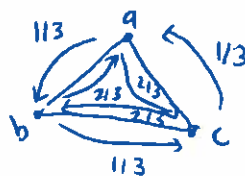
Oct 12

$\underline{P}$  is time reversible with respect to  $\underline{\pi}$  if  $\pi_i P_{ij} = \pi_j P_{ji} \forall i, j$ .

Intuitively, reversibility means the M.C. "looks the same" forwards and backwards in time. (Simplest case: if  $X_0$  has dist.  $\underline{\pi}$  then  $P(X_0 = i, X_1 = j) = P(X_0 = j, X_1 = i)$ )

Example:

$$\underline{P} = \begin{matrix} & \begin{matrix} a & b & c \end{matrix} \\ \begin{matrix} a \\ b \\ c \end{matrix} & \begin{bmatrix} 0 & 1/3 & 2/3 \\ 2/3 & 0 & 1/3 \\ 1/3 & 2/3 & 0 \end{bmatrix} \end{matrix}$$



•  $\underline{P}$  is doubly stochastic,  $\underline{\pi} = [\frac{1}{3} \ \frac{1}{3} \ \frac{1}{3}]$

• Check:  $\pi_a P_{ab} = \frac{1}{3} \cdot \frac{1}{3} = \frac{1}{9}$   
 $\pi_b P_{ba} = \frac{1}{3} \cdot \frac{2}{3} = \frac{2}{9}$

So not time-reversible

- At each state, the MC has prob.  $\frac{1}{3}$  of taking a counterclockwise step
- At each ~~step~~ state, the MC has prob.  $\frac{2}{3}$  of taking a clockwise step.
- It is "likely" that a given step will be clockwise.

In a sequence of states  $i_0, i_1, \dots, i_n$   
 $\quad \quad \quad \parallel \quad \parallel$   
 $\quad \quad \quad x_0 \quad x_1 \quad x_n$

In forward time,  
 we expect to see  $acba$  more often than  $acbacba$ .  
 $(\frac{2}{3})^3$   $(\frac{1}{3})^3$

Reversing the sequence, we would see the second more often.

The chain does not look the same forwards and backwards in time.

$$\pi_i P_{ij} = \pi_j P_{ji} \quad \forall i, j.$$

Find  $\pi$  to check this.

Prop. 3.9: If  $x$  is a prob. vector and  $x_i P_{ij} = x_j P_{ji}$  for all  $i, j$  (\*)

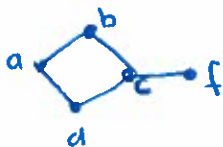
Then,  $x$  is a stationary distr., and  $P$  is reversible with respect to  $x$ .

Proof: Check that  $x_j = \sum_{i \in S} x_i P_{ij}$ , all  $i, j$ :

$$\sum_{i \in S} (x_i P_{ij}) = \sum_{i \in S} x_i P_{ji} = x_j \left( \sum_{i \in S} P_{ji} \right) = x_j \cdot 1 = x_j \quad \checkmark$$

row sum of row  $j$

Example: Simple random walk on an unweighted graph



$$P_{ij} = \frac{1}{\deg(i)} \quad \text{provided } i, j \text{ are "neighbors"}$$

Is  $P$  reversible?

Find  $\pi$ ?

Solve  $\pi_j = \sum_{i \in S} \pi_i P_{ij}$  all  $j$

Guess:Try  $x_j$  is proportional to  $\deg(j)$ (or  $x_j$  is  $\propto$  to  $\frac{1}{\deg(j)}$ )Put  $x_j = c \cdot \deg(j)$ , some constantCheck detailed balance equations:  $x_i P_{ij} = c \cdot \deg(i) \cdot \frac{1}{\deg(i)} = c$  if  $i, j$  neighbors

$$x_j P_{ji} = c \cdot \deg(j) \cdot \frac{1}{\deg(j)} = c \text{ if } j, i \text{ neighbors}$$

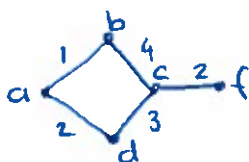
So we have (\*) holds for  $x_j = c \cdot \deg(j)$ .

Want  $1 = \sum_{j \in S} x_j = \sum_{j \in S} c \deg(j) = c \sum_{j \in S} \deg(j)$

Take  $c = \frac{1}{\sum_{j \in S} \deg(j)}$ , and  $\pi_j = c x_j = \frac{\deg(j)}{\sum_{k \in S} \deg(k)}$ .

This  $\pi$  is a stationary dist.,  $\underline{P}$  is reversible for  $\pi$ ,and  $\pi$  is unique if  $\underline{P}$  is irreducible.Since  $\sum_{j \in S} \deg(j) = 2e$ , where  $e$  is the number of edges,

we get  $\pi_j = \frac{\deg(j)}{2e}$ .

Example: Random walk on weighted graphs: $w(i, j)$  = weight of edge between  $i$  and  $j$ 

$$w(i) = \sum_{j \in S} w(i, j)$$

$$P_{ij} = \frac{w(i, j)}{w(i)}$$

$$w(a, b) = 1$$

$$w(a, d) = 2$$

$$w(a) = w(a, b) + w(a, d) = 1 + 2 = 3$$

$$P_{ab} = \frac{1}{3}, \quad P_{ad} = \frac{2}{3}$$

(If all weights are equal, say 1, then  $w(i) = \deg(i)$ )

Can we find  $\pi$ , check for time reversibility?

Try: make a guess for  $\pi_i$ , check if  $\pi_i P_{ij} = \pi_j P_{ji}$

Recall in unweighted case we guessed  $x_i = c \cdot \deg(i)$ .

Try  $x_j = c \cdot w(j)$  (or  $x_j = \frac{c}{w(j)}$ ).

$$\text{Check: } x_j P_{ij} = c \cdot w(j) \frac{w(i,j)}{w(j)} = c w(i,j) \quad (i,j \text{ neighbors})$$

$$x_i P_{ji} = c \cdot w(i) \frac{w(j,i)}{w(i)} = c w(j,i) \quad (w(i,j) = w(j,i))$$

Tells us  $x_j P_{ij} = x_i P_{ji} \forall i,j$ , to make  $\pi$  a prob. vector we want

$$1 = \sum_{j \in S} x_j = \sum_{j \in S} c \cdot w(j) = c \sum_{j \in S} w(j) \Rightarrow c = \frac{1}{\sum_{j \in S} w(j)}$$

$$\pi_i = x_i = c w(i)$$

Now we know  $\pi: \pi_i = \frac{w(i)}{\sum_{j \in S} w(j)}$  is a stationary dist. and  $P$  is reversible with respect to  $\pi$ .

Example ~~Random walk with reflection at 0.~~

Meaning of null recurrence

$$P(R_i < \infty | X_0 = i) = 1$$

$$E(R_i | X_0 = i) = \infty$$

Consider random walk with reflection at 0

$$P(i, i+1) = p, \quad P(i, i-1) = q = 1-p \quad (\text{for } i \geq 1)$$

$$P(0,1) = p.$$

For  $p = \frac{1}{2}$ , 0 is null recurrent.

Run simulation:

parameter  $p$ ,  $N = \#$  of trials.

Put  $X_0 = 0$ , run the random walk until  $R_0$  (1<sup>st</sup> time rw is at 0 again),

record this time, call this  $T_1$

- Repeat, repeat, repeat, ...  $N$  times in total, the successive return times called  $T_1, T_2, \dots, T_N$ .

What can we say about  $\frac{T_1 + T_2 + \dots + T_N}{N}$  as  $N \rightarrow \infty$ ?

$$p < \frac{1}{2}, \text{ positive recurrent, } E(R_0 | X_0 = 0) = \frac{1}{\pi_0} = \frac{2(1-p)}{1-2p}$$

In this case, for large  $N$  we expect, by Law of Large Numbers,

$$\frac{T_1 + \dots + T_N}{N} \approx E(R_0 | X_0 = 0) = \frac{2(1-p)}{1-2p}$$

How about  $p = \frac{1}{2}$ ? As  $N \rightarrow \infty$ ,  $\frac{T_1 + T_2 + \dots + T_N}{N} \rightarrow \infty$ .

$$p = .45, E(R | X_0 = 0) = 11, \frac{T_1 + \dots + T_{10,000}}{10,000} = 11.01 \quad \max\{T_1, \dots, T_{10,000}\} = 450$$

$$p = .5 \quad N = 20,000 \rightarrow \text{max return time} = 1,264,924,844$$

### 4.3

Def: Let  $X$  be a random ~~variable~~ <sup>variable</sup> with range  $\{0, 1, 2, \dots\}$ .

The probability generating fct (pgf) is the fct of a real variable,

$$G(s) = \sum_{n=0}^{\infty} s^n P(X=n) = E[S^X], \quad s \text{ a real number.}$$

We are most interested in  $0 \leq s \leq 1$ .

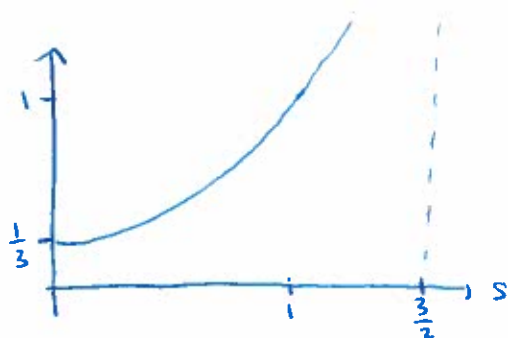
In this case, the series converges.

Example:  $P(X=n) = \frac{1}{3} \left(\frac{2}{3}\right)^n, n=0, 1, 2, \dots$

(Geometric)

The pgf is  $G(s) = E s^X = \sum_{n=0}^{\infty} s^n \frac{1}{3} \left(\frac{2}{3}\right)^n = \frac{1}{3} \sum_{n=0}^{\infty} \left(\frac{2}{3}s\right)^n = \frac{1}{3} \frac{1}{1 - \frac{2}{3}s}$  converges if  $|\frac{2}{3}s| < 1$   
 $|s| < \frac{3}{2}$

$$= \frac{1}{3-2s}$$



Start with a discrete probability dist  $\rightarrow$  one fct of a real variable  $Q(s)$

The pgf is a transform of the prob. dist. of  $X$ .

$\downarrow$   
 as is  $M(t) = Ee^{tx}$ , moment gen. fct  
 $\swarrow$   
 Laplace Transform  
 Fourier Transform  
 $z$ -transform

EXAM: Thurs, Nov 2

Example: Birth and death chain

$S = \{0, 1, 2, \dots\}$ ,  $q_n = 1 - p_n$ , all  $p_n$  satisfy  $0 < p_n < 1$  ( $0 < q_n < 1$ )



Infinitely many parameters  $\{p_n\}_{n=0}^{\infty}$

Random walk with reflection  
 is the special case  $p_n = p$  for all  $n$

Question: classify the chain  
 Check for time-reversibility  
 - find  $\pi$  s.t.  $\pi_i p_{ij} = \pi_j p_{ji}$  all  $i, j$

If  $\sum_{i=0}^{\infty} x_i < \infty$ ,  $\pi$  defined by

$$\pi_i = \frac{x_i}{\sum_{i=0}^{\infty} x_i} \text{ is a stat. dist.,}$$

which implies the chain is pos. recurrent

\*  $i=0, j=1$

$$x_0 p_{01} = x_1 p_{10}$$

$$x_0 p_0 = x_1 q_1 \Rightarrow x_1 = \frac{p_0}{q_1} x_0$$

\*  $i=1, j=2$

$$x_1 p_{12} = x_2 p_{21}$$

$$x_1 p_1 = x_2 q_2 \Rightarrow x_2 = \frac{p_1}{q_2} x_1 = \frac{p_0 p_1}{q_2} x_0$$

$$\leftarrow i=2, j=3 \Rightarrow x_3 = \frac{p_2}{q_3} x_2 = \frac{p_0 p_1 p_2}{q_1 q_2 q_3} x_0$$

$$\Rightarrow x_n = \frac{p_0 p_1 p_2 \dots p_{n-1}}{q_1 q_2 \dots q_n} x_0$$

Now, put 
$$y_n = \begin{cases} \frac{p_0 p_1 \dots p_{n-1}}{q_1 q_2 \dots q_n}, & n \geq 1 \\ 1, & n=0 \end{cases}$$

Then  $x_n = y_n x_0, n=0, 1, 2, \dots$

If  $\sum_{n=0}^{\infty} x_n = x_0 \sum_{n=0}^{\infty} y_n < \infty$ , then 
$$\pi_{ij} = \frac{x_j}{\sum_{n=0}^{\infty} x_n} = \frac{y_j x_0}{x_0 \sum_{n=0}^{\infty} y_n} = \frac{y_j}{\sum_{n=0}^{\infty} y_n}$$

In the random walk with reflection, 
$$y_i = \frac{p_1 p_2 \dots p_{i-1}}{q_1 \dots q_i} = \frac{p^i}{q^i} = \left(\frac{p}{q}\right)^i$$

$$\sum_{i=0}^{\infty} y_i = \sum_{i=0}^{\infty} \left(\frac{p}{q}\right)^i < \infty \text{ if } p < q$$

same as  $p < \frac{1}{2}$  ✓ pos. recurrence case.

$X$  is a random var. with range  $\{0, 1, 2, \dots\}$ ,

its pgf is 
$$G(s) = \sum_{k=0}^{\infty} \underbrace{P(X=k)}_{p_k} s^k = E(s^X), \quad s \text{ a real variable}$$

$$= \sum_{k=0}^{\infty} p_k s^k, \quad \text{a power series, radius of convergence is } \geq 1.$$

Check for absolute convergence,

$$\left\{ \sum_{k=0}^{\infty} |p_k s^k| = \sum_{k=0}^{\infty} p_k |s|^k \leq \sum_{k=0}^{\infty} p_k = 1 < \infty \text{ for } |s| \leq 1. \right.$$

Properties of pgf's:

1. 
$$\underline{G(1)} = \sum_{k=0}^{\infty} P(X=k) \cdot 1^k = \underline{1}, \quad \underline{G'(0)} = \sum_{k=0}^{\infty} P(X=k) s^k \Big|_{s=0} = P(X=0) + P(X=1)s + P(X=2)s^2 + \dots \Big|_{s=0} = \underline{P(X=0)}$$

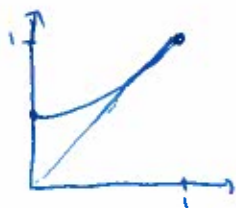
2. 
$$G(s) = \sum_{k=0}^{\infty} p_k s^k$$

Can differentiate term by term inside the interval of convergence  $|s| < 1$

$$\Rightarrow G'(s) = \sum_{k=1}^{\infty} p_k \cdot k s^{k-1} \geq 0, \quad G''(s) = \sum_{k=2}^{\infty} p_k k(k-1) s^{k-2} \geq 0 \text{ for } 0 \leq |s| < 1$$



$\Rightarrow G$  is increasing and concave up



$$P(X=0) \\ \parallel \\ G(0) > 0$$

increasing, concave up

↓ stays above diagonal  
(except at  $s=1$ )

There is no  $s \in (0,1)$  such that  $G(s) = s$



crosses diagonal

↳ There is exactly one  $s \in (0,1)$   
s.t.  $G(s) = s$ .

But can there be  $G(s)$  such that there are two distinct roots of  $G(s) = s$

in  $[0,1]$ ,  $0 < s_1 < s_2 < 1$  s.t.  $G(s_1) = s_1$ ,  $G(s_2) = s_2$ ?

No.

'Prove'



$$4. G'(s) = \sum_{k=1}^{\infty} k p_k s^{k-1} \quad 0 \leq s < 1$$

If the formula is correct at  $s=1$ , we would get

$$G'(1) = \sum_{k=1}^{\infty} k \cdot p_k \cdot 1 = E(X)$$

This is always true if  $E(X) < \infty$ .

If  $E(X) = +\infty$ , then one can show  $G'(1) = +\infty$ .

$$[G'(1) = \lim_{s \rightarrow 1} G'(s)]$$

$$G''(s) = \sum_{k=2}^{\infty} p_k k(k-1) s^{k-2}, \quad 0 \leq s < 1.$$

$$\text{If true for } s=1, G''(1) = \sum_{k=2}^{\infty} k(k-1) p_k \cdot 1 = \sum_{k=0}^{\infty} k(k-1) p_k = E(X(X-1))$$

$\uparrow$   
 $g(x) = x(x-1)$

$$E(g(X)) = \sum_{k=0}^{\infty} g(k) p_k.$$

$$5. E(X) = G'(1)$$

$$\text{Var}(X) = E(X^2) - \underbrace{(E(X))^2}_{G'(1)^2}$$

$$\text{We know } G''(1) = E(X(X-1)) = E(X^2 - X) = E(X^2) - E(X)$$

$$\Rightarrow E(X^2) = G''(1) + E(X) = G''(1) + G'(1)$$

$$\Rightarrow \text{Var}(X) = G''(1) + G'(1) - (G'(1))^2$$

Example:  $X \sim \text{Geom}(p)$ ,  $P(X=k) = p \cdot (1-p)^k$ ,  $k=0,1,2,\dots$ ,  $0 < p < 1$

The pgf is  $G(s) = \sum_{k=0}^{\infty} p(1-p)^k \cdot s^k = p \sum_{k=0}^{\infty} ((1-p)s)^k = \frac{p}{1-(1-p)s} = p(1-(1-p)s)^{-1}$

if  $|1-(1-p)s| < 1$ ,  $|s| < \frac{1}{1-p}$  ← larger than 1

$$G'(s) = -p(1-(1-p)s)^{-2} \cdot (-(1-p)) = \frac{p(1-p)}{(1-(1-p)s)^2}$$

$$G'(1) = \frac{p(1-p)}{(1-(1-p))^2} = \frac{p(1-p)}{p^2} = \frac{1-p}{p} = E(X)$$

To find  $E(X)$  by the def'n,  $E(X) = \sum_{k=0}^{\infty} k P(X=k) = \sum_{k=0}^{\infty} k p (1-p)^k$

$= p \sum_{k=0}^{\infty} k (1-p)^k$   
not a geometric series. more work!

6.  $P(X=k) = \frac{G^{(k)}(0)}{k!}$ ,  $k=0,1,2,\dots$

implies: if  $X$  and  $Y$  have the same generating function, then  $P(X=k) = P(Y=k)$ , so  $X$  and  $Y$  have the same distribution.

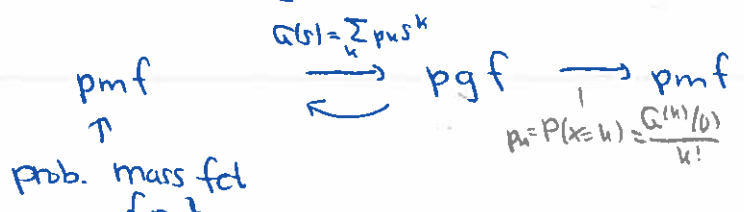
Example: Fact: If  $X \sim \text{Geom}(p)$  then  $G(s) = \frac{p}{1-(1-p)s}$ ,  $|s| < \frac{1}{1-p}$ .

Suppose we know a r.v.  $Y$  has pgf  $H(s) = \frac{1}{3-2s}$ , then

$$Y \sim \text{Geom}\left(\frac{1}{3}\right)$$

Put  $p = \frac{1}{3}$  in  $G(s) = \frac{p}{1-(1-p)s}$ , we get  $\frac{1/3}{1-\frac{2}{3}s} = \frac{1}{3-2s}$ .

Here, for  $X$  taking values in  $\{0,1,2,\dots\}$ , we have formulas for



Compare with moment generating fct  $\psi(s) = E(e^{sX})$  (any

for  $X$ ), we have formulas for

in continuous case density fct  $f \rightarrow$  mgf  $\xrightarrow{?}$  density fct

$$\psi(s) = \int_{-\infty}^{\infty} f(x) e^{sx} dx$$

$$G(s) = E(s^X) = \sum_{k=0}^{\infty} s^k P(X=k), |s| < 1.$$

Oct 19

Thm: If  $X$  has pgf  $G(s)$  then  $P(X=k) = \frac{G^{(k)}(0)}{k!}$ ,  $k=0,1,2, \dots$

$G^{(k)}$  the  $k^{th}$  derivative.

$\Rightarrow G(s)$  determines the distribution of  $X$ .

Proof:  $G(s)$  is a power series in  $s$ , radius of convergence at least one, all its derivatives are power series with same radius of convergence, valid  $|s| < 1$ .

$$G(s) = \sum_{k=0}^{\infty} p_k s^k, \quad G(0) = p_0 \checkmark$$

(keep  $k=1$ )  $G'(s) = \sum_{k=1}^{\infty} k p_k s^{k-1}, \quad G'(0) = 1 \cdot p_1$

(keep  $k=2$ )  $G''(s) = \sum_{k=2}^{\infty} k(k-1) p_k s^{k-2}, \quad G''(0) = 2 \cdot (2-1) p_2 = 2! p_2$

(keep  $k=3$ )  $G'''(s) = \sum_{k=3}^{\infty} k(k-1)(k-2) p_k s^{k-3}, \quad G'''(0) = 3 \cdot 2 \cdot 1 p_3 = 3! p_3$

$$p_1 = \frac{G'(0)}{1!}$$

$$p_2 = \frac{G''(0)}{2!}$$

$$p_3 = \frac{G'''(0)}{3!}$$

Can do a formal induction argument for the general case.

$X_1, X_2, \dots$  independent, pgf's  $G_1, G_2, G_3, \dots$   
 $(\Rightarrow s^{X_1}, s^{X_2}, \dots$  are independent)

(a)  $Y = X_1 + \dots + X_n$

Y has pgf  $E(s^Y) = E(s^{X_1 + \dots + X_n}) = E(s^{X_1} s^{X_2} \dots s^{X_n})$   
 $\stackrel{\text{independent}}{=} E(s^{X_1}) \dots E(s^{X_n}) = G_1(s) \dots G_n(s)$

If the  $X_i$  have the same distribution, equivalent to same pgf  $G(s)$ , then ~~Es~~ if  $Y = X_1 + \dots + X_n$ , Y has pgf  $E(s^Y) = (G(s))^n$ .

Ex: If  $X \sim \text{Bern}(p)$ ,  $P(X=0) = 1-p$ ,  $P(X=1) = p$  ( $p$  is a parameter,  $0 \leq p \leq 1$ )

X has pgf  $E(s^X) = \sum_{k=0}^{\infty} P(X=k) s^k = (1-p)s^0 + ps^1 = 1-p+ps$

If  $X \sim \text{Bin}(n, p)$ , then X has pgf  $E(s^X) = (1-p+ps)^n$   
Binomial

Since (a) by def'n  $E(s^X) = \sum_{k=0}^n \binom{n}{k} p^k (1-p)^{n-k} s^k = \sum_{k=0}^n \binom{n}{k} (ps)^k (1-p)^{n-k}$

Binomial formula  $(ps + (1-p))^n \checkmark$

(b) We can write  $X = X_1 + \dots + X_n$  where  $X_i$  independent,  $X_i \sim \text{Bern}(p)$ .

Now, by our thm, X has pgf  $E(s^X) = (G(s))^n$  where  $G(s) = \text{pgf of Bern}(p) = 1-p+ps$ .

(b) r.v.s  $N, X_1, X_2, \dots$  all independent

N has pgf  $H(s)$

the  $X_i$  all have pgf  $G(s)$

$Y = X_1 + \dots + X_N$ , random sum has pgf  $H(G(s))$

[when  $N=k$ ,  $Y = X_1 + \dots + X_k$   
 If  $N=0$ , take  $Y=0$ ]

Ex: (two-state-experiment)

Toss a biased coin, prob. of heads is  $1/5$ , tails is  $4/5$ , repeatedly. ↓ 10 times

Assume successive toss are independent.

Roll a fair die, and let  $N \sim \text{Bin}(10, 1/5)$  be the number of spots that came up.  
 Now, roll a fair die and then toss the coin that many times.  $N$  times, count the nr of times 2 comes up, call this  $Y$ .

Find the pgf of  $Y$ , and use it to find  $P(Y=2)$ .

Let  $X_i = \begin{cases} 1 & \text{if } i^{\text{th}} \text{ toss of die comes up } 2 \\ 0 & \text{if not} \end{cases}, i=1, 2, \dots$   
 $P(X_i=1) = \frac{1}{6}$

Then  $Y = X_1 + \dots + X_N$

①  $N$  has pgf  $H(t) = (1 - \frac{1}{5} + \frac{1}{5}s)^n = (\frac{4}{5} + \frac{1}{5}s)^n$  b/c  $N \sim \text{Bin}(10, \frac{1}{5})$ .

The  $X_i$  have pgf  $G(s) = (1 - \frac{1}{6} + \frac{1}{6}s) = (\frac{5}{6} + \frac{1}{6}s)$  b/c  $X_i \sim \text{Bern}(\frac{1}{6})$ .

So,  $Y$  has pgf  $\varphi(s) = H(G(s)) = H(\frac{5}{6} + \frac{1}{6}s)$   
 $= (\frac{4}{5} + \frac{1}{5}(\frac{5}{6} + \frac{1}{6}s))^{10} = (\frac{4}{5} + \frac{1}{6} + \frac{1}{30}s)^{10} = (\frac{29}{30} + \frac{1}{30}s)^{10} = \varphi(s)$

This says  $Y$  must be  $\text{Bin}(10, \frac{1}{30})$ , so  $P(Y=2) = \binom{10}{2} (\frac{1}{30})^2 (\frac{29}{30})^8$   
 (or  $= \frac{\varphi''(0)}{2!}$ )

Claim:  $E(Y) = E(X_1 + \dots + X_N) = E(X_1) \cdot E(N)$ .

Proof:  $E(Y) = \varphi'(1) = \frac{d}{ds} (H(G(s)))|_{s=1} = H'(G(s)) G'(s)|_{s=1}$   
 $= H'(G(1)) G'(1) = EN EX_1$ .

$G'(1) = EX_1, H'(G(1)) = H'(1) = EN$

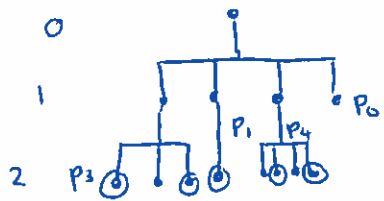
4.1 Intro to branching processes

individuals, produce "offspring"  
 (backn, ...)

Assume single fixed known offspring distribution  $\{p_k\}, k=0, 1, \dots$

where the prob. any particular indiv. produces  $k$  offspring is  $p_k$ .

- all indiv. reproduce indep.
- start with a single indiv.



Prob (this event) =  $p_4 \cdot (p_3 \cdot p_1 \cdot p_4 \cdot p_0)$

Extinction question: Given the sequence  $\{p_k\}_{k=0,1,2,\dots}$ , what is the probability of eventual extinction?

some generation is empty, has no individuals

Let  $Z_n$  = the number of individuals in the  $n^{\text{th}}$  generation

$Z_0 = 1$  (usually, not always)

$Z_1$  = the number of offspring of initial individual.

$Z_2$  = the nr of offspring of all individuals in 1<sup>st</sup> generation.

In Ex. above  $Z_0 = 1, Z_1 = 4, Z_2 = 8, \dots$

Claim:  $(Z_n)_{n=0,1,2,\dots}$  is a Markov chain. ✓

Question: Given  $(p_k)$ , what is the transition matrix  $\underline{P} = (P_{ij})$ ?

$P_{ij} = (Z_1 = j | Z_0 = i) = ?$

Let  $X_k$  = # of offspring of individual  $k$  in generation,  $k=1, 2, \dots, i$



$P_{ij} = P(Z_1 = j | Z_0 = i) = P(X_1 + \dots + X_i = j)$

$Z_n = \sum_{i=1}^{Z_{n-1}} X_i$

Fact: (p. 159) Classification of states

Let  $(Z_n)$  be a branching process such that  $p_0 > 0$ .

In this case state 0 is (always) absorbing,  $P_{00} = P(Z_n = 0 | Z_0 = 0) = 1$

hence is recurrent.

Every other state is transient.

Idea:

Since  $p_0 > 0$ , there is positive probability that the next generation is empty.  $P_{i0} = (p_0)^i > 0, i \geq 1$ .

Oct 24

### Branching processes

Given an offspring dist.  $\{p_k\}_{k=0,1,2,\dots}$

- Each individual, independently of all other individuals, produces  $k$  offspring with probability  $p_k, k=0,1,2,\dots$
- $Z_n = \#$  of individuals in generation  $n, n=0,1,2,\dots$
- $\{Z_n\}$  is a Markov chain, state space  $S = \{0,1,2,3,\dots\}$ , trans matrix  $\underline{P}$ .

Fact:

State 0 is absorbing,  $P_{00} = 1$ . Assume that  $p_0 > 0$ .

State  $i$  for  $i \geq 1$  is transient.

Proof: 1)  $P_{i0} = P(Z_1=0 | Z_0=i) = (\underline{P})_{i0} = p_0 \dots p_0 = (p_0)^i > 0$  for any  $i$ .

2) We need to check that  $P(R_i < \infty | Z_0=i) < 1$ .

3) Given  $Z_0=i$ . Then  $(R_i < \infty \text{ then } Z_1 \neq 0)$ , so  
 $\{R_i < \infty\} \subset \{Z_1 \neq 0\}$

$$P(R_i < \infty | Z_0=i) \leq P(Z_1 \neq 0 | Z_0=i) = 1 - P(Z_1=0 | Z_0=i) = 1 - (p_0)^i < 1 \quad \checkmark$$

Thm: If  $\mu$  is the mean of the offspring distribution,

$$\mu = \sum_{k=0}^{\infty} k p_k, \text{ and } z_0 = 1, \text{ then } E(z_n | z_0 = 1) = \mu^n, n=0,1,2, \dots$$

Pf:  $n=0, E(z_0 | z_0 = 1) = 1 = \mu^0.$

$$n=1, E(z_1 | z_0 = 1) = \mu \checkmark$$

Now, fix  $n$ , and assume

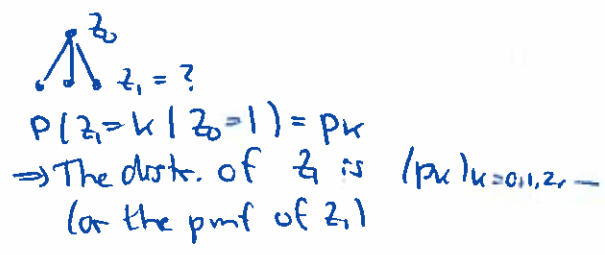
$$E(z_n | z_0 = 1) = \mu^n, \text{ consider } z_{n+1}.$$

If we let  $X_1, X_2, \dots$  be i.i.d. r.v. with

dist.  $(p_k)_{k=0,1,2, \dots}$ , then  $z_{n+1} = X_1 + X_2 + \dots + X_{z_n}$ , a random sum,

where  $X_1, X_2, \dots$  are independent of  $z_n$ .

$$\text{By our thm on pgf, } E(z_{n+1}) = E(X_1 + \dots + X_{z_n}) = E(X_1) \cdot E(z_n) = \mu \cdot \mu^n = \mu^{n+1} \checkmark$$



See text for a formula for  $\text{Var}(z_n | z_0 = 1)$ .

What happens to  $E(z_n | z_0 = 1)$  as  $n \rightarrow \infty$ ?

$$\lim_{n \rightarrow \infty} E(z_n | z_0 = 1) = \lim_{n \rightarrow \infty} \mu^n = \begin{cases} 0, & \mu < 1 \\ 1, & \mu = 1 \\ +\infty, & \mu > 1 \end{cases}$$

What does this suggest about the behavior of the branching process?

- We expect "extinction" if  $\mu < 1$  "population dies out"
- $\mu = 1$  ?
- $\mu > 1$  We expect probability  $< 1$  of extinction.

Def: Extinction means  $P(z_n = 0 \text{ for some } n \geq 1) = 1 = P(\bigcup_{n=1}^{\infty} \{z_n = 0\}) = 1$

[Assume  $p_0 > 0, z_0 \neq 0$ ]

more formally, let  $E_n = \{z_n = 0\}, n=1,2,3, \dots$



Then (i)  $E_1 \subset E_2 \subset E_3 \subset \dots$ , and  $\{z_n = 0 \text{ for some } n\} = \bigcup_{n=1}^{\infty} E_n$ .

extinction event

"Survival" means "not extinction" or  $P(z_n = 0 \text{ for some } n \geq 1) < 1$ .

Claim: If  $\mu < 1$ , then there is extinction, or,  $P(z_n = 0 \text{ for some } n) = 1$ .

Lemma: For any sequence of events  $E_1, E_2, \dots$  with  $E = \bigcup_{n=1}^{\infty} E_n$ ,

$$P(E) = \lim_{N \rightarrow \infty} P\left(\bigcup_{n=1}^N E_n\right).$$

Pf: ① Follows from additivity assumption of all probability spaces.

or ② In some sense,  $\bigcup_{n=1}^N E_n$  "converges" to  $\bigcup_{n=1}^{\infty} E_n = E$ .

Fact: If  $e = \text{extinction probability} = P(z_n = 0 \text{ for some } n | z_0 = 1)$ ,

then  $e = \lim_{N \rightarrow \infty} P(z_n = 0 | z_0 = 1)$ .

Pf: Use Lemma with  $E_n = \{z_n = 0\}$  and note that  $\bigcup_{n=1}^N E_n = E_N$  (since  $E_1 \subset E_2 \subset \dots \subset E_N$ ).

$$P\left(\bigcup_{n=1}^{\infty} E_n\right) = \lim_{N \rightarrow \infty} P\left(\bigcup_{n=1}^N E_n\right) = \lim_{N \rightarrow \infty} P(E_N).$$

Back to case  $\mu < 1$ : Can we find  $P(z_n = 0 | z_0 = 1)$ ?

1) For any rv  $X$  with possible values  $0, 1, 2, 3, \dots$

$$P(X \geq 1) \leq EX \text{ because } EX = \sum_{k=1}^{\infty} k P(X=k) \geq \sum_{k=1}^{\infty} 1 P(X=k) \\ = P(X \geq 1).$$

2) Apply to  $X = z_n$ ,  $P(z_n \geq 1 | z_0 = 1) \leq E(z_n | z_0 = 1) = \mu^n \rightarrow 0$  as  $n \rightarrow \infty$

3)  $P(z_n = 0 | z_0 = 1) = 1 - P(z_n \neq 0 | z_0 = 1) = 1 - P(z_n \geq 1 | z_0 = 1)$  for  $\mu < 1$

$$e = \lim_{n \rightarrow \infty} P(z_n = 0 | z_0 = 1) = 1 - \lim_{n \rightarrow \infty} P(z_n \geq 1 | z_0 = 1) \stackrel{2)}{=} 1 - 0 = 1. \quad \square$$

4.4

Goal: find  $e = \lim_{n \rightarrow \infty} P(Z_n = 0 | Z_0 = 1)$  in terms of  $(p_k)_{k=0}^{\infty}$ .

If we knew the pgf of  $Z_n$ , say  $H_n(s)$ , then

$$P(Z_n = 0 | Z_0 = 1) = H_n(0).$$

Thm: Let the offspring dist. have pgf  $G(s)$ .

Define  $(G_n)_{n=0,1,2,\dots}$  by  $G_0(s) = s$ ,  $G_1(s) = G(s)$ , and

$$\begin{aligned} G_{n+1}(s) &= G(G_n(s)), \quad n=0,1,2,\dots \\ &= \underbrace{G \circ G \circ \dots \circ G}_{(n+1)\text{-times}}(s) \end{aligned}$$

Then  $G_{n+1}(s) = G_n(G(s))$  and  $G_n(s)$  is the pgf of  $Z_n$  (given  $Z_0 = 1$ ).

(Note  $P(Z_n = 0 | Z_0 = 1) = G_n(0)$ ).

Pf: Fix  $n$ , let  $X_1, X_2, X_3, \dots$  be i.i.d. r.v.'s with distr.  $(p_k)_{k=0,1,2,\dots}$

Then  $Z_{n+1} = X_1 + X_2 + \dots + X_{Z_n}$ .

By Thm pgf's and random sums,  $G_{Z_{n+1}}(s) = (G_{Z_n} \circ G_{X_1})(s) = G_{Z_n}(G(s))$   
 $= G_n(G(s)) = G_{n+1}(s)$ . □

Example: Offspring dist.  $G_{\text{Geom}(\frac{1}{3})}$ ,  $p_k = \frac{1}{3}(\frac{2}{3})^k$ ,  $k=0,1,2,\dots$

The pgf is  $G(s) = \frac{1}{3-2s} = G_1(s)$ .

$$G_2(s) = G(G(s)) = \frac{1}{3-2G(s)} = \frac{1}{3-\frac{2}{3-2s}} = \frac{3-2s}{3-2s} = \frac{3-2s}{9-6s-2} = \frac{3-2s}{7-6s}$$

Can check  $G_3(s) = G_2(G(s)) = \frac{3-2G(s)}{7-6G(s)} = \dots = \frac{7-6s}{15-14s}$ .

We know  $P(Z_1 = 0 | Z_0 = 1) = G(0) = \frac{1}{3}$   
 $P(Z_2 = 0 | Z_0 = 1) = G_2(0) = \frac{3}{7}$   
 $P(Z_3 = 0 | Z_0 = 1) = G_3(0) = \frac{7}{15}$ .

$$e = \lim_{n \rightarrow \infty} P(Z_n = 0 | Z_0 = 1) = \lim_{n \rightarrow \infty} G_n(0).$$

Can we find this somehow? Yes

### Thm 4.2 (Main Thm)

Let  $(Z_n)$  be a branching process with offspring dist.  $(p_k)$  which has mean  $\mu$  and pgf  $G(s)$ . Assume  $Z_0 = 1$ , <sup>and  $p_1 \neq 1$</sup>  and  $e = \text{extinction probability} = P(Z_n = 0 \text{ for some } n)$ .  
omit this from notation

Then ① If  $\mu \leq 1$  then  $e = 1$ .

② If  $\mu > 1$ , then  $e < 1$  (survival is possible) and  $e$  is the smallest root of  $G(s) = s$ ,  $s \in [0, 1)$ .

Example:  $G(s) = \frac{1}{3-2s} = (3-2s)^{-1}$ ,  $G'(s) = -(3-2s)^{-2}(-2) = \frac{2}{(3-2s)^2}$

$$\mu = G'(1) = \frac{2}{1} = 2 > 1, \text{ so } e < 1.$$

To find  $e$  set  $G(s) = s$ :  $\frac{1}{3-2s} = s \Leftrightarrow 1 = 3s - 2s^2 \Leftrightarrow 2s^2 - 3s + 1 = 0$

[This has always one solution we know:  $s = 1$ ]  
 $\Rightarrow s - 1$  is always a factor of  $G(s) - s = 0$

$$(s-1)(2s-1) = 0$$

Roots are  $s = 1$ ,  $s = \frac{1}{2}$ ,

so  $\boxed{e = \frac{1}{2}}$ .



Oct 26

Exam: Th, see BB for topics.

### Thm (Extinction Thm) (4.2)

hypothesis as above

Then (a)  $e$  is the smallest root of  $G(s) = s$ ,  $s \in [0, 1)$   
(b) If  $\mu \leq 1$  then  $e = 1$ .  
(c) If  $\mu > 1$  then  $e < 1$ .

Proof: Define  $e_n = P(Z_n = 0)$ , recall  $\boxed{\lim_{n \rightarrow \infty} e_n = e}$  and also  $\lim_{n \rightarrow \infty} e_{n+1} = e$ .

Recall  $G_n(s)$  is the pgf of  $Z_n$ ,  $G_{n+1}(s) = G(G_n(s))$ , and  $e_n = G_n(0)$

I.  $e$  solves  $G(s) = s$ :

$$e_{n+1} = P(Z_{n+1} = 0) = G_{n+1}(0) = G(G_n(0)) = G(e_n)$$

That is,  $e_{n+1} = G_n(e_n)$  for all  $n$ .

$\lim_{n \rightarrow \infty} e_{n+1} = e$   $\uparrow$   $G$  is a continuous fct on  $[0,1]$   
and  $e_n \rightarrow e$  as  $n \rightarrow \infty$ , so  $G(e_n) \rightarrow G(e)$  as  $n \rightarrow \infty$ .

$$\Rightarrow \lim_{n \rightarrow \infty} e_{n+1} = \lim_{n \rightarrow \infty} G(e_n) = G(e) \quad \checkmark$$

$\stackrel{e}{=}$

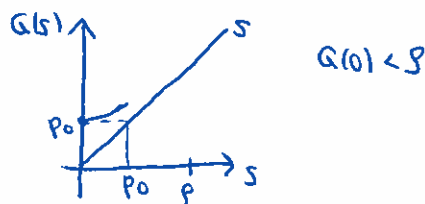
II. Let  $\beta$  be the smallest root of  $G(s) = s$  in  $[0,1]$ . Then  $e = \beta$ .

Case 1:  $p_0 = 0$ ,  $G(0) = p_0 = 0$ . So 0 is a root of  $G(s) = s$ , and  $\beta = 0$ ,

so  $e = \beta$ . [no 0 offspring  $\Rightarrow Z_n > 0 \forall n \Rightarrow e = 0$ ]

Case 2:  $p_0 > 0$

Then  $\beta > p_0 = G(0)$ .



Since  $G$  is an increasing fct,  $G(G(0)) < G(\beta) = \beta$   
 $\parallel$   
 $G_2(0)$

Same argument gives  $G_3(0) = G(G_2(0)) < G(\beta) = \beta$ .

In fact  $G_n(0) < \beta$  for every  $n$ .

We know  $G_n(0) \rightarrow e$  as  $n \rightarrow \infty$ , so taking limits we obtain

$$e = \lim_{n \rightarrow \infty} G_n(0) \leq \beta$$

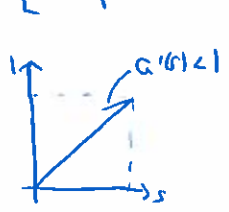
of  $G(s) = s$ , and  $\beta$  is the smallest such root, so  $e = \beta$ .  $\Rightarrow$  (a).

(b) If  $\mu \leq 1$  then there is no root of  $G(s) = s$  in  $(0,1)$ , or  $\beta = 1$ ,  $\Rightarrow e = 1$ .

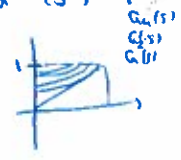
Why? Suppose  $\mu = 1$ . Then  $G'(1) = 1$ . Since  $G'(s)$  is increasing,

$G'(s) < G'(1) = 1 = \mu$  for  $s < 1$ .

[If  $p_i = 1$ , then  $G(s) = s \forall s \in [0, 1]$ ,  $G'(s) = 1 \forall s$ ]



$$\sum_{k=0}^{\infty} s^k p_k$$

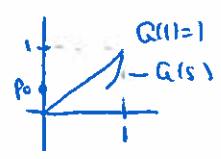


This tells us that  $G(s) > s$  for all  $0 \leq s < 1$ , so no root in  $(0, 1)$ .

(c) Supp.  $\mu > 1$ .



There is a unique root in  $(0, 1)$ , so  $\beta < 1$ , and  $e = \beta p$ .



$\mu = G'(1) > 1$

Calculus shows that  $G'(s) > 1$  for  $s$  close to 1.

$G'(s) \rightarrow G'(1) = \mu > 1$  as  $s \rightarrow 1$

$\Rightarrow G(s) < s$  for  $s$  close to 1.

$G(0) > 0, G(1) < 1$ .

Consider  $G(s) - s$ :  $s=0, G(s) - s > 0$

and if  $s$  is close to 1,  $G(s) - s < 0$ .

So there must be some  $s_0$  with  $G(s_0) - s_0 = 0$ , since  $0 < s_0 < 1$ .

This  $s_0$  is  $\beta$ .

□

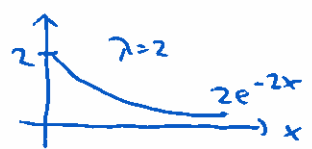
Chapter 6 - Poisson processes

Continuous time

Recall:  $X$  is an exponential rv with parameter  $\lambda > 0$  (we write

$X \sim \text{Exp}(\lambda)$  | if  $X$  has pdf

$$f(x) = \begin{cases} 0 & \text{if } x < 0 \\ \lambda e^{-\lambda x} & \text{if } x \geq 0 \end{cases}$$



$E(X) = \frac{1}{\lambda}, \text{Var}(X) = \frac{1}{\lambda^2}$ .

Fact:  $P(X > t) = e^{-\lambda t}$

$$\int_t^{\infty} \lambda e^{-\lambda x} dx = \lim_{A \rightarrow \infty} \int_t^A \lambda e^{-\lambda x} dx = \lim_{A \rightarrow \infty} [e^{-\lambda x}]_t^A = \lim_{A \rightarrow \infty} (-e^{-\lambda A} + e^{-\lambda t})$$

$$= 0 + e^{-\lambda t}$$

Recall:  $X$  is Poisson with parameter  $\lambda > 0$ , ( $X \sim \text{Pois}(\lambda)$ )

if  $X$  has possible values  $0, 1, 2, \dots$  and  $P(X=k) = e^{-\lambda} \frac{\lambda^k}{k!}$ ,  $k=0, 1, 2, \dots$

and  $EX = \lambda$ ,  $\text{Var}(X) = \lambda$

Prop: If  $X \sim \text{Exp}(\lambda)$  (any  $\lambda > 0$ ), then  $X$  has the memoryless property, i.e. for all  $s, t > 0$   $P(X > s+t | X > s) = P(X > t)$ .



Proof:

$$P(X > s+t | X > s) = \frac{P(X > s+t, X > s)}{P(X > s)} = \frac{P(X > s+t)}{P(X > s)} = \frac{e^{-\lambda(s+t)}}{e^{-\lambda s}} = e^{-\lambda t} = P(X > t)$$

Counting Processes

$(N_t)_{t \geq 0}$   
 $\uparrow$  a "continuous" variable

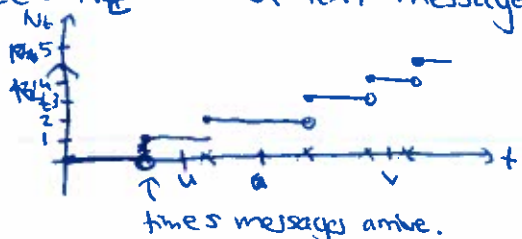
Stochastic process indexed by  $[0, \infty)$ , each  $N_t$  is a  $\overbrace{\text{nonnegative}}^{\text{nonnegative}}$  integer-valued s.t.

1) if  $s \leq t$  then  $N_s \leq N_t$

2) process can take jumps of only size 1

Example: Turn on cellphone, call at this time  $t=0$ , text messages come in.

Let  $N_t = \#$  of text messages that have arrived by time  $t$ .



$$N_u = 1, N_v = 4$$

The nr of messages that came in during the time interval  $(u, v] = N_v - N_u$  an increment in the fct.  $t \mapsto N_t$ .

Def: (#1) A Poisson process  $(N_t)_{t \geq 0}$  with rate  $\lambda (> 0)$

is a counting process with the following properties:

1)  $N_0 = 0$  (usually).

2) For  $t > 0$ ,  $N_t$  is a Poisson rv, parameter  $\lambda t$

$\leadsto E(N_t) = \lambda t \leadsto$  expect about  $\lambda t$  arrivals in  $t$  time units  
 $\leadsto$  rate of arrivals =  $\frac{E(N_t)}{t} = \lambda$

3) (stationary increments)

For each  $s, t > 0$ , the rv  $N_{t+s} - N_s$  has the same distribution

as  $N_t - N_0 = N_t$ , that is  $N_{t+s} - N_s \sim \text{Pois}(\lambda t)$



4) (independent increments)

If times  $(t_i)$  satisfy

$$0 \leq t_0 < t_1 < t_2 < \dots < t_n$$



then the increments

$N_{t_1} - N_{t_0}, N_{t_2} - N_{t_1}, \dots, N_{t_n} - N_{t_{n-1}}$  are independent r.v.'s.

Example: Suppose  $(N_t)_{t \geq 0}$  is a PP with rate  $\lambda = 0.3$   
 $\downarrow$   
 # of text messages that arrive by time  $t$  [during  $(0, t]$ ]

Find (a) the prob. no messages arrive in 1<sup>st</sup> 4 minutes

$$\rightarrow P(N_4 = 0) = \frac{(4\lambda)^0}{0!} e^{-4\lambda} = e^{-4(0.3)} = e^{-1.2}$$

$N_4 \sim \text{Pois}(4\lambda)$

(b) the prob. that 1 message arrived between times 2 and 3 given that 5 messages arrived by time 2.

$$P(N_3 - N_2 = 1 \mid N_2 = 5) = P(N_3 - N_2 = 1) \quad \text{(independent increments)}$$

$\parallel$   
 $N_2 - N_0$

$P(A|B) = P(A)$  if  
 $A, B$  are independent

Stat. increments

$$\downarrow$$

$$= P(N_3 - N_2 = 1) = e^{-\lambda} \cdot \lambda \cdot \frac{1}{1!} = e^{-\lambda} \lambda = e^{-3} (0.3)$$

$\parallel$   
 $N_1 \sim \text{Pois}(\lambda)$

Oct 31

Exam #2  $\rightarrow$  Thursday, sol'n to hw in library, format same as before  
 (no poisson processes)

Poisson proc: (3) (stat. increments)

For two increments:  $N_t - N_s$  and  $N_w - N_u$  have the same (joint) distribution as  $N_{t-s} - N_0$  and  $N_{w-s} - N_{u-s}$

For 1 increment, say  $N_t - N_s$ , this has the same dist. as  $N_{t-s} - \underbrace{N_0}_{=0}$ , so  $N_t - N_s$  has Poisson dist., param.  $\lambda \cdot (t-s)$

(4) (indep. incr.):  $N_t - N_s$  and  $N_w - N_u$  are independent

Ex. Cont'd: (c) Find the probability that 6 messages are received in first 10 minutes, and exactly one of these was received in 1<sup>st</sup> 3 minutes

$$P(N_{10} = 6, N_3 = 1) = P(N_3 = 1, N_{10} = 6) \neq P(N_3 = 1) P(N_{10} = 6)$$

[  $P(N_5 = i, N_t = k) \neq P(N_5 = i) P(N_t = k)$  ]



$$P(N_3 = 1, N_{10} = 6) = P(N_3 = 1, N_{10} - N_3 = 5)$$

$$= P(N_3 = 1) P(N_{10} - N_3 = 5) \stackrel{\text{independent increments}}{=} P(N_3 = 1) P(N_7 = 5)$$

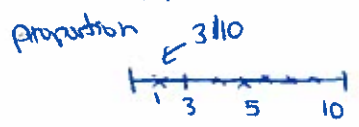
$$= \frac{e^{-3\lambda} (3\lambda)^1}{1!} \frac{e^{-7\lambda} (7\lambda)^5}{5!}$$

(d) Given that exactly 6 messages were received in 1<sup>st</sup> ten minutes, what is the prob. that exactly 1 message is received in 1<sup>st</sup> 3 minutes?

$$P(N_3 = 1 | N_{10} = 6) = \frac{P(N_3 = 1, N_{10} = 6)}{P(N_{10} = 6)} \stackrel{(c)}{=} \frac{\frac{e^{-3\lambda} (3\lambda)^1}{1!} \frac{e^{-7\lambda} (7\lambda)^5}{5!}}{\frac{e^{-10\lambda} (10\lambda)^6}{6!}}$$

$$= \frac{e^{-3\lambda} e^{-7\lambda}}{e^{-10\lambda}} \frac{(3\lambda)^1 (7\lambda)^5}{(10\lambda)^6} \cdot \frac{6!}{1! \cdot 5!} = 1 \cdot \frac{3^1 7^5}{10^6} \cdot \frac{\lambda^6}{\lambda^6} \binom{6}{1} = \binom{6}{1} \left(\frac{3}{10}\right)^1 \left(\frac{7}{10}\right)^5$$

Binomial  $\binom{6}{n} \binom{6}{p} \binom{6}{k=1}$



$P(X=1)$  where  $X \sim \text{Bin}\left(6, \frac{3}{10}\right)$

(e) Find  $E(N_3 \cdot N_7)$  ( $\neq E N_3 \cdot E N_7$ ) [only  $N_3$  and  $N_7 - N_3$  are independent!]

$$= E(N_3 (N_7 - N_3) + N_3^2) = E(N_3 (N_7 - N_3)) + E(N_3^2) = E(N_3) E(N_7 - N_3) + E(N_3^2)$$

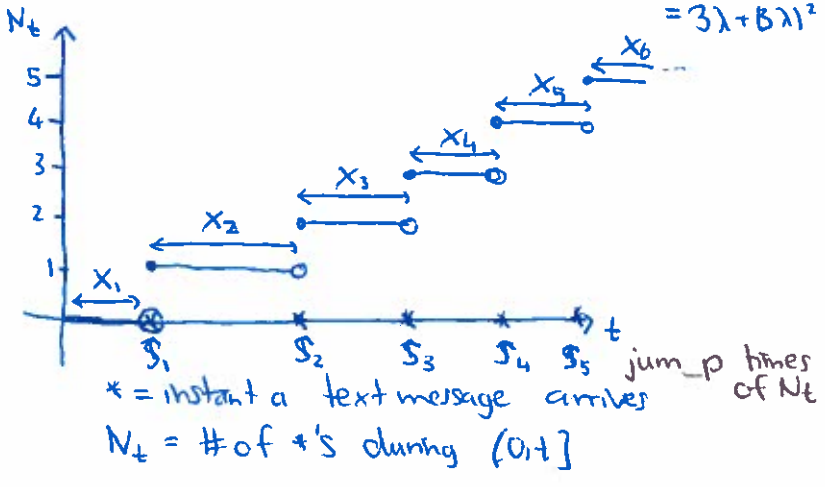
$N_7 - N_3$  has same prob. dist. as  $N_4$

$$\cong E N_3 \cdot E(N_4) + E(N_3^2)$$



Recall: If  $X \sim \text{Pois}(\lambda)$ , then  $EX = \lambda$ ,  $\text{Var}(X) = \lambda = E(X^2) - (E(X))^2$   
 $E(X^2) = \text{Var}(X) + (E(X))^2$

$\Rightarrow E(N_3 \cdot N_7) = E(N_3) E(N_7) + \underbrace{E(N_3^2)}_{= 3\lambda + 6\lambda^2} = (3\lambda)(7\lambda) + 3\lambda + (3\lambda)^2$



Put  $S_0 = 0$  and for  $k \geq 1$

$S_k =$  time of  $k^{\text{th}}$  jump of  $(N_t)$

These are random variables, call these the "arrival times".

Define the "inter arrival times"  $(X_k)_{k=1,2,\dots}$  by  $X_k = S_k - S_{k-1}$  random variables.

Thm:  $X_1, X_2, \dots$  are indep. identically distr. (i.i.d.)

with the exponential ( $\lambda$ ) distribution. [each  $X_i$  has pdf  $f(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$   
 mean =  $\frac{1}{\lambda}$   
 variance =  $\frac{1}{\lambda^2}$ ]

$S_k = X_1 + X_2 + \dots + X_k$  [ $X_k = S_{k+1} - S_k, \dots, X_1 = S_1 - S_0 = S_1, X_2 = S_2 - S_1 = S_2 - X_1 \Rightarrow X_1 + X_2 = S_2$ ]

As a consequence, the  $(S_k)_{k \geq 1}$  are gamma r.v.'s,  $S_k \sim \text{Gamma}(k, \lambda)$ , and

pdf is  $f_k(x) = \begin{cases} \frac{\lambda^k x^{k-1}}{(k-1)!} e^{-\lambda x} & \text{for } x \geq 0 \\ 0 & \text{for } x < 0 \end{cases}$  mean is  $\frac{k}{\lambda}$   
 variance  $\frac{k}{\lambda^2}$ .

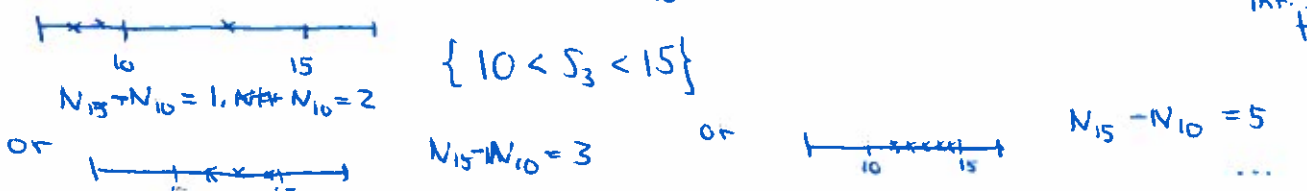
Example: Suppose  $(N_t)_{t \geq 0}$ , Poisson process rate  $\lambda = 3$ .

(a) Find the expected time of the arrival of the 3<sup>rd</sup> message

- difficult to consider just using  $(N_t)$   
 $\rightarrow = E(S_3) = \frac{3}{\lambda} = \frac{3}{3} = 10$ .

(b) Find the probability the 3<sup>rd</sup> message arrived between 10 and 15.

This is  $P(10 < S_3 < 15) = \int_{10}^{15} f_3(x) dx = \int_{10}^{15} \frac{\lambda^3 x^2}{2!} e^{-\lambda x} dx = \dots$   
int. by parts twice...



[hard to find just using  $(N_t)$  !]

Nov 7

Exam ① **F** branch. process,  $\{p_k\}$ ,  $p_k > 0 \forall k \Rightarrow$  mod.

$0 \neq 1$  bc  $\underline{p_{\infty}} = 1$ , so  $p_{0j}^n = 0 \forall n, j \neq 0$ .

$p_{\infty}^n = 1$  all  $n$   $\nearrow$

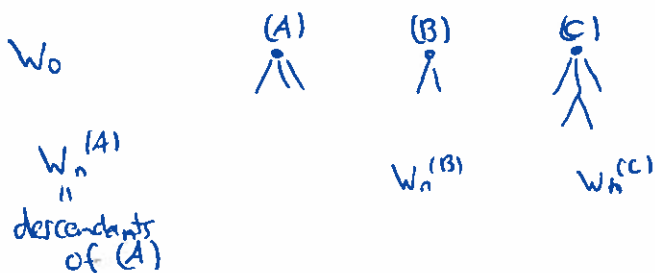
**E** finite mod., time-rev. MC has lim. dist:  $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$ ,  $\underline{\pi} = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \end{bmatrix}$

**F** Every MC must have at least one pos. recurrent state.

True if state space is finite.

False for simple symm. rw on  $\{0, \pm 1, \pm 2, \dots\}$ , all states null recurrent.

⑥  $(Z_n)_{n \geq 0}$ ,  $e, \mu, (p_k)$ ,  $Z_0 = 1$ ,  $(W_n)$  branch. process, same  $(p_k)$ ,  $W_0 = 3$



indiv. produce  
independently

(a)  $P(W_n = 0 \text{ for some } n \mid W_0 = 3) = P(W_n^{(A)} = 0 \text{ for some } n, W_n^{(B)} = 0 \text{ for some } n, W_n^{(C)} = 0 \text{ for some } n \mid W_0 = 3)$

$\stackrel{\text{independence}}{=} P(W_n^{(A)} = 0 \text{ for some } n \mid W_0^{(A)} = 1) \cdot P(W_n^{(B)} = 0 \text{ for some } n \mid W_0^{(B)} = 1) \cdot P(W_n^{(C)} = 0 \text{ for some } n \mid W_0^{(C)} = 1)$

$= P(Z_n = 0 \text{ for some } n \mid Z_0 = 1)^3 = e^{-3} = 1 - e^{-3}$

$\Leftrightarrow e = 1$   $\leftarrow$  that's the case when  $\boxed{\mu \leq 1}$

(b)  $P(W_n \neq 0 \text{ for all } n \mid W_0 = 3) = 1 - e^{-3}$

Thm:  $(X_k)$  are iid  $\text{Expo}(\lambda)$ .  
 $\Rightarrow (S_k)_{k \geq 1}$  are  $\text{Gamma}(k, \lambda), \dots$

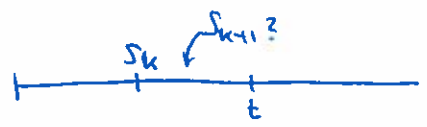
pdf  $f_k(t) = \frac{\lambda^k t^{k-1}}{(k-1)!} e^{-\lambda t}, t \geq 0$

We will show: the  $(S_k)$  are  $\text{Gamma}(k, \lambda)$  and the  $(X_k)$  are  $\text{Expo}(\lambda)$ .

I find the pdf  $f_k$  of  $S_k$  by finding its cdf  $F_k$  and then setting

$f_k = F_k'$

Fix  $t$ .



$F_k(t) = P(S_k \leq t) = P(N_t \geq k) = 1 - P(N_t < k) = 1 - \sum_{j=0}^{k-1} P(N_t = j) = 1 - \sum_{j=0}^{k-1} \frac{e^{-\lambda t} (\lambda t)^j}{j!}$

Exercise: Check  $\frac{d}{dt} F_k(t) = \frac{\lambda^k t^{k-1}}{(k-1)!} e^{-\lambda t}$  (telegraphing server) ✓

$\frac{d}{dt} F_k(t) = - \sum_{j=0}^{k-1} \left( \frac{-\lambda e^{-\lambda t} (\lambda t)^j}{j!} + \frac{e^{-\lambda t} \lambda^j t^{j-1}}{j!} \right) = - \sum_{j=0}^{k-1} \left( \frac{-\lambda^{j+1} e^{-\lambda t} t^j}{j!} + \frac{e^{-\lambda t} \lambda^j t^{j-1}}{j!} \right)$   
 $= -e^{-\lambda t} \left[ \sum_{j=0}^{k-1} \frac{-\lambda^{j+1} t^j}{j!} + \sum_{j=0}^{k-2} \frac{\lambda^{j+1} t^j}{j!} \right] = -e^{-\lambda t} \left( -\frac{\lambda^k t^{k-1}}{(k-1)!} \right) = \frac{\lambda^k t^{k-1}}{(k-1)!} e^{-\lambda t}$

The dist. of  $X_{k+1}$ ? Find  $P(X_{k+1} \leq \frac{u}{\lambda})$  and differentiate

$1 - P(X_{k+1} > u)$  ← we want

$P(X_{k+1} > u) = P(S_{k+1} - S_k > u)$  [cdf:  $F_X(x) = P(X \leq x)$ ,  $F_X'(x) = \int_{-\infty}^x f(x) dt$ ]

We can find this if we can find the joint pdf of  $(S_k, S_{k+1})$   $\frac{d}{dx} F(x) = f(x)$  pdf

If we can find  $F_{k,k+1}$  [ $F_{k,k+1}(s,t) = P(S_k \leq s, S_{k+1} \leq t)$ ], then  $P(X \in A) = \int_A f dx$

joint cdf of  $(S_k, S_{k+1})$ , then  $f_{k,k+1}(s,t) = \frac{\partial^2}{\partial s \partial t} F_{k,k+1}(s,t)$

Problem: Can we find  $F_{k,k+1}(s,t) = P(S_k \leq s, S_{k+1} \leq t)$  for  $s < t$ ?

Easier to find  $G_{k,k+1}(s,t) = P(S_k \leq s, S_{k+1} > t) = P(N_s = k, N_t - N_s = 0)$

$= P(N_s = k, N_t = k) = P(N_s = k, N_t - N_s = 0) = P(N_s = k) P(N_t - N_s = 0)$

$= \frac{e^{-\lambda s} (\lambda s)^k}{k!} \frac{e^{-\lambda(t-s)} (\lambda(t-s))^0}{0!}$

Now, we have  $G_{k,k+1}(s,t) = P(S_k \leq s, S_{k+1} > t) =$  — specific formula.

We want  $F_{k,k+1}(s,t) = P(S_k \leq s, S_{k+1} \leq t)$ .

Can we relate  $F_{k,k+1}(s,t)$  and  $G_{k,k+1}(s,t)$ ?

$$\{S_k \leq s\} = \{S_k \leq s, S_{k+1} \leq t\} \cup \{S_k \leq s, S_{k+1} > t\}$$

$$P(S_k \leq s) = P(\text{ " " }) + P(\text{ " " })$$

$$P(S_k \leq s) = F_{k, k+1}(s, t) + G_{k, k+1}(s, t) \quad \text{or} \quad F_{k, k+1}(s, t) = P(S_k \leq s) - G_{k, k+1}(s, t)$$

$$f_{k, k+1}(s, t) = \frac{\partial^2}{\partial s \partial t} (F_{k, k+1}(s, t)) = \frac{\partial^2}{\partial s \partial t} (0 - G_{k, k+1}(s, t))$$

We get :  $(S_k, S_{k+1})$  has joint pdf

$$f_{k, k+1}(s, t) = -\frac{\partial^2}{\partial s \partial t} \left[ \frac{e^{-\lambda s} (\lambda)^k}{k!} e^{-\lambda(t-s)} \cdot 1 \right], s < t$$

Finally,  $P(X_{k+1} > u) = P(S_{k+1} - S_k > u) = \dots e^{-\lambda u}$  "a"

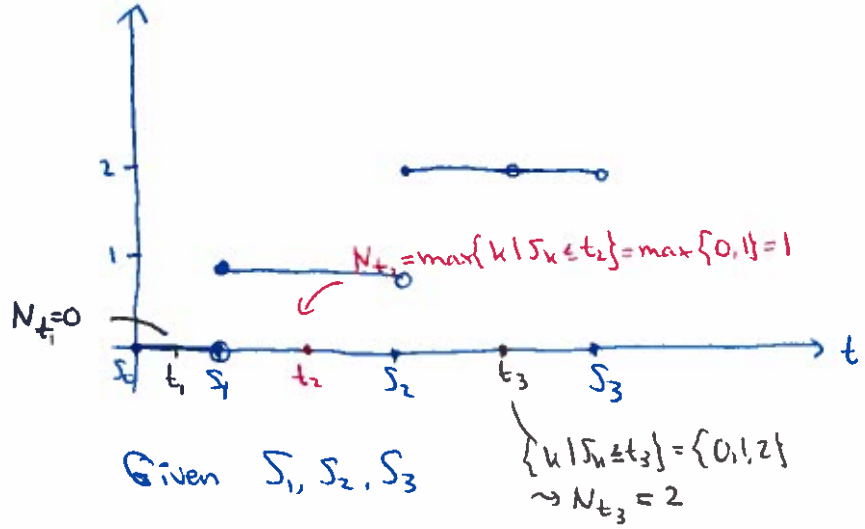
Now, start with iid rv's  $\{X_1, X_2, \dots\}$  (Positive)

Make a counting process out of these.

1) Define  $S_0 = 0, S_k = X_1 + \dots + X_k$ .

$$(S_1 = X_1)$$

2) Define  $(N_t)_{t \geq 0}$  by  $N_t = \max\{k: S_k \leq t\}, N_0 = 0$



Prop: If  $(X_1, X_2, \dots)$  are iid.  $\text{Expo}(\lambda)$ , and  $(S_k)$  and  $(N_k)$  are defined as above, then  $(N_t)_{t \geq 0}$  is a Poisson-process, rate  $\lambda$ .

( Def 2  $\Rightarrow$  Def 1 and Def 1  $\Rightarrow$  Def 2.

Nov 7

[ Def#2: A Poisson proc. with rate  $\lambda$  is a counting process def'd as above by  $X_1, X_2, \dots$  ]

Read "little oh" handout on BB. Read 8.2, 8.3.

We say " $f(x) = o(x)$  as  $x \rightarrow 0$ " to mean  $\lim_{x \rightarrow 0} \frac{f(x)}{x} = 0$ .

Intuitive meaning: 1)  $f(x)$  goes to 0 "faster" than  $x$  goes to 0 [as  $x \rightarrow 0$ ]  
 2)  $f(x)$  is negligible compared to  $x$  as  $x \rightarrow 0$ .  
 much more smaller.

Ex: -  $h^2 = o(h)$  as  $h \rightarrow 0$ .  $\lim_{h \rightarrow 0} \frac{h^2}{h} = 0$   
 - Is  $\sqrt{h} = o(h)$  as  $h \rightarrow 0$ ?  $\lim_{h \rightarrow 0} \frac{\sqrt{h}}{h} = \lim_{h \rightarrow 0} \frac{1}{\sqrt{h}} \neq 0$ .  
 -  $\sin(h) \neq o(h)$  as  $h \rightarrow 0$  ( $\frac{\sin h}{h} \rightarrow 1$  as  $h \rightarrow 0$ )

We say  $f(x) = g(x) + o(x)$  to mean  $f(x) - g(x) = o(x)$ , or  
 $\lim_{x \rightarrow 0} \frac{f(x) - g(x)}{x} = 0$ .

Nov 9

Little oh notation

$f(x) = o(g(x))$  as  $x \rightarrow 0$

means

$$\lim_{x \rightarrow 0} \frac{f(x)}{g(x)} = 0$$

Ex: ① Is  $\cos x = 1 + o(x)$  as  $x \rightarrow 0$ ?

$$\lim_{x \rightarrow 0} \frac{\cos x - 1}{x} \stackrel{\text{L'Hopital's Rule}}{=} \lim_{x \rightarrow 0} \frac{-\sin x}{1} = 0 \checkmark$$

② Is  $e^{2x} = 1 + 2x + o(x)$  as  $x \rightarrow 0$ ?

$$\lim_{x \rightarrow 0} \frac{e^{2x} - (1 + 2x)}{x} \stackrel{\text{L'Hopital's Rule}}{=} \lim_{x \rightarrow 0} \frac{2e^{2x} - 2}{1} = 0 \checkmark$$

Fact: Let  $f$  be a continuous fct. on  $[0, \infty)$ ,  $f(0) = 0$ .

Then

$f(x) = \lambda x + o(x)$  as  $x \rightarrow 0$  is equivalent to

$$f'(0) = \lambda$$

Pf. (a) If  $f(x) = \lambda x + o(x)$ ,  $f'(0) = \lim_{x \rightarrow 0} \frac{f(x) - f(0)}{x} = \lim_{x \rightarrow 0} \frac{\lambda x + o(x)}{x}$

$$= \lim_{x \rightarrow 0} \left( \lambda + \frac{o(x)}{x} \right) = \lambda$$

(b) If  $f'(0) = \lambda$ , then  $\lim_{x \rightarrow 0} \frac{f(x) - f(0)}{x} = \lambda$ ,  $\lim_{x \rightarrow 0} \frac{f(x)}{x} = \lambda$

Def.  $g(x) = \frac{f(x)}{x} - \lambda$ , so  $\lim_{x \rightarrow 0} g(x) = 0$ . Solve for  $f(x)$ ,

$$f(x) = (\lambda + g(x))x = \lambda x + \boxed{g(x)x}$$

Meaning of  $f(x) = \lambda x + o(x)$  is  $\lim_{x \rightarrow 0} \frac{f(x) - \lambda x}{x} = 0$ .

But  $\frac{f(x) - \lambda x}{x} = g(x)$ , thus  $\lim_{x \rightarrow 0} \frac{f(x) - \lambda x}{x} = \lim_{x \rightarrow 0} g(x) = 0$ .

$$[h(x) = h(0) + h'(0)x + \text{error} = \lambda x + \text{error}.]$$

### Def 3 (p. 234)

A counting process  $(N_t)_{t \geq 0}$  is a Poisson Process, rate  $\lambda$ , if

1.  $N_0 = 0$
2.  $(N_t)$  has stationary and independent increments.
3.  $P(N_h = 0) = 1 - \lambda h + o(h)$  as  $h \rightarrow 0$ .

$$o(h) = o(h)$$

$$\text{or } P(N_h \neq 0) = \lambda h + o(h)$$

4.  $P(N_h = 1) = \lambda h + o(h)$  as  $h \rightarrow 0$

5.  $P(N_h \geq 2) = o(h)$  as  $h \rightarrow 0$ .

$$[524 \Rightarrow 3]$$

Fact:  $o(h) + o(h) = o(h)$  as  $h \rightarrow 0$ .

Interpretation:

3. Unlikely to have an arrival in a short time period.

$$([0, h])$$

$$P(N_h) = 0 = P(N_{t+h} - N_t = 0)$$

4. The prob. of a single arrival in a short time period is "almost" proportional ( $\lambda$ ) to the length of the period.

5. It is very unlikely to have 2 or more arrivals in a short time period.

Note: 1) There is no mention of Poisson distribution.

2) These assumptions are reasonable in modeling a number of situations (not all).

Thm: All three "definitions" of Poisson processes are equivalent.

Note: Def 3 forces the Poisson dist. for  $N_t$ .

Thm: (Law of Rare events)

Let  $(S_n)_{n=1,2,\dots}$  be a sequence of Binomial r.v.'s s.t.  $S_n$  is Binomial with parameter  $n, p_n$  where  $\lim_{n \rightarrow \infty} p_n = 0$  and

$\lim_{n \rightarrow \infty} np_n = \lambda > 0$ . Then  $\lim_{n \rightarrow \infty} P(S_n = k) = \frac{e^{-\lambda} \lambda^k}{k!}$  for  $k=0,1,2,\dots$   
[e.g.  $p_n = \frac{\lambda}{n}$ ]

Binom  $(n, p_n)$  is approximately same as Poiss  $(\lambda)$  for large  $n$ .

If  $S_n$  is the nr of successes in  $n$  trials with success prob.  $p_n$ , where  $n \rightarrow \infty, p_n \rightarrow 0$  and  $np_n \rightarrow \lambda$ , then  $S_n$  converges in distribution to Poiss  $(\lambda)$ .

Pf: We need to show  $\binom{n}{k} p_n^k (1-p_n)^{n-k} \rightarrow \frac{e^{-\lambda} \lambda^k}{k!}$  as  $n \rightarrow \infty$  for each fixed  $k \geq 0$ .

Recall  $\lim_{n \rightarrow \infty} (1 + \frac{x}{n})^n = e^x$  any  $n \neq x$ .

This can be improved to: If  $\lim_{n \rightarrow \infty} x_n = x$ , then  $\lim_{n \rightarrow \infty} (1 + \frac{x_n}{n})^n = e^x$

Let  $k$  be fixed.

$$\begin{aligned}
 \binom{n}{k} p_n^k (1-p_n)^{n-k} &= \frac{n!}{(n-k)! k!} p_n^k \frac{(1-p_n)^n}{(1-p_n)^k} \\
 &= \frac{1}{k!} \frac{n(n-1)(n-2)\dots(n-k+1)}{k!} p_n^k \frac{(1-p_n)^n}{(1-p_n)^k} \quad \lim_{n \rightarrow \infty} np_n = \lambda \\
 &= \frac{1}{k!} \frac{n(n-1)\dots(n-k+1)}{n \cdot n \dots n} (np_n)^k \frac{(1 - \frac{np_n}{n})^n}{(1-p_n)^k} \quad p_n^k = \frac{(np_n)^k}{n^k} \\
 &= \frac{1}{k!} \cdot 1 \cdot (1 - \frac{1}{n}) \cdot (1 - \frac{2}{n}) \dots (1 - \frac{k-1}{n}) (np_n)^k \frac{(1 - \frac{np_n}{n})^n}{(1 - \frac{np_n}{n})^n} \frac{1}{(1-p_n)^k} \rightarrow \frac{1}{k!} \\
 \text{Let } n \rightarrow \infty, \text{ get } & \frac{1}{k!} \cdot \underbrace{1 \dots 1}_{k \text{ times}} \lambda^k e^{-\lambda} \cdot \frac{1}{k!} \\
 &= \frac{e^{-\lambda} \lambda^k}{k!}
 \end{aligned}$$

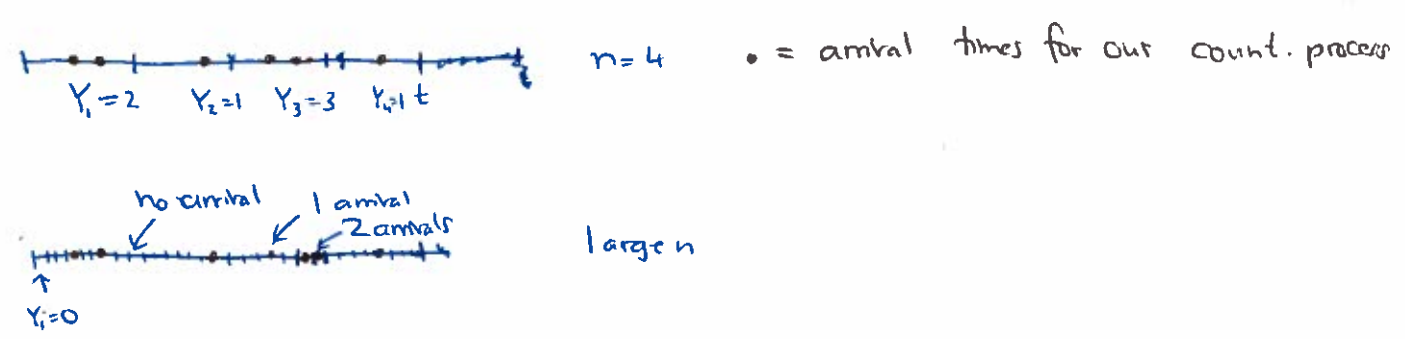
□

Sketch of Def 3 implies for fixed t,  $N_t \sim \text{Pois}(\lambda t)$ .

Fix t, we must show  $P(N_t = k) = e^{-\lambda} \frac{\lambda^k}{k!}$ .

Idea: Show the properties of Def 3 imply  $N_t$  is approx. a Binomial rv with parameter n,  $p_n \approx \frac{\lambda t}{n}$ . Then use Law of rare events.

Step I: Divide  $[0, t]$  into n subintervals of length  $\frac{t}{n}$ .



Let  $Y_i = \#$  of arrivals in subinterval i.

Let  $T_n = Y_1 + \dots + Y_n =$  total nr of arrivals in  $[0, t]$

$N_t = T_n$ , and  $Y_1, Y_2, \dots, Y_n$  are independent rv's.

But  $T_n$  is not binomial (some of the  $Y_i$ 's may be 2, 3, ...)



Step 2:

Def.  $X_i = \begin{cases} 0 & \text{if } Y_i = 0 \\ 1 & \text{if } Y_i \geq 1 \end{cases}$  and  $S_n = X_1 + \dots + X_n$ , which  
 [  $N_t \approx S_n$  is possible ]

is Binomial, parameters  $n$ ,  $p_n = P(X_i = 1) = P(Y_i \geq 1) = P(Y_i = 1) + P(Y_i \geq 2)$

Consider  $Y_i = N_{\frac{t}{n}}$ .  $\Rightarrow p_n = P(N_{\frac{t}{n}} = 1) + P(N_{\frac{t}{n}} \geq 2) \stackrel{\text{from Def. 3}}{=} \lambda \cdot \frac{t}{n} + O(\frac{t}{n}) + O(\frac{t}{n})$   
 $\Rightarrow p_n = \frac{\lambda t}{n} + O(\frac{t}{n})$ .

Step 3:

$\bullet P(S_n \neq T_n) \rightarrow 0$  as  $n \rightarrow \infty$  (check)  
 "  $P(\text{at least one } Y_i \geq 2)$

$\bullet P(N_t = S_n) = P(N_t = \overset{T_n}{X}, S_n = T_n) + P(N_t = S_n, S_n \neq T_n) \xrightarrow{b/c} 0$   
 $= 1$  [since  $N_t = T_n$ ]

$\bullet P(N_t = k) \approx P(S_n = k) \rightarrow ?$  as  $n \rightarrow \infty$

$S_n$  is Binomial  $(n, p_n = \frac{\lambda t}{n} + O(\frac{t}{n}))$ .  $np_n = n(\frac{\lambda t}{n} + O(\frac{t}{n})) = \lambda t + n O(\frac{t}{n}) = \lambda t + O(t) \xrightarrow{\text{since } h = \frac{t}{n} \rightarrow 0 \text{ (as } n \rightarrow \infty)} \lambda t + 0$

By law of rare events,  $P(S_n = k) \rightarrow \frac{e^{-\lambda t} (\lambda t)^k}{k!}$

which shows  $P(N_t = k) = \frac{e^{-\lambda t} (\lambda t)^k}{k!}$



$N_t = \sum_{i=1}^n Y_i$  which is approx. Binom  $(n, p_n)$ ,  $p_n = \frac{\lambda t}{n} + O(\frac{t}{n})$   
Pois  $(\lambda t)$

Def #2:

$X_1, X_2, \dots$  are i.i.d. expon. r.v. with param  $\lambda$ ,  $S = 0$ ,  
 $S_k = X_1 + \dots + X_k$ ,  $k = 1, 2, \dots$ ,  $(N_t)$  def'd by  $N_0 = 0$ ,  $N_t = n$  iff  $k | S_n \leq t$   
 $t > 0$

# 6.4 Thinning and superposition

$(N_t)_{t \geq 0}$  rate  $\lambda$  Poisson process.



arrival times are  $x$  ( $S_k$ 's)

Now "mark" the arrival times with marks of  $2^k$  types  $\begin{matrix} 00 \\ 1, 2 \end{matrix}$

such that 1) marks are independent

2) mark an arrival as Type 1 with probability  $p_1$   
 Type 2 with probability  $p_2$   
 (  $p_1 + p_2 = 1$  )

Can let  $U_1, U_2, U_3, \dots$  be i.i.d. with  $P(U_i = p_1) = p_1, P(U_i = p_2) = p_2$  all  $i$ , which are independent of  $(N_t)_{t \geq 0}$ .

Define  $N_t^{(0)}$  = the nr of Type 0 arrivals by time  $t$ .

$N_t^{(1)}$  = ...  
 $N_t^{(2)}$  = ...

Note that  $N_t = N_t^{(1)} + N_t^{(2)}$ .

Thm: (True for all  $k \geq 2$ )  $(N_t)_t$  is Poisson proc., rate  $\lambda, p_0, p_1 = 1 - p_0$ .

- $(N_t^{(0)})_{t \geq 0}$  is a Poisson process, rate  $\lambda p_0$  / each  $N_t^{(0)}$  is a Poisson r.v. not process with parameter  $\lambda p_0 t$
- $(N_t^{(1)})_{t \geq 0}$  is a ...  $\lambda p_2$
- $(N_t^{(0)})_{t \geq 0}, (N_t^{(1)})_{t \geq 0}$  are independent

Example: Consider births at a local hospital, assume the prob. a given birth is male to be  $p_m = .48$ , the prob. of ... is female to be  $p_f = .52$ .

Assume the nrs over time is a  $\sqrt{\text{rate } \lambda = 2}$  Poisson proc., and successive births

are independent of one another and the Poisson proc.  $\{N_t\}_{t \geq 0}$ .

Def.  $N_t^m = \#$  of male births by time  $t$  (each  $t > 0$ )

$N_t^f = \#$  female " " " "

Then by Thm,  $(N_t^m)_{t \geq 0}$  is a Poisson proc., rate  $\lambda_{pm} = 2(.48)$

$(N_t^f)_{t \geq 0}$  rate  $\lambda_{pf} = 2(.52)$

and the two processes are independent.

Find the probability that at least one male and no females are

born during a 3 hour period  
 $= [0, 3]$

We want  $P(N_3^m \geq 1, N_3^f = 0) \stackrel{\text{indep.}}{=} P(N_3^m \geq 1) P(N_3^f = 0)$

$$= (1 - P(N_3^m = 0)) P(N_3^f = 0) = \left(1 - \frac{e^{-3\lambda_{pm}} (3\lambda_{pm})^0}{0!}\right) \left|\frac{e^{-3\lambda_{pf}} (3\lambda_{pf})^0}{0!}\right|$$

"Pf of Thm":

Check  $(N_t^{(0)})_{t \geq 0}$  is a Poisson proc., rate  $\lambda_{p0}$ .

Use Def 3:  $N_0^{(0)} = 0 \checkmark$  ( $N_0 = 0$ )

Increments - stationary, independent (for  $(N_t^{(0)})$ ) [inherited from  $(N_t)_{t \geq 0}$ ]

(3) follows from (4), (5)

$$(5) \quad 0 \leq P(N_h^{(0)} \geq 2) = P(N_h^{(0)} \geq 2, N_h \geq 2) \leq P(N_h \geq 2) = o(h) \text{ as } h \rightarrow 0 \checkmark$$

$$(4) \quad P(N_h^{(0)} = 1) = P(N_h^{(0)} = 1, N_h = 1) + P(N_h^{(0)} \neq 1, N_h = 1)$$

↑  
requires  $N_h \geq 1$

$$P(N_h^{(0)} = 1, N_h = 1) = P(N_h^{(0)} = 1, \text{the single mark is type 0})$$

$$\stackrel{\text{indep.}}{=} P(N_h = 1) p_0 = (\lambda h + o(h)) p_0 = \lambda p_0 h + o(h)$$

$$P(N_h^{(0)} = 1, N_h \geq 2) \leq P(N_h \geq 2) = o(h) \text{ as } h \rightarrow 0.$$

$$\text{We get } P(N_h^{(0)} = 1) = \lambda p_0 h + [o(h) + o(h)] = \lambda p_0 h + o(h).$$

Given stab. + indep. increments, this shows  $(N_t^{(0)})_{t \geq 0}$  is a Poisson process, rate  $\lambda p_0$ . (and  $(N_t^{(1)})_{t \geq 0}$  --- rate  $\lambda p_1$ ).

Check independence of  $(N_t^{(0)}), (N_t^{(1)})$ .

We will show only: for any fixed  $t > 0$ ,  $P(N_t^{(0)} = i | N_t^{(1)} = j) = P(N_t^{(0)} = i) = \frac{e^{-\lambda p_0 t} (\lambda p_0 t)^i}{i!}$ .

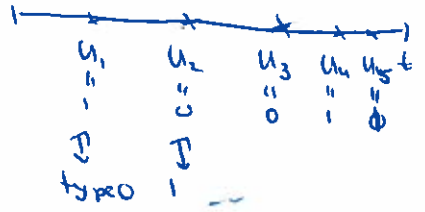
$$P(N_t^{(0)} = i | N_t^{(1)} = j) = \frac{P(N_t^{(0)} = i, N_t^{(1)} = j)}{P(N_t^{(1)} = j)} \leftarrow \text{know this}$$

$$P(N_t^{(0)} = i, N_t^{(1)} = j) = P(N_t^{(0)} = i, N_t = i+j) \leftarrow \text{dependent}$$

Let  $U_1, U_2, U_3, \dots$  be iid Bernoulli r.v.'s, ~~parameter  $p_0$~~ .

and  $W_k = U_1 + U_2 + \dots + U_k$  be the nr of type 0 arrivals in the 1st  $k$  arrivals. Binomial r.v., param.  $k, p_0$

eg.  $N_t^{(0)} = U_1 + U_2 + \dots + U_5 = 1 + 0 + 0 + 1 + 1 = 3$



$$\Rightarrow P(N_t^{(0)} = i, N_t^{(1)} = j) = P(N_t^{(0)} = i, N_t = i+j) = P(W_{i+j} = i, N_{i+j} = i+j) \stackrel{\text{indep.}}{=} P(W_{i+j} = i) \cdot P(N_t = i+j) = \binom{i+j}{i} p_0^i p_1^j e^{-\lambda t} (\lambda t)^{i+j} \frac{1}{(i+j)!}$$

$$\text{We now have } P(N_t^{(0)} = i | N_t^{(1)} = j) = \frac{\binom{i+j}{i} p_0^i p_1^j \frac{e^{-\lambda t} (\lambda t)^{i+j}}{(i+j)!}}{\frac{e^{-\lambda p_1 t} (\lambda p_1 t)^j}{j!}}$$

$$= \text{simplify, get } = \frac{e^{-\lambda p_0 t} (\lambda p_0 t)^i}{i!} = P(N_t^{(0)} = i).$$

Superposition p. 240

Thm: If  $(N_t^{(1)})_{t \geq 0}, \dots, (N_t^{(k)})_{t \geq 0}$  are indep. Poisson proc. with rates  $\lambda_1, \dots, \lambda_k$ , then  $N_t = N_t^{(1)} + \dots + N_t^{(k)}, t \geq 0$ , is a Poisson proc. with rate  $\lambda = \lambda_1 + \dots + \lambda_k$ .

One-dimensional Poisson process:

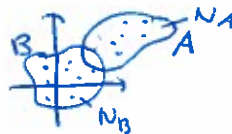
$(N_t)_{t \geq 0}$



$x_i$ 's are random arrival times.

$N_t - N_s = \#$  of arrivals during  $(s, t]$  (=3)

New notation:  $N_I = \#$  of arrivals in interval  $I = (s, t]$  random points



$N_A, N_B$  not independent

6.6 Spatial Poisson Processes

Def: We have r.v.'s  $N_A$  for each region  $A \subseteq \mathbb{R}^2$ ,

which are Poisson, parameter  $\lambda \cdot |A|$

(and if  $A, B \subseteq \mathbb{R}^2$  are disjoint, then  $N_A, N_B$  are independent) // area of  $A$



$N_A, N_B$  independent

Stationarity increments?

One dimension:  $N_{t+s} - N_s$  is a Poisson r.v. with param  $\lambda t$  (and  $N_t - N_0$  is Pois., param.  $\lambda t$ )

Pois( $\lambda|A|$ )



Shift it by  $x$  in x-direction,  $y$  in y-direction to get  $A'$

$\text{Pois}(\lambda|A'|) = \text{Pois}(\lambda|A|)$

$E(N_A) = \lambda|A|$

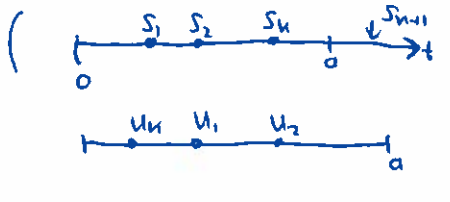
Increase  $\lambda$ , expect  $N_A$  to increase. "completely random"

Fact: Given  $N_A = k$ , the distribution of the points in  $A$  is the same as the distribution of the points  $U_1, \dots, U_k$ , where  $U_1, U_2, \dots, U_k$  are iid, uniform random vectors in  $A$ .

6.5 Poisson processes and the uniform distribution

$(N_t)_{t \geq 0}$  Poisson process, rate  $\lambda$ .

Prop: (p. 245): Fix  $a > 0$ . For any  $k \geq 1$ , the conditional distribution of the arrival times given  $N_a = k$  is the same as a set of  $k$  iid Uniform  $(0, a)$  r.v.'s. More precisely, given iid  $U_1, U_2, \dots, U_k$ ,



Given  $N_a = k$   
 $(S_1, S_2, S_k)$

← Here  $U_{(1)} = U_k, U_{(2)} = U_1, U_{(3)} = U_2$

$(U_1, U_2, U_k)$

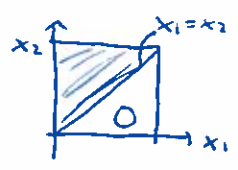
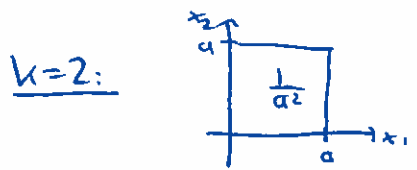
uniform on  $(0, a)$ , define the order statistic  $U_{(1)}, \dots, U_{(k)}$  to the sequence of points obtained from  $U_k \rightarrow U_1$  arranged in increasing order.

- $U_{(1)} < U_{(2)} < U_{(3)} < \dots < U_{(k)}$
- $\{U_{(1)}, \dots, U_{(k)}\} = \{U_1, \dots, U_k\}$ .

[k=2:  $(U_{(1)}, U_{(2)})$  is either  $(U_1, U_2)$  or  $(U_2, U_1)$  if  $U_1 \geq U_2$  or  $U_2 \geq U_1$ ]

Then  $(S_1, S_2, \dots, S_k)$  given  $N_a = k$  has the same distribution as  $(U_{(1)}, U_{(2)}, \dots, U_{(k)})$ .

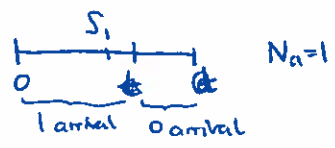
Note  $(U_1, \dots, U_k)$  has joint pdf  $f(x_1, \dots, x_k) = \left(\frac{1}{a}\right)^k$  (for all  $0 < x_i < a$ ) as its joint pdf.  $(U_{(1)}, \dots, U_{(k)})$  does not have as its joint pdf.



$(U_{(1)}, U_{(2)})$  has pdf  $g(x_1, x_2) = \frac{2}{a^2}$  for  $0 < x_1 < x_2 < a$

Text:  $f(u_{(1)}, \dots, u_{(k)})(x_1, \dots, x_k) = \frac{k!}{a^k}$  if  $0 < x_1 < x_2 < \dots < x_k$ .

Sketch of pf: k=1



Let  $F(t) = P(S_1 \leq t | N_a = 1)$   $0 < t < a$  (a conditional cdf for  $S_1$  given  $N_a = 1$ )

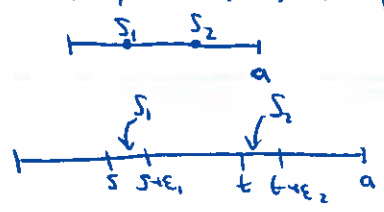
The conditional pdf of  $S_1$  given  $N_a = 1$  is  $\frac{d}{dt} F(t)$ .

$$P(S_1 \leq t | N_a = 1) = \frac{P(S_1 \leq t, N_a = 1)}{P(N_a = 1)} = \frac{P(N_t = 1, N_a - N_t = 0)}{P(N_a = 1)} = \frac{P(N_t = 1) P(N_a - N_t = 0)}{P(N_a = 1)}$$

$$= \frac{\frac{e^{-\lambda t} (\lambda t)^1}{1!} e^{-\lambda(a-t)} (\lambda(a-t))^0}{e^{-\lambda a} (\lambda a)^1 / 1!} = \frac{e^{-\lambda t} e^{-\lambda(a-t)} \lambda a}{e^{-\lambda a} \lambda a} = \frac{t}{a}$$

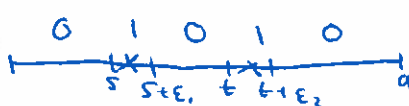
$\frac{d}{dt} \left(\frac{t}{a}\right) = \frac{1}{a}$ , Unif  $(0, a)$  pdf

k=2



Fix  $0 < s < t < a$ , and  $\epsilon_1, \epsilon_2 > 0$  such that

$$f_{(S_1, S_2 | N_a=2)}(s, t) = \lim_{\substack{\epsilon_1 \rightarrow 0 \\ \epsilon_2 \rightarrow 0}} \frac{\{P(s < S_1 < s + \epsilon_1, t < S_2 < t + \epsilon_2 | N_a=2)\}}{\epsilon_1 \epsilon_2}$$

$$\text{Num} = \frac{P(s < S_1 < s + \epsilon_1, t < S_2 < t + \epsilon_2, N_a=2)}{P(N_a=2)}$$


$$= \frac{P(N_s=0, N_{s+\epsilon_1}-N_s=1, N_t-N_{s+\epsilon_1}=0, N_{t+\epsilon_2}-N_t=1, N_a-N_{t+\epsilon_2}=0)}{P(N_a=2)}$$

factor by indep.

$$= \frac{P(N_s=0) P(N_{\epsilon_1}=1) P(N_{t-s-\epsilon_1}=0) P(N_{\epsilon_2}=1) P(N_{a-t-\epsilon_2}=0)}{P(N_a=2)}$$

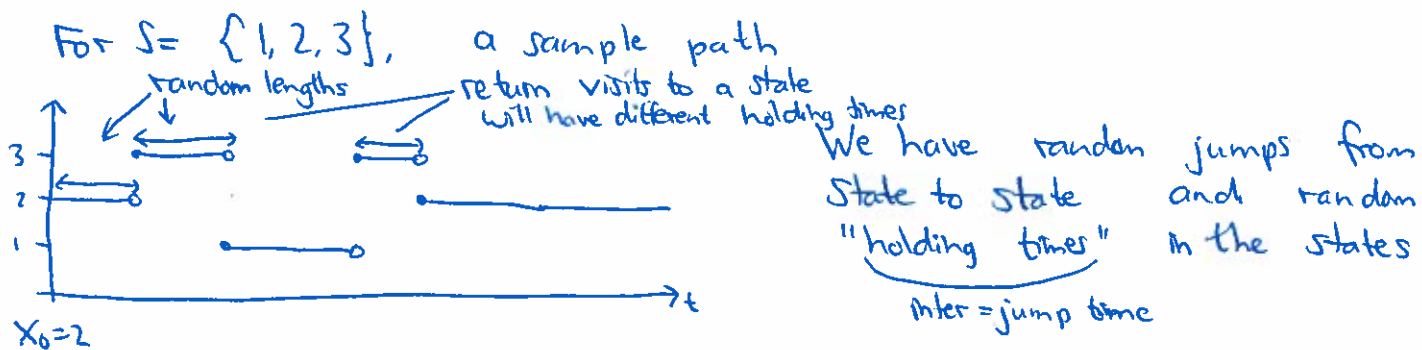
put in Pois prob.  
cancel like terms

$$\frac{\lambda^2 \epsilon_1 \epsilon_2 e^{-\lambda a}}{e^{-\lambda a} (\lambda a)^2 / 2} = \frac{2 \epsilon_1 \epsilon_2}{a^2}$$

$$\Rightarrow f_{(S_1, S_2 | N_a=2)}(s, t) = \lim_{\epsilon_1, \epsilon_2 \rightarrow 0} \frac{2 \epsilon_1 \epsilon_2}{a^2 \epsilon_1 \epsilon_2} = \frac{2}{a^2} \quad \checkmark \quad \text{The pdf of } (U_{(1)}, U_{(2)})$$

### 7.1 Cont. Time MC's

Want a stochastic process  $(X_t)_{t \geq 0}$  with state space  $S$  which jumps randomly from one state to another at random times.



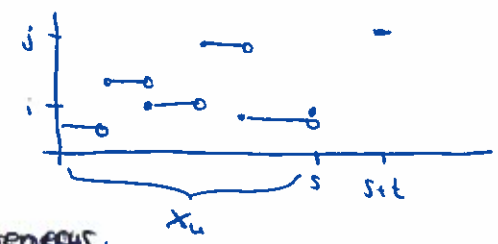
Def: A continuous time stochastic process  $(X_t)_{t \geq 0}$  with discrete state space is a cont. time MC if it has the

Markov property,  $P(X_{s+t}=j | X_s=i, X_u = x_u, 0 \leq u < s)$

$$= P(X_{s+t}=j | X_s=i)$$

where  $s, t \geq 0$ , and  $x_u$  is any given sample (path) of states

up to time  $s$  ( $x_u \in S$ )



We assume the MC is time homogeneous,

$$\text{so } P(X_{s+t} = j | X_s = i) = P(X_t = j | X_0 = i) \text{ for all } s, t \geq 0.$$

This assumption allows us to define

$$P_{ij}(t) = P(X_{s+t} = j | X_s = i) = P(X_t = j | X_0 = i).$$

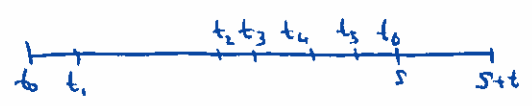
$\underline{P}(t) = (P_{ij}(t))_{i,j \in S}$  is called the transition function (fct of t).

[Before  $P_{ij} = P(X_j = j | X_0 = i)$ ]

For every  $t$ ,  $\underline{P}(t)$  is a stochastic matrix.

Note:  $\underline{P}(0) = \underline{I}$  (identity matrix as before)

The Markov property is equivalent to:



For any  $n$ , any times  $0 = t_0 < t_1 < t_2 < \dots < t_n = s$

$$P(X_{s+t} = j | X_s = i, X_{t_0} = i_0, X_{t_1} = i_1, \dots, X_{t_n} = i_n) = P(X_{s+t} = j | X_s = i).$$

Basic Problem:

Before, in discrete time, we defined our MC using a trans matrix  $\underline{P}$ .

But now, we have no "single"  $\underline{P}$  to use.

(Take  $\underline{P}(t)$  to be our data, how do we find  $P(X_{1/2} = j | X_0 = i)$ ?  
 $P(X_{3/2} = j | X_0 = i)$ ?  
is a

Fact: A Poisson process  $(N_t)_{t \geq 0}$  (let's allow  $N_0 \neq 0$ ) is a continuous time MC with transition fct (for  $j \geq i$ ) [Use stationary increments]

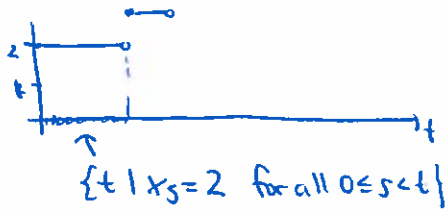
$$P_{ij}(t) = P(N_t = j | N_0 = i) = P(N_t - N_0 = j - i) = \frac{e^{-\lambda t} (\lambda t)^{j-i}}{(j-i)!}$$



Holding times:

Let  $T_i$  be the (first) holding time in state  $i$ .

If we start at state  $i$ ,  $T_i = \max\{t: X_s = i \text{ for all } 0 \leq s < t\}$ .



For a rate  $\lambda$  Poisson process,  $T_i$  is exponential with parameter  $\lambda$ .

Claim: In general,  $T_i$  is an exponential rv with some parameter  $q_i > 0$ .

[In the discrete case,  $T_i$  was geometric  
 $H: P(H_i = k) = a(1-a)^{k-1}$ ]

[midterm #2]

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### Continuous Time MC's

Reading - 7.1, 7.2

Memoryless property:  $\bullet P(X > s+t | X > s) = P(X > t)$  for all  $s, t > 0$

Further properties of the exponential distribution (p. 230-231)

$\hookrightarrow \text{Exp}(\lambda), P(X \leq t) = 1 - e^{-\lambda t}$  or  $P(X > t) = e^{-\lambda t}$  for  $t > 0$

(1) The exponential dist. ~~and~~ has the memoryless property and

is the only dist. with the memoryless property (Exer. 6.11)

(2) Let  $X_1, X_2, \dots, X_n$  be independent exp. r.v.'s such that

$X_i$  has param.  $\lambda_i > 0$ , and let  $M = \min\{X_1, X_2, \dots, X_n\}$ .

Then:

(a)  $M$  is an expon. r.v., parameter  $\lambda = \lambda_1 + \dots + \lambda_n$ .

Pf:  $P(M > t) = P(\min\{X_1, \dots, X_n\} > t) = P(X_1 > t, X_2 > t, \dots, X_n > t)$   
 $= P(X_1 > t) P(X_2 > t) \dots P(X_n > t) = e^{-\lambda_1 t} \cdot e^{-\lambda_2 t} \dots e^{-\lambda_n t}$

$$= e^{-\lambda_1 t - \dots - \lambda_n t} \quad \checkmark \quad \text{expo, param. } \lambda = \lambda_1 + \dots + \lambda_n$$

$$(b) \quad P(M = X_k) = \frac{\lambda_k}{\lambda_1 + \dots + \lambda_n}$$

$X_k$  is the minimum of the  $X_i$ .

Pf: Take  $k=1$ .  $P(M = X_1) = P(X_1 < X_2, X_1 < X_3, \dots, X_1 < X_n)$

[ Note: If the rv's were discrete, could write

$$P(X_1 < X_2, X_1 < X_3) = \sum_{k=0}^{\infty} P(X_1 < X_2, X_1 < X_3 \mid X_1 = k) P(X_1 = k)$$

LOTP ← discrete

$$= \sum_{k=0}^{\infty} P(k < X_2, k < X_3 \mid X_1 = k) P(X_1 = k)$$

independence

$$= \sum_{k=0}^{\infty} P(k < X_2) P(k < X_3) P(X_1 = k)$$

$$P(M = X_1) = P(X_1 < X_2, X_1 < X_3, \dots, X_1 < X_n)$$

$$= \int_0^{\infty} P(X_1 < X_2, \dots, X_1 < X_n \mid X_1 = t) f_{X_1}(t) dt$$

pdf of  $X_1$

Continuous law of total probability

$$= \int_0^{\infty} P(t < X_2, t < X_3, \dots, t < X_n \mid X_1 = t) f_{X_1}(t) dt$$

$$= \int_0^{\infty} P(t < X_2, \dots, t < X_n) f_{X_1}(t) dt = \dots$$

$$\left[ f_{Y \mid X=x}(y) = \frac{f_{X,Y}(x,y)}{f_X(x)} \Rightarrow f_{X,Y}(x,y) = f_{Y \mid X=x}(y) f_X(x) \right]$$

$$\Rightarrow P((X,Y) \in A) = \int_A f_{Y \mid X=x}(y) f_X(x) dx$$

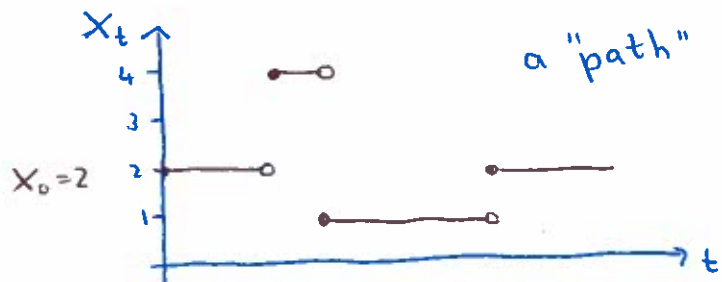
in  $\mathbb{R}^2$

$$\dots = \int_0^{\infty} P(X_2 > t) \dots P(X_n > t) \lambda_1 e^{-\lambda_1 t} dt$$

$$= \int_0^{\infty} e^{-\lambda_2 t} e^{-\lambda_3 t} \dots e^{-\lambda_n t} e^{-\lambda_1 t} dt = \lambda_1 \int_0^{\infty} e^{-\underbrace{(\lambda_1 + \dots + \lambda_n)}_{=: \lambda} t} dt$$

$$= \frac{\lambda_1}{\lambda} \int_0^{\infty} \lambda e^{-\lambda t} dt = \frac{\lambda_1}{\lambda} \cdot 1 = \frac{\lambda_1}{\lambda_1 + \dots + \lambda_n} \quad \checkmark$$

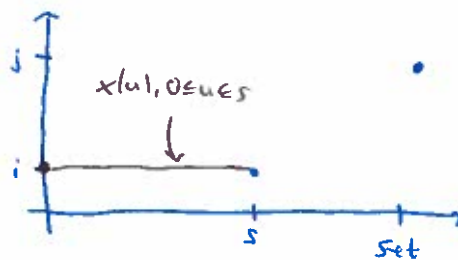
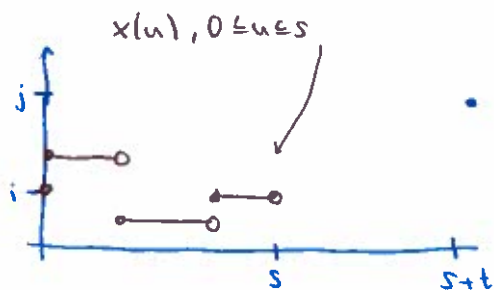
Continuous  $(X_t)_{t \geq 0}$ , finite state space  $S = \{1, 2, 3, 4\}$



Markov Property (I): Given a path  $(x(u))_{0 \leq u \leq s}$

$$P(X_{s+t} = j \mid X_s = i, \text{ and } X_u = x(u) \text{ for all } 0 \leq u \leq s)$$

$$= P(X_{s+t} = j \mid X_s = i) = P(X_t = j \mid X_0 = i)$$



Markov Property II: Given times  $0 = t_0 < t_1 < t_2 < \dots < t_k < s$  and states  $i_1, i_2, \dots, i_k, i, j$ ,

$$P(X_{s+t} = j \mid X_{t_k} = i_k, X_{t_{k-1}} = i_{k-1}, \dots, X_{t_1} = i_1, X_s = i) = P(X_{s+t} = j \mid X_s = i) = P(X_t = j \mid X_0 = i)$$

Define  $P_{ij}(t) = P(X_t = j \mid X_0 = i)$  all  $i, j \in S$ , all  $t \geq 0$

$$\underline{P}(t) = (P_{ij}(t))_{i,j \in S}, \text{ all } t \geq 0.$$

Chapman - Kolmogorov Equations

matrix mult.

$$\text{For all } s, t \geq 0, \quad \underline{P}(t+s) = \underline{P}(t) \cdot \underline{P}(s) \quad (= \underline{P}(s) \cdot \underline{P}(t))$$

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Pf.  $P_{ij}(s+t) \stackrel{\text{def}}{=} P(X_{s+t} = j | X_0 = i) \stackrel{\text{additivity}}{=} \sum_{k \in S} \underbrace{P(X_{s+t} = j | X_s = k, X_0 = i)}_{= P(X_{s+t} = j | X_s = k, X_0 = i) \cdot P(X_s = k | X_0 = i)}$

$\cdot P(X_s = k | X_0 = i)$

$= \sum_{k \in S} P(X_{t+s} = j | X_s = k, X_0 = i) P(X_s = k | X_0 = i)$

[Mult. form.:  $P(A \cap B) = P(A|B)P(B)$   
 $P(A \cap B \cap C) = P(A|B \cap C)P(B|C)$ ]

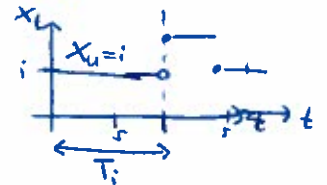
Markov  
 $= \sum_{k \in S} P(X_{t+s} = j | X_s = k) \cdot P_{ik}(s)$

$= \sum_{k \in S} P_{kj}(t) \cdot P_{ik}(s) = \sum_{k \in S} P_{ik}(s) P_{kj}(t) = (P(s) \cdot P(t))_{ij}$

We have shown:  $\underbrace{P_{ij}(t+s)}_{(P(t+s))_{ij}} = (P(s) \cdot P(t))_{ij} \Rightarrow P(t+s) = P(s) \cdot P(t) \quad \square$

Def. The holding time in state  $i$  (starting in state  $i$ ) is

$T_i = \max_{(\text{sup})} \{ s \mid X_u = i \text{ for all } 0 \leq u \leq s \}$



or, to say  $T_i = s$  means  $\begin{cases} X_u = i \text{ for all } 0 \leq u < s \\ X_s \neq i \end{cases}$

Prop: Each  $T_i$  is an exponential r.v., call its parameter  $q_i$ .

Pf: Will show  $T_i$  has the memoryless property.

For  $s, t > 0$ ,  $P(\underbrace{T_i}_{> s+t} > s+t \mid T_i > s, X_0 = i)$   
 $= \frac{P(T_i > s+t, T_i > s \mid X_0 = i)}{P(T_i > s \mid X_0 = i)}$

By the def. of  $T_i$ , for any number  $s$ ,

$\{T_i > s\} = \{X_u = i \text{ for all } 0 \leq u \leq s\}$

$\Rightarrow P(T_i > s+t, T_i > s \mid X_0 = i) = P(T_i > s+t, X_u = i \text{ for all } 0 \leq u \leq s \mid X_0 = i)$

$$= P(T_i > t+s \mid X_u = i \text{ for all } 0 \leq u \leq s) \cdot P(X_u = i \text{ for all } 0 \leq u \leq s \mid X_0 = i)$$

Markov? 
$$= P(T_i > s+t \mid X_s = i) \cdot P(X_u = i \text{ for all } 0 \leq u \leq s \mid X_0 = i)$$

$$= P(T_i > s+t \mid X_s = i) \cdot P(T_i > s \mid X_0 = i)$$

time homog? 
$$= P(T_i > t \mid X_0 = i) \cdot P(T_i > s \mid X_0 = i)$$

$$\Rightarrow P(T_i > s+t \mid T_i > s, X_0 = i) = \frac{P(T_i > t \mid X_0 = i) \cdot P(T_i > s \mid X_0 = i)}{P(T_i > s \mid X_0 = i)}$$

$$= P(T_i > t \mid X_0 = i)$$

[ let  $g(s) = P(T_i > s \mid X_0 = i)$   
 is  $g(s+t) = g(t)g(s)$  all  $s, t > 0$ . ]

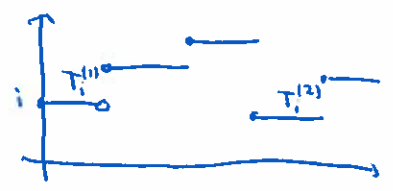
~~This is the~~

We have shown  $P(T_i > s+t \mid X_0 = i) = P(T_i > t \mid X_0 = i) \cdot P(T_i > s \mid X_0 = i)$

This is the (conditional) memoryless property, so  $T_i$  must be exponential, same parameter  $\lambda$ .

$$g(t) = e^{-\lambda t}, \text{ same } \lambda.$$

Fact:

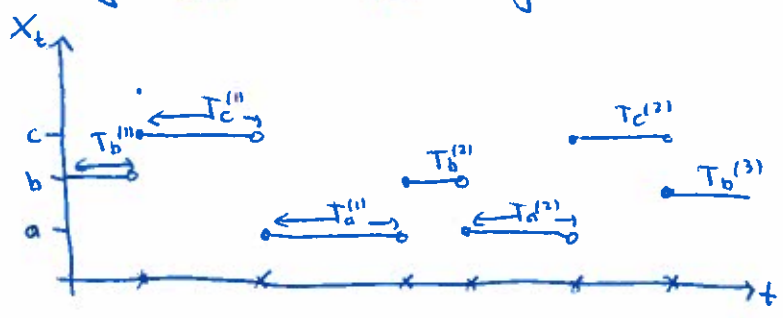


All successive times are exponential.

Nov 30

Continuous Time MC  $(X_t)_{t \geq 0}$

$T_i =$  holding time in state  $i$  given  $X_0 = i = \sup \{t \mid X_s = i \text{ for all } s < t\}$



Let  $T_i^{(1)}, T_i^{(2)}, T_i^{(3)}, \dots$   
 be the successive holding times in state  $i$

Thm: All holding times are exponential rv's, they are all independent of one another. For each  $i$ , there is a  $q_i > 0$  such that each  $T_i^{(n)}$ ,  $n=1,2,-$  are exponential with parameter  $q_i$ .

[ ~~$T_i^{(n)}$~~  has the memoryless property as a consequence of the Markov property.]



Mathematical Issues

Discrete time chains,  $\underline{P}$ ,  $v(i) = E(R_i | X_0=i)$ ,  $i \in S = \{1, \dots, n\}$

the 1<sup>st</sup> step analysis equations are:

$$v(i) = 1 + \sum_{j \neq i} P_{ij} v_j, \text{ each } i \in S: \text{ n linear equations in n unknowns } v(1), v(2), \dots, v(n).$$

Questions:

- ① How do we know these equations have a solution?  
(can compute  $v(i)$ , fulfill the eqn's)
- ② How do we know there cannot be two soln's?  
(not clear for us)

Given MC  $(X_t)_{t \geq 0}$ ,  $\underline{P}(t)_{t \geq 0}$ ,  $P_{ij}(t) = P(X_t=j | X_0=i)$ .

- Holding Times  $T_i$  exp. param.  $q_i$  ↓ Thm
- Embedded discrete time Markov chain  $(Y_n, n=0,1,2,-)$

in ex.:  $Y_0=b, Y_1=c, Y_2=a, Y_3=b, Y_4=a, Y_5=c, Y_6=b, \dots$

with some transition matrix  $\underline{\tilde{P}}$ ,  $\tilde{P}_{ij} = P(Y_1=j | Y_0=i)$ .

$\tilde{P}$  stoch. with diag. entries 0

Continuous time chain  $\rightarrow \begin{cases} q_i \\ \tilde{P}_{ij} \end{cases}$

Example:  $S = \{a, b\}$



$$\underline{\tilde{P}} = \begin{matrix} a & b \\ b & \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \end{matrix}$$

Probl. of Def'n: don't have  $\underline{p}(t)$ .

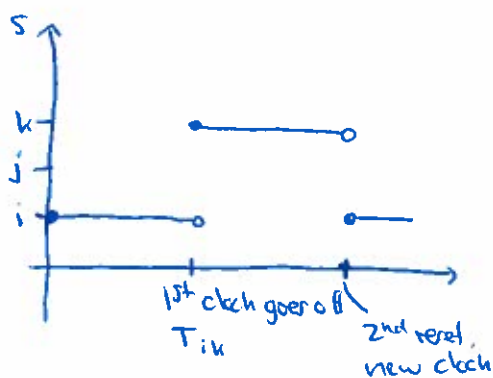
Second description:

"build" MC out of given "alarm clock rates"  $(q_{ij})$ ,  $i \neq j$ ,  $i, j \in S$ ,

each  $q_{ij} \geq 0$  if  $i \neq j$ . def'n  $q_{ii} = 0$ .

Given  $(q_{ij})$

Fix  $i$ ,  $(T_{ij})_{j \in S}$



1. The first jump.

- Fix  $i$ , put  $X_0 = i$  (also  $Y_0 = i$ )
- $\forall j$  with  $q_{ij}$ , imagine an "alarm clock" which goes off after a random time  $T_{ij} \sim \text{Exp}(q_{ij})$
- If the first clock to go off is clock  $k$  ( $T_{ik} < T_{ij}$  all  $j \neq k$ ), then the chain jumps to state  $k$  (put  $Y_1 = k$ )

2. ~~1st~~ 2nd jump

- 1st jump to state  $k \rightarrow$  consider new alarm clocks all set to 0 (indep.  $T_{kj}' \sim \text{Exp}(q_{kj})$ )
- repeat prev. process

3. repeat again and again...

We call  $q_{ij}$  the (instantaneous) rate of jumping from  $i$  to  $j$ .

the (instantaneous) of making a jump away from  $i$  is  $\sum_{j \neq i} q_{ij}$ .

Back to first jump, fixed  $i$ , this time is  $\min\{\text{all } T_{ij}, j \in S\}$

By Prop. last time, this is an exponential, independent exp. rv.

parameter  $\sum_{j \neq i} q_{ij}$

• Start of at state  $i$ ,  $X_0=i$ , set all clocks to 0

• If clock  $(i, a)$  is the 1<sup>st</sup> clock that rings, and it rings at time  $t_1$ , define

$$X_t = \begin{cases} i & \text{for } 0 \leq t < t_1 \\ a & t = t_1 \end{cases}$$

•  $(a, b)$  next clock that rings, at time  $t_2$ , define

$$X_t = \begin{cases} a & t_1 \leq t < t_2 \\ b & t = t_2 \end{cases}$$

Thm:  $(X_t)_{t \geq 0}$  has the Markov property (Refer on memoryless property!)

Def: Given  $(q_{ij})$ , define the associated generator to be the matrix  $\underline{Q} = (Q_{ij})_{i,j \in S}$

where  $Q_{ij} = \begin{cases} q_{ij} & \text{if } j \neq i \\ -\sum_{i \neq j} q_{ij} & \text{if } j = i \end{cases}$

[row sums of  $\underline{Q}$  all 0!]

& neg. diagonal elt's

Ex:  $S = \{a, b, c\}$

$$\underline{Q} = \begin{matrix} & \begin{matrix} a & b & c \end{matrix} \\ \begin{matrix} a \\ b \\ c \end{matrix} & \begin{bmatrix} -(q_{ab}+q_{ac}) & q_{ab} & q_{ac} \\ q_{ba} & -(q_{ba}+q_{bc}) & q_{bc} \\ q_{ca} & q_{cb} & -(q_{ca}+q_{cb}) \end{bmatrix} \end{matrix}$$

Comparison of 2 definitions

(I) Holding times parameters  $q_i$ , discrete time jump matrix  $\tilde{P}_{ij}$

(II)  $q_{ij}$

What are  $q_i, \tilde{P}_{ij}$  for (II)?

$\uparrow$   
 $q_i = \sum_{j \neq i} q_{ij}$

1<sup>st</sup> jump time is exponential, minimum of  $(i,j)$  clocks, so  $\text{Exp}(\sum_{j \neq i} q_{ij})$   
 $\uparrow$   
 $\min\{a_{ll}(i), j \in S, \text{clocks}\}$

(the 1<sup>st</sup> jump time is the same as the 1<sup>st</sup> holding time)  
 $\text{Exp}(q_i)$



How about  $\tilde{P}_{ik} = P(Y_1 = k | Y_0 = i)$ ? Given  $(q_{ij})$

$$= P((i,k) \text{ rthgs } \overset{\text{first of the}}{\text{first before the}} (i,j) \ j \in S)$$

$$= P(T_{ik} < T_{ikj}, j \neq k) = P(T_{ik} = \min\{T_{ij}, j \in S\})$$

$$= \frac{q_{ik}}{\sum_{j \neq i} q_{ij}}$$

That is, given  $(q_{ij})$ ,  $q_i = \sum_{j \neq i} q_{ij}$

$$\tilde{P}_{ik} = \frac{q_{ik}}{\sum_{j \neq i} q_{ij}} = \frac{q_{ik}}{q_i}$$

$$\tilde{P}_{ii} = 0 \quad \forall i \quad (q_{ii} = 0)$$

Thm:  $\underline{Q} = \underline{P}'(0) = \frac{d}{dt} \underline{P}(t) \Big|_{t=0}$  or  $q_{ij} = P'_{ij}(0)$ , all  $i, j$

$(P'_{ij}(t))_{i,j \in S}$

Proof: Recall Chapman-Kolmogorov eqn's,

$$\underline{P}(t+s) = \underline{P}(s) \underline{P}(t) = \underline{P}(t) \underline{P}(s).$$

$$P'_{ij}(0) = \lim_{h \rightarrow 0} \frac{P_{ij}(h) - P_{ij}(0)}{h}$$

① Suppose  $i \neq j$ , then  $P_{ij}(0) = 0$  ( $= 1$  for  $i=j$ ) [ $\underline{P}(0) = \underline{I}$ ]

In this case,  $P'_{ij}(0) = \lim_{h \rightarrow 0} \frac{P_{ij}(h)}{h}$

For small  $h$ ,  $P_{ij}(h) = P(X_h = j | X_0 = i) = P(X_h = j, \text{ only one jump in } [0, h] | X_0 = i) + P(X_h = j, \geq 2 \text{ jumps in } [0, h] | X_0 = i)$

2<sup>nd</sup> term:  $\leq P(T_i + \min_{k \neq i} \{T_{ik}\} \leq h | X_0 = i)$

$\uparrow$   
 $P(\text{Exp}(q_{ii}) + \text{Exp}(\sum_{j \neq i} q_{ij}) \leq h)$

Fact: If  $z_1, z_2$  are independent exponential rv's, parameters  $\lambda_1, \lambda_2$   
 $\Rightarrow P(z_1 + z_2 \leq h) = o(h)$ .

Given this,  $P(X_n=j) \geq \text{two jumps in } [0, h] \mid X_0=i) = o(h)$   
as  $h \rightarrow 0$ .

Recall for the Poisson process  $(N_t)_{t \geq 0}$  rate  $\lambda$   $P(N_h \geq 2) = o(h)$   
 $\uparrow$   
two or more jumps

CTMC  $(X_t)_{t \geq 0}$  Finite state space  $|S| = N$

Dec 5

trans. fct  $\underline{P}(t)$ ,  $P_{ij}(t) = P(X_t=j \mid X_0=i)$ ,  $\underline{P}'(t) = (P'_{ij}(t))$

holding times  $T_i$ , exponential, parameter  $q_i > 0$

independent  $\rightarrow$  embedded chain  $(Y_n)_{n=0,1,\dots}$  trans. matrix  $\underline{\tilde{P}}$

Clock description:  $(q_{ij})_{i \neq j}$ ,  $\underline{Q}_{ij} = \begin{cases} q_{ij}, & i \neq j \\ -\sum_{j \neq i} q_{ij}, & j = i \end{cases}$   
 $\uparrow$   
Generator  $\rightarrow Q_{ii} = -q_i$

$$q_i = \sum_{j \neq i} q_{ij}, \quad \tilde{P}_{ij} = \frac{q_{ij}}{q_i}$$

Thm:  $\underline{P}'(0) = \underline{Q}$ .

Sketch of pf: For  $i \neq j$ ,  $P'_{ij}(0) = \lim_{h \rightarrow 0} \frac{P_{ij}(h) - P_{ij}(0)}{h}$

$$P_{ij}(h) = P(X_h=j \mid X_0=i) = P(X_h=j, \geq 2 \text{ jumps in } [0, h] \mid X_0=i)$$

$$+ P(X_h=j, 1 \text{ jump in } [0, h] \mid X_0=i)$$

$$= o(h) + P(T_i < h, \text{ one jump, } \tilde{Y}_1=j \mid X_0=i)$$

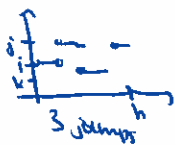
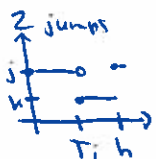
$$= o(h) + [P(T_i < h, \tilde{Y}_1=j \mid X_0=i) + o(h)]$$

$$= P(T_i < h, \tilde{Y}_1=j \mid X_0=i) + o(h)$$

$$= P(T_i < h \mid X_0=i) P(\tilde{Y}_1=j \mid X_0=i) + o(h)$$

$$= (1 - e^{-q_i h}) \cdot \frac{q_{ij}}{q_i} + o(h)$$

$$= (q_i h + o(h)) \cdot \frac{q_{ij}}{q_i} + o(h) = q_{ij} h + o(h)$$



Fact:  $1 - e^{-\lambda h} = \lambda h + o(h)$   
(use l'Hopital's Rule)

$$\text{So, } P_{ij}'(0) = \lim_{h \rightarrow 0} \frac{q_{ij} h + o(h)}{h} = \lim_{h \rightarrow 0} \left[ q_{ij} + \frac{o(h)}{h} \right] = q_{ij} + 0 \quad \checkmark$$

This shows  $P_{ij}'(0) = q_{ij}$ ,  $i \neq j$ .

The case  $j=i$  is easier.

“0”

Thm (p. 275):  $\underline{Q}$  determines  $\underline{P}(t)$ ,  $t \geq 0$  by either of:

$$\underline{P}'(t) = \underline{P}(t) \underline{Q} \quad (\text{forward eqn's})$$

$$\underline{P}'(t) = \underline{Q} \underline{P}(t) \quad (\text{backward eqn's})$$

Each of these is a system of  $N^2$  coupled differential equations.  
[ $N=N, S$  statespace for CTMC]

In component form,

$$P_{ij}'(t) = \sum_k P_{ik}(t) Q_{kj}$$

$$= -P_{ii}(t)$$

$$= -q_i P_{ij}(t) + \sum_{k \neq j} P_{ik}(t) Q_{kj}$$

$$\uparrow$$

$u=j$  term:  $Q_{ji} = -q_j$

Proof: Use C-K eqns,  $\underline{P}(s+t) = \underline{P}(s) \underline{P}(t)$ , or  $\underline{P}(t+h) = \underline{P}(h) \underline{P}(t) = \underline{P}(t) \underline{P}(h)$

$$\Rightarrow \underline{P}'(t) = \lim_{h \rightarrow 0} \frac{\underline{P}(t+h) - \underline{P}(t)}{h} = \lim_{h \rightarrow 0} \frac{\underline{P}(h) \underline{P}(t) - \underline{P}(t)}{h}$$

$$= \lim_{h \rightarrow 0} \frac{(\underline{P}(h) - \underline{I}) \underline{P}(t)}{h} \quad \underline{I} = \underline{P}(0)$$

$$= \lim_{h \rightarrow 0} \left( \frac{\underline{P}(h) - \underline{P}(0)}{h} \right) \underline{P}(t) = \underline{P}'(0) \underline{P}(t) \stackrel{\text{thm}}{=} \underline{Q} \underline{P}(t)$$

This is the system of backward equations.

Example:

2 states



$$\underline{Q} = \begin{bmatrix} -\lambda & \mu \\ \lambda & -\mu \end{bmatrix}$$

(FE) Write  $\underline{P}_{ii}'(t)$  ( $i=j=1$ )

$$= -q_1 P_{11}(t) + P_{12}(t) q_{21} = -\lambda P_{11}(t) + \mu P_{12}(t)$$

$$\underline{P}(t) = \begin{bmatrix} P_{11}(t) & P_{12}(t) \\ P_{21}(t) & P_{22}(t) \end{bmatrix}$$

$$(BE) \quad \underline{P}'(t) = \sum_{k=1}^2 q_{1k} P_{k1}(t) = q_{12} P_{21}(t) + q_{11} P_{11}(t)$$

$$= \underline{-\lambda P_{11}(t) + \lambda P_{21}(t)}$$

In (FE) can use  $P_{11}(t) + P_{12}(t) = 1$

$$\begin{aligned} \Rightarrow \underline{P_{11}'(t)} &= -\lambda P_{11}(t) + \mu P_{12}(t) \\ &= -\lambda P_{11}(t) + \mu (1 - P_{11}(t)) \\ &= \underline{P_{11}(t) (-(\lambda + \mu)) + \mu} \end{aligned}$$

$$P_{11}(0) = 1$$

Let  $y = y(t) = P_{11}(t)$

$$y' = -(\lambda + \mu)y + \mu$$

$$y' + (\lambda + \mu)y = \mu, \quad y(0) = 1.$$

1<sup>st</sup> order, linear, constant coeff. diff. eqn.

Solution if  $\mu = 0$ :  $y = C_1 e^{-(\lambda + \mu)t} + C_2$ ,  $C_1, C_2$  are constants

$$\text{Check: } y' = -C_1 (\lambda + \mu) e^{-(\lambda + \mu)t} + 0$$

$$y' + (\lambda + \mu)y = -C_1 (\lambda + \mu) e^{-(\lambda + \mu)t} + (\lambda + \mu) [C_1 e^{-(\lambda + \mu)t}] + C_2$$

$$= (\lambda + \mu) C_2 \stackrel{!}{=} \mu \quad \Rightarrow C_2 = \frac{\mu}{\lambda + \mu}$$

$$\Rightarrow y = C_1 e^{-(\lambda + \mu)t} + \frac{\mu}{\lambda + \mu}$$

$$\text{Set } t=0, y(0) = C_1 \cdot 1 + \frac{\mu}{\lambda + \mu} \stackrel{!}{=} 1 \Rightarrow C_1 = 1 - \frac{\mu}{\lambda + \mu} = \frac{\lambda}{\lambda + \mu}$$

$$\Rightarrow P_{11}(t) = \frac{\lambda}{\lambda + \mu} e^{-(\lambda + \mu)t} + \frac{\mu}{\lambda + \mu}$$

$$\Rightarrow P_{12}(t) = -\frac{\lambda}{\lambda + \mu} e^{-(\lambda + \mu)t} + \frac{\lambda}{\lambda + \mu}. \quad (P_{11}(t) + P_{12}(t) = 1)$$

$$\underline{P}(t) = \frac{1}{\lambda + \mu} \begin{bmatrix} \lambda e^{-(\lambda + \mu)t} + \mu & \lambda - \lambda e^{-(\lambda + \mu)t} \\ \mu - \mu e^{-(\lambda + \mu)t} & \lambda + \mu e^{-(\lambda + \mu)t} \end{bmatrix}$$

Note  $\lim_{t \rightarrow 0} \underline{P}(t) = \begin{bmatrix} \frac{\mu}{\lambda + \mu} & \frac{\lambda}{\lambda + \mu} \\ \frac{\mu}{\lambda + \mu} & \frac{\lambda}{\lambda + \mu} \end{bmatrix}$

### 7.3 Long Term Behaviour

Def: A probability distribution  $\underline{\pi}$  is the limiting distribution of  $(X_t)_{t \geq 0}$  if  $\lim_{t \rightarrow \infty} P_{ij}(t) = \pi_j$ , all  $i, j$ .

A prob. dist.  $\underline{\pi}$  is a stationary dist. if  $\underline{\pi} \underline{P}(t) = \underline{\pi}$  for all  $t \geq 0$ .

#### Thm 7.2

Let  $(X_t)_{t \geq 0}$  be a finite state space, irreducible continuous time MC, with transition fct.  $\underline{P}(t)$ .

Then there exists a unique stationary distribution  $\underline{\pi}$  which is also the limiting dist.

$$\pi_j = \lim_{t \rightarrow \infty} P(X_t = j | X_0 = i) \text{ for all } i, j.$$

def'n of "irreducible"

discrete time:  $\forall i, j \quad P_{ij}^n > 0$  for some  $n$

cont. time:  $\forall i, j \quad P_{ij}(t) > 0$  for some  $t$  (depending on  $i, j$ )

[discrete time: need "aperiodic" to get the thm] <sup>counter example:  $\underline{P} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$</sup>

Lemma: If for some  $t$ ,  $P_{ij}(t) > 0$ , then  $P_{ij}(s) > 0$  for all  $s > 0$ .

(Periodicity is impossible [for CTMC]).

Example:  $\underline{Q} = \begin{bmatrix} -\lambda & \lambda \\ \mu & -\mu \end{bmatrix}$ ,  $\pi_1 = \frac{\mu}{\lambda + \mu}$ ,  $\pi_2 = \frac{\lambda}{\lambda + \mu}$ . (limiting dist.)

Can check:  $\underline{\pi} \underline{P}(t) = \underline{\pi}$  for all  $t > 0$ .

Question: How do we find  $\pi$ ?

Thm: (p. 286)

A prob. dist.  $\pi$  is a stationary dist. for a MC with generator  $Q$  iff  $\pi Q = 0$ .

Proof: (a) Suppose  $\pi$  is stationary, then  $\pi P(t) = \pi$  for all  $t > 0$ .

$$\text{Then } \pi P(t) - \pi = 0 \quad \forall t > 0$$

$$\Leftrightarrow \pi (P(t) - I) = 0 \quad \forall t > 0 \quad [I = P(0)]$$

$$\Leftrightarrow \pi (P(t) - P(0)) = 0 \quad \text{for all } t > 0$$

$$\Rightarrow \pi \left( \frac{P(t) - P(0)}{t} \right) = 0 \quad \text{---}$$

$$\text{Let } t \rightarrow 0, \text{ get } \pi P'(0) = 0 \quad \text{or } \pi Q = 0.$$

(b) Suppose  $\pi Q = 0$ . Then.

$$0 = \pi Q \quad \Rightarrow \quad 0 = Q P(t) = \pi Q P(t) \stackrel{\text{BE}}{=} \pi P'(t) \quad \forall t > 0$$

$$\text{BE: } P'(t) = Q P(t)$$

This implies  $\pi P(t)$  must be constant in  $t$ .

$$\text{Put } t=0 \quad \underbrace{\text{the constant must be}}_{\pi P(0)} \quad \pi P(0) = \pi I = \pi.$$

$$\Rightarrow \pi P(t) = \pi \quad \forall t > 0, \text{ or } \pi \text{ is stationary. } \quad \square$$

Dec 7

Fact: CTMS cannot be periodic.

Thm 7.2: --

$\pi_j$  represents the long term expected proportion of time

$$\text{spent in state } j, \quad \pi_j = \lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t P(X_t = j \mid X_0 = i) dt.$$

Lemma: If  $P(X_t = j | X_0 = i) > 0$  for some  $t > 0$  then

$$P(X_s = j | X_0 = i) > 0 \text{ for all } s > 0.$$

Partial pf. Assume  $P_{ij}(t) > 0$  for some  $t$ , fixed. Let  $s > t$ .

The idea to show  $P_{ij}(s) > 0$  is . One way this can happen is to have  $X_t = j$  and then have the chain stay at  $j$  for  $(s-t)$  time.

$$P_{ij}(s) = (P(t) \cdot P(s-t))_{ij} = \sum_{k \in S} P_{ik}(t) P_{kj}(s-t) \geq P_{ij}(t) P_{jj}(s-t)$$

Take any state  $a$ , and any time  $u$ ,

$$\begin{aligned} P_{aa}(u) &= P(X_u = a | X_0 = a) \geq P(X_v = a \text{ for all } 0 \leq v \leq u | X_0 = a) \\ &= P(T_a > u | X_0 = a) \stackrel{\substack{| \\ T_a \text{ expn. i.v.}}}{=} e^{-q_a u} \end{aligned}$$

$$\Rightarrow P_{ij}(s) \geq P_{ij}(t) e^{-q_j(s-t)} > 0 \quad \square$$

Thm:  $\pi$  is the stationary dist. if and only if  $\pi Q = 0$ .

( $Q$  is the generator.)

Example 7.14. A baby has 3 possible states:

e (eating), s (sleeping), p (playing).

The baby eats on average for  $\frac{1}{2}$  hr, plays on average for 1 hr, and sleeps on av. 3 hrs. After eating, the baby has a 50%

chance of sleeping or playing, after playing, there is a 50%

chance of eating or sleeping, after sleeping, the baby always plays.

What proportion of the day does the baby spend sleeping?

Let  $(X_t)$  be a cont. time MC,  $X_t =$  the state of the baby at time  $t$ , either e, s, p.

We want  $\pi$ , so we need  $\underline{Q}$ .

We know?  $q_e, q_p, q_s$

Assume the times spent in the states are exponential rv's.

$q_e =$  parameter of holding time  $T_e \Rightarrow$  (expected value of an exponential rv. with param.  $\lambda$  is  $\frac{1}{\lambda}$ )  
 $= \frac{1}{1/2} = 2$ .

$$q_p = \frac{1}{1} = 1$$

$$q_s = \frac{1}{3}$$

We know  $\tilde{P}$  embedded chain matrix (for  $Y_h$ )

$$\tilde{P} = \begin{matrix} & \begin{matrix} e & p & s \end{matrix} \\ \begin{matrix} e \\ p \\ s \end{matrix} & \begin{bmatrix} 0 & 1/2 & 1/2 \\ 1/2 & 0 & 1/2 \\ 0 & 1 & 0 \end{bmatrix} \end{matrix} \quad \text{[always 0 on diagonal]}$$

Recall  $\tilde{P}_{ij} = \frac{q_{ij}}{q_i} \quad (i \neq j) \Rightarrow q_{ij} = q_i \tilde{P}_{ij}$

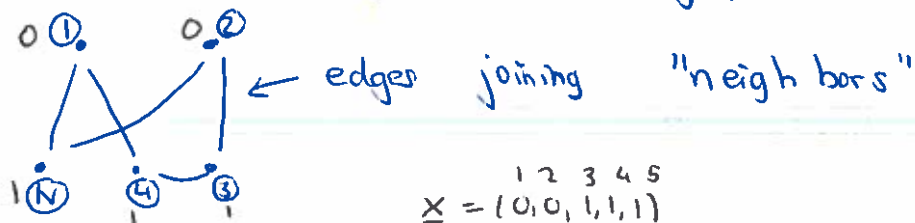
$$\underline{Q} = \begin{matrix} & \begin{matrix} e & p & s \end{matrix} \\ \begin{matrix} e \\ p \\ s \end{matrix} & \begin{bmatrix} -2 & 1 & 1 \\ 1/2 & -1 & 1/2 \\ 0 & 1/3 & -1/3 \end{bmatrix} \end{matrix}$$

Solve  $[\pi_e \ \pi_p \ \pi_s] \begin{bmatrix} -2 & 1 & 1 \\ 1/2 & -1 & 1/2 \\ 0 & 1/3 & -1/3 \end{bmatrix} = [0 \ 0 \ 0]$

$$\Rightarrow \underline{\pi} = \left[ \frac{1}{14} \quad \frac{4}{14} \quad \frac{9}{14} \right], \quad \pi_s = \frac{9}{14}.$$

## Contact Process

Simple model for "infection" on a graph,  $N$  vertices.



$$x = (0, 1, 1, 1, 1)$$



At each time unit, a vertex is either infected (1) or healthy (0). The state of the system  $\underline{x} = (x(1), x(2), \dots, x(N))$

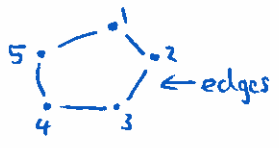
where 
$$x(i) = \begin{cases} 1 & \text{if vertex } i \text{ is infected} \\ 0 & \text{if } \dots \dots \dots \text{ healthy} \end{cases}$$

(Our state space consists of  $N$ -tuples of 1's + 0's)

Let  $X_t =$  the state of our system at time  $t$   
 $= (x_t(1), x_t(2), \dots, x_t(N))$ .

Assume

- ① an infected vertex "recovers" independently of everything else at exponential rate 1 [Time to recover is an expon. rv, param. 1]
- ② We have a parameter  $\lambda > 0$  such that:  
 a healthy vertex <sup>becomes</sup> is infected at expm. rate  $\lambda \cdot (\# \text{ of infected neighbors})$
- ③ Only a single vertex can change at an instant.  
 (flip from 0 to 1 or 1 to 0)



Current State	$i$	$2$	$3$	$4$	$5$	$(0, 0, 1, 1, 0)$	$\rightarrow (0, 0, 0, 1, 0)$ rate 1
Next State could be						$(0, 0, 1, 1, 1)$	at rate $\lambda \cdot 1$

Notation:

Given  $x = (x(1), x(2), \dots, x(N))$

define  $x^i$  the same as  $x$  except coordinate  $i$  is flipped

$$x^i(j) = \begin{cases} x(j) & \text{if } j \neq i \\ 1-x(i) & \text{if } j = i \end{cases}$$

Define  $Q$  for  $(X_t)$  by:

for  $x = (x(1), \dots, x(N)), y = (y(1), \dots, y(N))$

$$q_{xy} = \begin{cases} 1 & \text{if } y = x^i \text{ and } x(i) = 1 \\ \lambda \cdot \# \text{ of infected} & \text{if } y = x^i \text{ and } x(i) = 0 \\ \text{neighbors of } i \text{ in } x & \end{cases} \quad \text{for any } i$$

This defines  $\underline{Q}$ , and therefore also  $(X_t)_{t \geq 0}$ .

Question: What happens as  $t \rightarrow \infty$ ?

① nothing if  $X_0 = (0, 0, \dots, 0)$

② Take  $X_0 \neq (0, 0, \dots, 0)$

Take the graph to be  $\mathbb{Z}$



nearest neighbor case.

Thm: Start with a finite nr of infected individuals. There is a critical value  $\lambda_c$ ,  $0 < \lambda_c < \infty$ , such that:

subcritical case: if  $\lambda < \lambda_c$ , then  $X_t$  becomes extinct eventually  $X_t = 0$

supercritical case: if  $\lambda > \lambda_c$ , then  $X_t$  survives for all time with positive probability

critical case: if  $\lambda = \lambda_c$

$\lambda_c$  unknown, but believed to be  $\approx 1.65$  (Simulation)

Rigorous:  $1 \leq \lambda \leq 2$ .

Final Exam: • Friday Dec 15, 8-10 am, 115 Carnegie

• Approx.  $\frac{2}{3}$  will be devoted to last  $\frac{1}{3}$  of course

$\frac{1}{3}$  will approx. uniform over the whole course

• All HW solutions are now in the library

• Graded HW set 10 - will be outside my office starting at noon Monday

1. 2. 3. 4. 5. 6. 7. 8. 9. 10. 11. 12. 13. 14. 15. 16. 17. 18. 19. 20. 21. 22. 23. 24. 25. 26. 27. 28. 29. 30. 31. 32. 33. 34. 35. 36. 37. 38. 39. 40. 41. 42. 43. 44. 45. 46. 47. 48. 49. 50. 51. 52. 53. 54. 55. 56. 57. 58. 59. 60. 61. 62. 63. 64. 65. 66. 67. 68. 69. 70. 71. 72. 73. 74. 75. 76. 77. 78. 79. 80. 81. 82. 83. 84. 85. 86. 87. 88. 89. 90. 91. 92. 93. 94. 95. 96. 97. 98. 99. 100.

# Appendix B (B.1, B.2, B.3)

-  $F(x) = P(X \leq x)$  cumulative distr. fct (cdf) of  $X$

-  $X$  random var., discrete r.v. if values in a finite / countably inf. set

$P(X=x)$  prob. mass fct (pmf) of  $X$

joint pmf of  $X$  and  $Y$ :  
 $P(X=x, Y=y)$

$$R \subset \mathbb{R} \rightarrow P(X \in R) = \sum_{x \in R} P(X=x)$$

expectation / mean:  $E(X) = \sum_x x P(X=x)$

$$Y = g(X) \rightarrow E(Y) = \sum_x g(x) P(X=x) = \sum_y y P(Y=y)$$

$$E(aX+b) = aE(X) + b, \quad E(X+Y) = E(X) + E(Y)$$

Variance:  $\text{Var}(X) = E((X - E(X))^2) = E(X^2) - (E(X))^2$

$$\text{Var}(aX+b) = a^2 \text{Var}(X)$$

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y)$$

standard deviation:  $SD(X) = \sqrt{\text{Var}(X)}$

Covariance:  $\text{Cov}(X, Y) = E(XY) - E(X)E(Y)$

correlation:  $\text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{SD(X)SD(Y)}$

events  $A, B$  independent:  $P(A \cap B) = P(A)P(B)$

$$\Leftrightarrow P(X=x, Y=y) = P(X=x)P(Y=y) \quad \forall x, y$$

$$X, Y \text{ indep.} \Rightarrow E(XY) = E(X) \cdot E(Y) \Rightarrow \text{Cov}(X, Y) = 0$$

Cts r.v.  $\rightarrow P(X=x) = 0 \quad \forall x \in \mathbb{R} \setminus \{0, \infty\} / (a, b)$

$\rightarrow$  prob. density fct  $f$ :  $f \geq 0, \int_{-\infty}^{\infty} f = 1, P(X \in R) = \int_R f dx, R \in \mathbb{R}$

cdf:  $F(x) = P(X \leq x) = \int_{-\infty}^x f(t) dt \rightarrow F'(x) = f(x)$

Ex:  $f(x) = cx^2, 0 < x < 3 \rightarrow 1 = \int_0^3 f(x) dx = \int_0^3 cx^2 = 9c \rightarrow c = \frac{1}{9}$

$$P(1 < X < 2) = \int_1^2 f(x) dx = \frac{7}{27}$$

$Y = X^2$  density fct?  $F(y) = P(Y \leq y) = P(X^2 \leq y) = P(X \leq \sqrt{y})$

$$\rightarrow f_Y(y) = \frac{d}{dy} P(X \leq \sqrt{y}) = \frac{1}{2\sqrt{y}} f_X(\sqrt{y}) = \frac{1}{2\sqrt{y}} \cdot \frac{y}{9} = \frac{\sqrt{y}}{18}, 0 < y < 9$$

$$E(X) = \int_{-\infty}^{\infty} x f(x) dx, \quad \text{Var}(X) = \int_{-\infty}^{\infty} (x - E(X))^2 f(x) dx$$

$X, Y$  cts  $\rightarrow$  joint density of  $X, Y$ :  $f(x, y)$  with  $D(x, y) \subset \mathbb{R}^2 = \{(x, y) \mid f(x, y) > 0\} \subset \mathbb{R}^2$

**MAT 526**  
**Little oh notation.**

**Definition**

For a function  $f$  to say  $f(x)$  is little oh of  $x$  as  $x$  goes to 0 means that  $\lim_{x \rightarrow 0} \frac{f(x)}{x} = 0$ .

For this we write

$$f(x) = o(x) \text{ as } x \rightarrow 0$$

More generally, for two functions  $f, g$ ,

$$f(x) = o(g(x)) \text{ as } x \rightarrow a \text{ means that } \lim_{x \rightarrow a} \frac{f(x)}{g(x)} = 0$$

and

$$g(x) = f(x) + o(x) \text{ means } g(x) - f(x) = o(x)$$

**Intuitively:** The informal interpretation of " $f(x) = o(x)$  as  $x$  approaches 0" is:

$f(x)$  is much smaller than  $x$  or is negligible compared to  $x$  when  $x$  is small.

**Example (Exercise)**

Determine which of the following statements is true. Hint: Use L'Hôpital's Rule.

- (a)  $x^2 = o(x)$  as  $x \rightarrow 0$  ✓
- (b)  $\sqrt{x} = o(x)$  as  $x \rightarrow 0$  NO
- (c)  $\sin x = o(x)$  as  $x \rightarrow 0$  NO
- (d)  $\cos(x) = 1 + o(x)$  as  $x \rightarrow 0$  ✓
- (e)  $e^{2x} = 1 + 2x + o(x)$  as  $x \rightarrow 0$  ✓

Here is some numerical evidence. For " $x$  small" consider  $x = .01$  and  $x = .0001$ .

| $f(x)$                           | $x^2$       | $\sqrt{x}$ | $\sin x$    | $1 - \cos x$             | $e^{2x} - 1 - 2x$ |
|----------------------------------|-------------|------------|-------------|--------------------------|-------------------|
| $\frac{f(x)}{x} \Big _{x=.01}$   | 0.0100000   | 10.0000    | 0.999983    | 0.00499996               | 0.0201340         |
| $\frac{f(x)}{x} \Big _{x=.0001}$ | 0.000100000 | 100.000    | 0.999999983 | $5.00000 \times 10^{-6}$ | 0.000200013       |



### First-Step Analysis Equations

Let  $(X_n)$  be a Markov chain with finite state space  $\mathcal{S}$  with transition matrix  $\underline{P}$ . For  $a \in \mathcal{S}$  define

$$H_a = \begin{cases} +\infty & \text{if } X_n \neq a \text{ for all } n \geq 0 \\ \min\{n \geq 0 : X_n = a\} & \text{otherwise} \end{cases}$$

$$R_a = \begin{cases} +\infty & \text{if } X_n \neq a \text{ for all } n \geq 1 \\ \min\{n \geq 1 : X_n = a\} & \text{otherwise} \end{cases}$$

Note that if  $X_0 = i \neq a$  then  $H_a = R_a$ .

**Theorem (1).** Fix a state  $a$ , and for  $i \in \mathcal{S}$  define

$$u(i) = P(H_a < \infty \mid X_0 = i) \tag{1}$$

$$v(i) = E(R_a \mid X_0 = i) \tag{2}$$

Then

$$u(i) = P_{ia} + \sum_{j \neq a} P_{ij} u(j), \quad \text{all } i \neq a \tag{3}$$

$$v(i) = 1 + \sum_{j \neq a} P_{ij} v(j), \quad \text{all } i \tag{4}$$

**Theorem (2).** Fix a set of states  $B$  and define

$$H_B = \min\{H_a, a \in B\} \quad \text{and} \quad R_B = \min\{R_a, a \in B\},$$

and

$$u_B(i) = P(H_B < \infty \mid X_0 = i) \quad \text{and} \quad v_B(i) = E(R_B \mid X_0 = i)$$

Then

$$u_B(i) = \sum_{j \in B} P_{ij} + \sum_{j \notin B} P_{ij} u_B(j), \quad \text{all } i \notin B \tag{5}$$

$$v_B(i) = 1 + \sum_{j \notin B} P_{ij} v_B(j), \quad \text{all } i$$

**Remark.** Theorem (1) is a special case of Theorem (2) (take  $B = \{a\}$ ).

**Exercise 1.** Prove (3) using equation (5) below, and the fact that

$$u(i) = P(H_a < \infty \mid X_0 = i) = \lim_{k \rightarrow \infty} P(H_a \leq k \mid X_0 = i)$$

*Hint.* Apply the “complement rule” in (5).

**Exercise 2.** Prove (4) using equation (6) below and the fact (see Lemma on Homework Set #5),

$$E(R_a \mid X_0 = i) = \sum_{k=0}^{\infty} P(R_a > k \mid X_0 = i) = 1 + \sum_{k=1}^{\infty} P(R_a > k \mid X_0 = i)$$

*Hint:* Interchange order of summation appropriately.

**Lemma.** For all  $k \geq 1$ ,

$$P(H_a > k \mid X_0 = i) = \sum_{j \neq a} P_{ij} P(H_a > k - 1 \mid X_0 = j) \quad \text{all } i \neq a \quad (5)$$

$$P(R_a > k \mid X_0 = i) = \sum_{j \neq a} P_{ij} P(R_a > k - 1 \mid X_0 = j) \quad \text{all } i \quad (6)$$

*Proof.* Consider (5). By the definition of  $H_a$ , for  $X_0 \neq a$ ,

$$\{H_a > k\} = \{X_m \neq a \text{ for all } 1 \leq m \leq k\}. \quad (7)$$

Summing in (7) over the possible states for  $X_m$ ,  $1 \leq m \leq k$ , and using the ‘‘multiplication rule’’, we get

$$\begin{aligned} P(H_a > k \mid X_0 = i) &= \sum_{x_1 \neq a} \sum_{x_2 \neq a} \cdots \sum_{x_k \neq a} P(X_1 = x_1, \dots, X_k = x_k \mid X_0 = i) \\ &= \sum_{x_1 \neq a} \sum_{x_2 \neq a} \cdots \sum_{x_k \neq a} P(X_2 = x_2, \dots, X_k = x_k \mid X_1 = x_1, X_0 = i) P(X_1 = x_1 \mid X_0 = i) \\ &= \sum_{x_1 \neq a} P_{ix_1} \left[ \sum_{x_2 \neq a} \cdots \sum_{x_k \neq a} P(X_2 = x_2, \dots, X_k = x_k \mid X_1 = x_1, X_0 = i) \right] \end{aligned} \quad (8)$$

By the Markov property and then time homogeneity, the probabilities in (8) are

$$\begin{aligned} P(X_2 = x_2, \dots, X_k = x_k \mid X_1 = x_1, X_0 = i) &= P(X_2 = x_2, \dots, X_k = x_k \mid X_1 = x_1) \\ &= P(X_1 = x_2, \dots, X_{k-1} = x_k \mid X_0 = x_1) \end{aligned} \quad (9)$$

By (9), the term in (8) in brackets equals

$$\begin{aligned} \sum_{x_2 \neq a} \cdots \sum_{x_k \neq a} P(X_1 = x_2, \dots, X_{k-1} = x_k \mid X_0 = x_1) \\ = P(X_1 \neq a, X_2 \neq a, \dots, X_{k-1} \neq a \mid X_0 = x_1) = P(H_a > k - 1 \mid X_0 = x_1) \end{aligned}$$

Plugging this into (8) and changing variables gives

$$P(H_a > k \mid X_0 = i) = \sum_{x_1 \neq a} P_{ix_1} P(H_a > k - 1 \mid X_0 = x_1) = \sum_{j \neq a} P_{ij} P(H_a > k - 1 \mid X_0 = j) \quad (10)$$

which is (5).

The proof of (6) is similar.  $\square$



# Examples:

## Gambler's Ruin

- gambler places sequence of independent bets w/ prob.  $0 \leq p \leq 1$ .
- on each bet gambler's fortune goes up \$1 or down \$1
- $S_n \stackrel{\text{def}}{=} \text{gambler's fort. at time } n, n=0, 1, 2, 3, \dots$  - prob  $p$  prob  $q=1-p$
- $S_0 \stackrel{\text{def}}{=} \dots$  initial fort. (given)
- g. "ruined" if  $S_n = 0$ , some  $n$
- "target" level  $N$

given  $p, N, S_0 = k, k=0, 1, 2, \dots, N$   $x_k \stackrel{\text{def}}{=} P(\text{ruin} | S_0 = k) = ?$

$x_0 = 1, x_N = 0$

$x_k = px_{k+1} + qx_{k-1}, 1 \leq k \leq N-1$  (up w/ prob.  $p$ , down w/ prob.  $q$ )  
difference eqn

## LOTP

2 boxes, Box #1: 4 red, 8 green chips; Box #2: 9 red, 6 green chips  
 select #1 w/ prob.  $1/6$ , #2 w/ prob.  $5/6$ ; then draw a chip from selected box. Prob. the chip is red?

$A = \{\text{sel. chip is red}\}, B_1 = \{\text{select box \#1}\}, B_2 = \{\dots \text{\#2}\} \Rightarrow B_1, B_2$  form a partition:  $B_1 \cap B_2 = \emptyset, B_1 \cup B_2 = \Omega, P(B_1) = 1/6, P(B_2) = 5/6$   
 $P(A|B_1) = 4/12, P(A|B_2) = 9/15 \Rightarrow P(A) = P(A|B_1)P(B_1) + P(A|B_2)P(B_2) = \dots = \frac{10}{18}$

## Gambler's Ruin

→ Markov chain:  $X_n \stackrel{\text{def}}{=} \text{gambler's fort. at time } n$ ; sequ. of bets are independent w/  $P(\text{win}) = p, P(\text{lose}) = q = 1-p$   
 $X_{n+1} = \begin{cases} X_n + 1 & \text{w/ prob. } p \\ X_n - 1 & \text{w/ prob. } q \end{cases}$  does not depend on  $X_{n-1}, \dots, X_0$ .

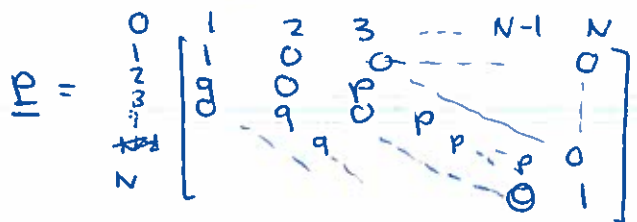
→ time-homog.:  $P(X_{n+1} = k+1 | X_n = k) = p \forall n$

Target level  $N$ , win prob.  $p, (X_n)$ .

What is  $P$ ?

$$P_{ij} = \begin{cases} 1 = P_{00} & \text{if } i=j=0 \\ p & \text{if } j=i+1 \\ q & \text{if } j=i-1 \\ 1 = P_{NN} & \text{if } i=j=N \end{cases} \text{ if } 0 < i < N$$

and all other  $P_{ij}$  equal 0



$q = 1 - p$

→ stoch. matrix

$$\pi_0 = \frac{q-p}{2q}, \pi_j = \frac{q-p}{2q} \left(\frac{p}{q}\right)^{j-1} \text{ for } j \geq 1.$$

It suffices to consider state 0.

$$P(R_0 < \infty | X_0 = 0) = P(H_0 < \infty | X_0 = 1) \quad (\text{Starting at 1, } H_0 = R_0)$$

$\uparrow$  1st time after time 0       $\uparrow$  1st time including time 0

Put  $u(i) = P(H_0 < \infty | X_0 = i), i \geq 0$  (really want just  $i=1$ ).

$$\text{Then } u(i) = P_{i0} + \sum_{j \neq 0} P_{ij} u(j)$$

For  $i \geq 2, P_{i0} = 0$  and  $u(i) = pu(i+1) + qu(i-1)$  or  $pu(i+1) - u(i) + qu(i-1) = 0$

$$u(i) = \begin{cases} A + Bi, & p = \frac{1}{2} \\ A + B\left(\frac{q}{p}\right)^i, & p \neq \frac{1}{2}. \end{cases} \quad (\text{DE HW}) \quad \text{Consider } u(1) = P_{10} + P_{12} u(2), u(0) = 1$$

$$= P_{10} u(0) + P_{12} u(2) = pu(2) + qu(0)$$

$p = \frac{1}{2}$ :  $u(i) = A + Bi$

If  $B \neq 0, \lim_{i \rightarrow \infty} |u(i)| = +\infty$ , impossible, all  $u(i)$  are between 0 and 1.

$$\Rightarrow u(i) = A \quad \forall i \geq 1. \quad \text{Consider } i=1, u(1) = \frac{1}{2} + \frac{1}{2}u(2) \Rightarrow A = \frac{1}{2} + \frac{1}{2}A \Rightarrow A = 1 \Rightarrow u(i) = 1 \text{ all } i \geq 1$$

$$\Rightarrow P(R_0 < \infty | X_0 = 0) = u(1) = 1 \Rightarrow \text{recurrence.}$$

$p < \frac{1}{2}$ :  $u(i) = A + B\left(\frac{q}{p}\right)^i, i \geq 1$ . Since  $\frac{q}{p} > 1, \left(\frac{q}{p}\right)^i \rightarrow \infty$  as  $i \rightarrow \infty$ . If  $B \neq 0$ , then  $|u(i)| \rightarrow \infty$  as  $i \rightarrow \infty$ , impossible.  $\Rightarrow B = 0 \Rightarrow u(i) = A, \text{ all } i \geq 1$ .

$$i=1: u(1) = q + pu(2) \Rightarrow A(1-p) = q$$

$$A = q + pA \quad Aq = q \Rightarrow A = 1 \Rightarrow u(i) = 1, \text{ all } i \geq 1$$

$$\Rightarrow P(R_0 < \infty | X_0 = 0) = u(1) = 1 \Rightarrow \text{recurrence.}$$

$p \leq \frac{1}{2} \Rightarrow$  recurrence.

$p > \frac{1}{2}$ : In analogy with random walk on  $\{0, \pm 1, \pm 2, \dots\}$  which is transient for  $p > \frac{1}{2}$ , we get transience. [got this by showing  $\sum_{n=0}^{\infty} P_{00}^{2n} < \infty$ ]

$\Rightarrow$  know:  $p > \frac{1}{2}$ : transient  
 $p \leq \frac{1}{2}$ : recurrent case.

Positive vs null recurrence?  
 if there is a stat. dist.      if there is no stat. dist.

$$\pi_j = \sum_{i=0}^{\infty} \pi_i P_{ij} \quad \leftarrow \text{can be solved or not with } \sum_{j=0}^{\infty} \pi_j = 1.$$

$$P_{ij} > 0? \quad i=j-1 \text{ or } i=j+1$$

$$\pi_j = \pi_{j-1} p + \pi_{j+1} q \quad \text{for } j \geq 2.$$

$$j=0: \pi_0 = \sum_{i=0}^{\infty} \pi_i P_{i0} = \pi_1 P_{10} = q \pi_1 \quad \pi_1 = \frac{1}{q} \pi_0$$

$$j=1: \pi_1 = \sum_{i=0}^{\infty} \pi_i P_{i1} = \pi_0 P_{01} + \pi_2 P_{21} = \pi_0 + \pi_2 q \Rightarrow q \pi_2 = \pi_1 - \pi_0 = \frac{1}{q} \pi_0 - \pi_0 = \pi_0 \left(\frac{1}{q} - 1\right)$$

$$\Rightarrow \pi_2 = \frac{\frac{1}{q} - 1}{q} \cdot \frac{1}{q} \pi_0 = \frac{1-q}{q^2} \pi_0 = \frac{p}{q^2} \pi_0$$

$$\Rightarrow \pi_1 = \frac{1}{q} \pi_0, \pi_2 = \frac{p}{q^2} \pi_0, \pi_j = q \pi_{j+1} + p \pi_{j-1}, j \geq 1$$

$\rightarrow$  general soln:  $\pi_j = \begin{cases} A + B_j & p = \frac{1}{2} \\ A + B\left(\frac{p}{q}\right)^j & p < \frac{1}{2} \end{cases}$

# Random walk on graphs <sup>network</sup> (Ex. 2.8)

[large ex: world wide web]

graph has vertices and edges

{a, b, c, d}



$i, j$  are "neighbors", write  $i, j$  if there is an edge joining  $i$  and  $j$ .

degree of vertex  $i$ ,  $\deg(i) = \#$  edges connected to  $i$  [ $\deg(a)=3, \deg(b)=\deg(d)=2, \deg(c)=3$ ]

A random walk  $(X_n)$  jumps from one vertex to another at each time step, it jumps independently "uniformly at random" according to the nr of edges at current node.

If  $X_n = b$ ,  $X_{n+1} = \begin{cases} a \text{ w/ prob } 1/2 \\ c \text{ w/ prob } 1/2 \end{cases}$

If  $X_n = c$ ,  $X_{n+1} = \begin{cases} a \text{ w/ prob } 1/3 \\ b \text{ w/ prob } 1/3 \\ c \text{ w/ prob } 1/3 \end{cases}$

In general,  $P_{ij} = \begin{cases} \frac{1}{\deg(i)} & \text{if } i, j \\ 0 & \text{otherwise} \end{cases}$

$P = \begin{matrix} & \begin{matrix} a & b & c & d \end{matrix} \\ \begin{matrix} a \\ b \\ c \\ d \end{matrix} & \begin{bmatrix} 0 & 1/3 & 1/3 & 1/3 \\ 1/2 & 0 & 1/2 & 0 \\ 1/3 & 1/3 & 0 & 1/3 \\ 1/2 & 0 & 1/2 & 0 \end{bmatrix} \end{matrix}$

## Example (3.6) Ehrenfest urn model for diffusion of a gas across a membrane (dog-flea model)

- 2 urns A, B (containers),  $N$  distinct (labeled) balls (like  $N=10$ ) in the urns
- "Dynamics": at each timestep, pick a ball "uniformly at random" (equal prob. for all balls) and move it from the urn it is in to the other urn.

$\Rightarrow (X_n)$  MC, state space  $\{0, \dots, N\}$ ;  $X_n = \#$  of balls in urn A after  $n$ -th move

$X_n = i \Rightarrow N-i$  balls in urn B

$P_{ij} = \begin{cases} \frac{N-i}{N} & j=i+1 \\ \frac{i}{N} & j=i-1 \\ 0 & \text{otherwise} \end{cases}$



$X_{n+1} = i+1?$   
Choose from B  
 $X_{n+1} = i-1? \rightarrow A$

Questions: - If  $X_0 = N$ , what happens as  $n \rightarrow \infty$ ?

- equilibrium?

- If  $X_0 = N$ , how long on average does it take to have all balls in B?

## Example: Not everything is a MC

5 quarters, 5 dimer, 5 nickels. draw a coin at random, put it on the table draw again, etc.  $X_n =$  amount of money on the table after  $n$ th draw.

$X_0 = 0$  [ $X_{15} = 2.00 = X_{16} = X_{17} = \dots$ ]

$\sim (X_n)$  no MC

- intuitive

- formally: can violate Markov

property for any  $n$ , any seq. of states.

$P(X_5 = .45 | X_0 = 0, X_1 = .25, X_2 = .30,$

$X_3 = .35, X_4 = .40) \neq P(X_5 = .45 | X_0 = 0, X_1 = .10, X_2 = .20, X_3 = .30, X_4 = .40).$

$p = \frac{1}{2}$ : need  $\sum_{j=0}^{\infty} \pi_j = 1 < \infty$ . This requires  $\lim_{j \rightarrow \infty} \pi_j = 0$ .  $\pi_j = A + B_j$ .

In order to have a stat. distr., we need  $\lim_{j \rightarrow \infty} (A + B_j) = 0$ . False if  $B \neq 0$ .  
 $\Rightarrow \pi_j = A, j \geq 2$ .  $\lim_{j \rightarrow \infty} \pi_j = A = 0$  iff  $A = 0$   
 $\Rightarrow \pi_j = 0, j \geq 2$ .  $[0 = \pi_2 = \frac{p}{q} \pi_0, \text{ so } \pi_0 = 0 \text{ and } \pi_1 = 0] \Rightarrow \pi_j = 0 \text{ all } j, \sum_{j=0}^{\infty} \pi_j = 0$   
 $\Rightarrow$  no stat. distr. in the case  $p = \frac{1}{2}$ .  $\Rightarrow$  null recurrent case.

$p < \frac{1}{2}$ :  $\pi_j = A + B(\frac{p}{q})^j, j \geq \frac{1}{2}$ .  $\frac{p}{q} < 1 \Rightarrow (\frac{p}{q})^j \rightarrow 0$  as  $j \rightarrow \infty$ .  
 $\Rightarrow \lim_{j \rightarrow \infty} \pi_j = \lim_{j \rightarrow \infty} (A + 0) = A \stackrel{?}{=} 0$  (no matter what  $B$  is)

If  $\sum_{j=0}^{\infty} \pi_j < \infty$ , this forces  $A = 0$ .  $\Rightarrow \pi_j = B(\frac{p}{q})^j, j \geq 2 \Rightarrow \sum_{j=0}^{\infty} \pi_j = \pi_0 + \pi_1 + B \sum_{j=2}^{\infty} (\frac{p}{q})^j$   
 $\Rightarrow$  choose  $\pi_0, \pi_1, B$  to get  $\sum_{j=0}^{\infty} \pi_j = 1$ . geometric series,  $\frac{p}{q} < 1$ , converges  
 $(\Rightarrow$  pos. recurrent case.)

Ex: timetev

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

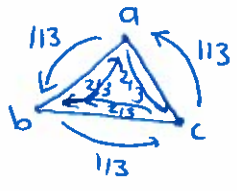
regular (since  $\text{med } P_{ii} > 0$ )  
 $\Rightarrow$  unique stat. distr.  
 check:  $\underline{\pi} = [\frac{4}{13} \quad \frac{6}{13} \quad \frac{3}{13}]$

$\pi_0 P_{01} = \pi_1 P_{10}?$   
 $\frac{4}{13} \cdot \frac{3}{4} = \frac{6}{13} \cdot \frac{1}{2} \checkmark$

$\pi_0 P_{02} = \pi_2 P_{20} \checkmark (0=0)$   
 $\pi_1 P_{12} = \pi_2 P_{21}$   
 $\frac{6}{13} \cdot \frac{1}{4} = \frac{3}{13} \cdot \frac{1}{2} \checkmark$

Ex:

$$P = \begin{matrix} & \begin{matrix} a & b & c \end{matrix} \\ \begin{matrix} a \\ b \\ c \end{matrix} & \begin{bmatrix} 0 & 1/3 & 2/3 \\ 2/3 & 0 & 1/3 \\ 1/3 & 2/3 & 0 \end{bmatrix} \end{matrix}$$



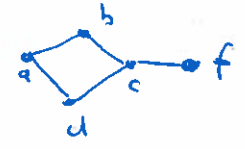
$P$  is doubly stochastic.  
 $\underline{\pi} = [\frac{1}{3} \quad \frac{1}{3} \quad \frac{1}{3}]$

Check:  $\pi_a P_{ab} = \frac{1}{3} \neq \frac{2}{3} = \pi_b P_{ba}$   
not time-reversible

- At each state, the MC has prob  $\frac{1}{3}$  of taking a counterclockwise step
  - At each state, the MC has prob  $\frac{2}{3}$  of taking a clockwise step.
  - $\Rightarrow$  "likely" that a given step will be clockwise.
- In a sequence of states  $X_0 = i_0, X_1 = i_1, \dots, X_n = i_n$  in forwards time, we expect to see  $acba$  more often than  $abca$ .  
 $(\frac{2}{3})^3$  vs  $(\frac{1}{3})^3$

Reversing the seq., we would see the second more often. The chain does not look the same forwards and backwards in time.

Ex: Simple random walk on an unweighted graph  
 $P_{ij} = \frac{1}{\text{deg}(i)}$  provided  $i, j$  are "neighbors"



Is  $P$  reversible? Find  $\underline{\pi}$ ?  $\rightarrow$  solve  $\pi_j = \sum_i \pi_i P_{ij} \forall j$

Guess: Try  $x_j$  proportional to  $\text{deg}(j)$  (or  $\frac{1}{\text{deg}(j)}$ ) Put  $x_j = c \text{deg}(j)$ , same constant  
 detailed balance eqns:  $x_i P_{ij} = c \text{deg}(i) \cdot \frac{1}{\text{deg}(i)} = c$  if  $i, j$  are neighbors  
 $x_i P_{ii} = c \text{deg}(i) \cdot \frac{1}{\text{deg}(i)} = c$  if  $i = j$

Example 2.11

random walk on weighted graphs  
 vertices, edges ( $i \sim j$  if  $\exists$  edge from  $i$  to  $j$ ),  
 weights  $w_{ij} \geq 0$  on edges  $i \sim j$



$$P_{ij} = \begin{cases} \frac{w_{ij}}{w_i} & \text{if } i \sim j \\ 0 & \text{if not} \end{cases}$$

$w_i :=$  total weight of edges containing vertex  $i$  ( $w_d = 10$ )

$w_d = 10, w_a = 6, w_b = 7, w_c = 5$

$$P = \begin{matrix} & \begin{matrix} a & b & c & d \end{matrix} \\ \begin{matrix} a \\ b \\ c \\ d \end{matrix} & \begin{bmatrix} 0 & 1/6 & 0 & 5/6 \\ 1/7 & 0 & 3/7 & 3/7 \\ 0 & 0 & 0 & 0 \end{bmatrix} \end{matrix} \text{ etc.}$$

Example  $n$ -step prob.

Suppose  $S = \{0, 1, 2\}$ ,  $P = \begin{matrix} & \begin{matrix} 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} 0 & 1 & 2 \\ .1 & .1 & .8 \\ .2 & .2 & .6 \\ .3 & .3 & .4 \end{bmatrix} \end{matrix}$  Find  $P(X_2=0 | X_0=0)$

- ① Use LOTP
- ②  $P_{00}^2 = (P \times P)_{00} = .27$ ,  $P^2 = \dots$

Supp.  $X_0$  has dist.  $\alpha = (.7 \ .2 \ .1)$  Find  $P(X_2=0)$ .  
 $P(X_2=0) = (\alpha P^2)_0 = (.7 \ .2 \ .1) \begin{bmatrix} .27 & .27 & .46 \\ .24 & .24 & .52 \\ .21 & .21 & .58 \end{bmatrix}_0 = \dots = \frac{124}{500}$

Example joint dist.

- $P(X_3=b, X_2=c, X_1=d, X_0=f | X_0=a) = P_{ab}^3 \cdot P_{bc}^4 \cdot P_{cd}^2 \cdot P_{af}$
- $P(X_1=0, X_2=0, X_3=2, X_4=1 | X_0=2) = P_{20} P_{00} P_{02} P_{21}$
- $P(X_7=2 | X_1=0, X_2=0, X_3=2, X_4=1) = P(X_7=2 | X_4=1) = P_{12}^3$
- $P(X_2=1, X_4=2, X_5=1, X_8=0 | X_0=0) = P_{01}^2 P_{12}^2 P_{21} P_{10}^{7-4=3 \text{ time steps}}$

Example 3.1 The two-state MC

Let  $0 \leq p, q \leq 1$ . ( $q = 1-p$ ).  $P = \begin{matrix} & \begin{matrix} 1 & 2 \end{matrix} \\ \begin{matrix} 1 \\ 2 \end{matrix} & \begin{bmatrix} 1-p & p \\ q & 1-q \end{bmatrix} \end{matrix}$

Special cases: ①  $p=q=0$   $P^n = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ ,  $P^n = P = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \forall n$

$\lim_{n \rightarrow \infty} P_{ij}^n = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$  exists  $\forall i, j$  but depends on both  $i, j \Rightarrow$  no lim. dist. for  $P$ .

②  $p=q=1$   $P = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$ ,  $P^n = \begin{cases} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} & \text{if } n \text{ is odd} \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} & \text{if } n \text{ is even.} \end{cases} \rightarrow P_{00}^n = (0, 1, 0, 1, 0, 1, \dots)$  has no limit

General case: ③  $0 < p+q < 2$ , let  $r = 1-p-q \Rightarrow -1 < r < 1$

$\Rightarrow P^n = \frac{1}{p+q} \begin{bmatrix} q+pr^n & p-pr^n \\ q-qr^n & p+qr^n \end{bmatrix}$  (\*) and  $\lim_{n \rightarrow \infty} P^n = \frac{1}{p+q} \begin{bmatrix} q & p \\ q & p \end{bmatrix}$  since  $\lim_{n \rightarrow \infty} r^n = 0$  ( $|r| < 1$ )

$\Rightarrow$  limiting dist.  $\lambda = (\lambda_1, \lambda_2)$ ,  $\lambda_1 = \lim_{n \rightarrow \infty} P_{01}^n = \frac{q}{p+q}$ ,  $\lambda_2 = \lim_{n \rightarrow \infty} P_{12}^n = \frac{p}{p+q}$

Want  $1 = \sum_{j \in S} x_j = \sum_{j \in S} c \deg(j) = c \sum_{j \in S} \deg(j)$ . Take  $c = \frac{1}{\sum_{j \in S} \deg(j)}$ , and

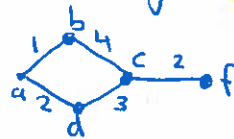
$\pi_j = c x_j = \frac{\deg(j)}{\sum_{k \in S} \deg(k)}$ .  $\Rightarrow \pi$  is a stat. dist.,  $P$  is reversible for  $\pi$ , and  $\pi$  is unique. ( $P$  is irred.)

Since  $\sum_{j \in S} \deg(j) = 2e$ , where  $e$  is the nr of edges, we get  $\pi_j = \frac{\deg(j)}{2e}$ .

Ex: Random walk on weighted graphs:

$w(i,j)$  = weight of edge between  $i$  and  $j$

$w(i,i) = \sum_{j \in S} w(i,j)$ ,  $P_{ij} = \frac{w(i,j)}{w(i)}$



$w(a,b) = 1$

$w(a,d) = 2$

$w(a) = w(a,b) + w(a,d) = 1 + 2 = 3$

$P_{ab} = \frac{1}{3}$ ,  $P_{ad} = \frac{2}{3}$

(If all weights are equal, say 1, then  $w(i) = \deg(i)$ )

Can we find  $\pi$ , check for time reversibility?

Try: make a guess for  $\pi_i$ , check if  $\pi_i P_{ij} = \pi_j P_{ji}$ .

Recall: unweighted case

$x_i = c \deg(i)$

Try  $x_j = c \cdot w(j)$  (or  $c w(i)$ )

$\Rightarrow x_i P_{ij} = c w(i) \frac{w(i,j)}{w(i)} = c w(i,j)$  ( $i, j$  neighbors)

$x_j P_{ji} = c w(j) \frac{w(j,i)}{w(j)} = c w(j,i)$  ( $w(i,j) = w(j,i)$ )

Tells us  $x_i P_{ij} = x_j P_{ji} \forall i, j$ . To make  $x$  a prob. vector we want

$1 = \sum_{j \in S} x_j = \sum_{j \in S} c w(j) = c \cdot \sum_{j \in S} w(j) \Rightarrow c = \frac{1}{\sum_{j \in S} w(j)}$   $\pi_i = c x_i = c w(i)$

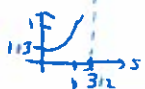
$\Rightarrow \pi_i = \frac{w(i)}{\sum_{j \in S} w(j)}$  is a stat. dist. and  $P$  is reversible w.r.t.  $\pi$ .

Ex:  $P(X=n) = \frac{1}{3} \left(\frac{2}{3}\right)^n$ ,  $n=0,1,2,\dots$  (geometric dist.)

The pgf is

$G(s) = E s^X = \sum_{n=0}^{\infty} s^n \frac{1}{3} \left(\frac{2}{3}\right)^n = \frac{1}{3} \sum_{n=0}^{\infty} \left(\frac{2}{3}s\right)^n = \frac{1}{3} \frac{1}{1 - \frac{2}{3}s} = \frac{1}{3-2s}$

Converges if  $|\frac{2}{3}s| < 1 \Leftrightarrow |s| < \frac{3}{2}$ .

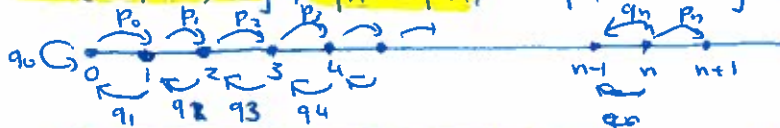


Ex: Birth and death chain

$S = \{0, 1, 2, \dots\}$ ,  $q_n = 1 - p_n$ , all  $p_n$  satisfy

$0 < p_n < 1$  ( $0 < q_n < 1$ )

Infinitely many parameters  $\{p_n\}_{n=0}^{\infty}$



Random walk with reflection is the special case  $p_n = p$  for all  $n$

Q: classify the chain, check for time-reversibility

- find  $x$   $x_i P_{ij} = x_j P_{ji}$  all  $i, j$

If  $\sum_{i=0}^{\infty} x_i < \infty$ ,  $\pi$  def'd by  $\pi_i = \frac{x_i}{\sum_{i=0}^{\infty} x_i}$  is a stat. dist., which implies the chain is pos. recurrent.

\*  $i=0, j=1$ :  $x_0 p_{01} = x_1 p_{10}$ ,  $x_0 p_0 = x_1 q_0 \Rightarrow x_1 = \frac{p_0}{q_0} x_0$

\*  $i=1, j=2$ :  $x_1 p_{12} = x_2 p_{21}$ ,  $x_1 p_1 = x_2 q_2 \Rightarrow x_2 = \frac{p_1}{q_2} x_1 = \frac{p_0 p_1}{q_0 q_1} x_0$

\*  $i=2, j=3$ :  $\dots x_3 = \frac{p_0 p_1 p_2}{q_1 q_2 q_3} x_0$

$\dots \Rightarrow x_n = \frac{p_0 p_1 \dots p_{n-1}}{q_1 q_2 \dots q_n} x_0$

Put  $\gamma_n = \frac{p_0 \dots p_{n-1}}{q_1 \dots q_n}$ ,  $n \geq 1$

$\Rightarrow x_n = \gamma_n x_0, n=0,1,2,\dots$

Proof of (3): (i) induction,  $n=1, P^{n+1} = P \times P^n$

(ii) textbook  $\rightarrow$  derivation.  $\rightarrow P_{11}^n = (P^{n-1}P)_{11} = P_{11}^{n-1}P_{11} + P_{12}^{n-1}P_{21} = P_{11}^{n-1}(1-p) + P_{12}^{n-1}q$   
 $= P_{11}^{n-1}(1-p) + (1-P_{11}^{n-1})q = q + (1-p-q)P_{11}^{n-1}, n \geq 1$   
 $= q + (1-p-q)q + (1-p-q)^2 P_{11}^{n-2} - \dots = \frac{q}{p+q} + \frac{p}{p+q}(1-p-q)^n, P_{22}^n = \dots \rightarrow P$

(iii) Use Difference Eqns

What happens if initial distr. is chosen to be  $\lambda$  the lim. distr.?

ie.  $P(X_0=1) = \frac{q}{p+q}, P(X_0=2) = \frac{p}{p+q}$  distr. of  $X_1$ ?  
 $P(X_1=1) \stackrel{\text{LTP}}{=} P(X_1=1|X_0=1)P(X_0=1) + P(X_1=1|X_0=2)P(X_0=2) = (1-p)\frac{q}{p+q} + q\frac{p}{p+q}$   
 $= \frac{q}{p+q} = P(X_0=1), P(X_1=2) = P(X_0=2)$   $\rightarrow$  distr of MC does not change from time 0 to the 1  $\rightarrow$  stationary distr.  
 $[P(X_1=1) = (\lambda P)_1]$

(iii) Let  $x_n = P_{11}^n = (P \times P^{n-1})_{11} = (P^{n-1} + P)_{11}$ .

$$P^{n-1} \times P = \begin{bmatrix} P_{11}^{n-1} & P_{12}^{n-1} \\ P_{21}^{n-1} & P_{22}^{n-1} \end{bmatrix} \begin{bmatrix} 1-p & p \\ q & 1-q \end{bmatrix} = \begin{bmatrix} (1-p)P_{11}^{n-1} + qP_{12}^{n-1} & \dots \\ \dots & \dots \end{bmatrix} \Rightarrow x_n = (1-p)P_{11}^{n-1} + qP_{12}^{n-1} = (1-p)x_{n-1} + q(1-x_{n-1}) = q + x_{n-1}(1-p-q)$$

$\Rightarrow x_n - r x_{n-1} = q$  1st order diff. eqn.

$\rightarrow$  char. eqn in  $t$  is  $t-r=0 \rightarrow$  sol.  $t=r$

$$\underline{ax_{n+1} + bx_n + c = z_n}$$
  
 Char. eqn  $ar^2 + br + c = 0$

(1) Soln to  $x_n - r x_{n-1} = 0$  is  $x_n = Ar^n$

(2) For part. soln, guess const. so  $x_n = c$   
 Plug in,  $x_n - r x_{n-1} = c - r c = q \rightarrow c = \frac{q}{1-r} = \frac{q}{p+q}$   $\rightarrow$  gen. soln  $x_n = Ar^n + \frac{q}{p+q}$   
 $x_0 = P_{11}^0 = 1 = Ar^0 + \frac{q}{p+q} \Rightarrow A = 1 - \frac{q}{p+q} = \frac{p}{p+q}$   $\Rightarrow x_n = \frac{1}{p+q} (q + p r^n)$

$\rightarrow \lambda = \begin{bmatrix} \frac{q}{p+q} & \frac{p}{p+q} \end{bmatrix}$  (also) stationary distr.

find stat. distr. with linear eqn's:

(3)  $p, q$  not both zero  $\rightarrow$  there is a single soln to  $\begin{cases} \pi_1 + \pi_2 = 1 \\ \pi_1 = \pi_1 P_{11} + \pi_2 P_{21} = \pi_1(1-p) + \pi_2 q \\ \pi_2 = \pi_1 P_{12} + \pi_2 P_{22} = \pi_1 p + \pi_2(1-q) \end{cases}$   
 $\Rightarrow \begin{cases} \pi_1 + \pi_2 = 1 \\ p\pi_1 - q\pi_2 = 0 \\ p\pi_1 - q\pi_2 = 0 \end{cases}$  same eqn  $\rightarrow$  one eqn redundant  $\Rightarrow \pi_1 = \frac{q\pi_2}{p} \rightarrow \frac{q\pi_2}{p} + \pi_2 = 1$   
 $\Rightarrow \pi_2 = \frac{p}{q+p}, \pi_1 = \frac{q}{q+p}$  (the lim. distr.)

(1)  $p=q=0, P = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$   $\Pi P = \Pi \Rightarrow \begin{cases} \pi_1 = \pi_1 \\ \pi_2 = \pi_2 \\ \pi_1 + \pi_2 = 1 \end{cases} \Rightarrow \pi_1 = \pi_1, \pi_2 = 1 - \pi_1 \rightarrow$  for any  $0 \leq c \leq 1$ ,  $\Pi = \begin{bmatrix} c & 1-c \end{bmatrix}$  is a stat. distr.

$\rightarrow$  there can be more than one stat. distr.

(2)  $p=q=1, P = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \Rightarrow \Pi = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \end{bmatrix}$  unique stat. distr.  
 but  $\lim_{n \rightarrow \infty} P^n$  does not exist  $[P^n = \begin{cases} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, n \text{ odd} \\ \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, n \text{ even} \end{cases}]$

If  $\sum_{n=0}^{\infty} x_n = x_0 \sum_{n=0}^{\infty} y_n < \infty$ , then  $\pi_i = \frac{x_i}{\sum_{n=0}^{\infty} x_n} = \frac{y_i x_0}{x_0 \sum_{n=0}^{\infty} y_n} = \frac{y_i}{\sum_{n=0}^{\infty} y_n}$

In the random walk with reflection,  $y_i = \frac{p_i p_{i-1} - p_{i-1} p_i}{q_i - q_{i-1}} = \frac{p_i}{q_i} = \left(\frac{p}{q}\right)^i$   
 $\sum_{i=0}^{\infty} y_i = \sum_{i=0}^{\infty} \left(\frac{p}{q}\right)^i < \infty$  if  $p < q$  same as  $p < \frac{1}{2}$  pos. recurrence case.

Ex: Fact: If  $X \sim \text{Geom}(p)$ , then  $G(s) = \frac{p}{1-(1-p)s}$ ,  $|s| < \frac{1}{1-p}$   
~~Let~~ Supp. we know a.r.v.  $Y$  has pgf  $H(s) = \frac{1}{3-2s}$ , then  $Y \sim \text{Geom}(\frac{1}{3})$ .  
 Put  $p = \frac{1}{3}$  in  $G(s) = \frac{p}{1-(1-p)s}$ , we get  $\frac{1/3}{1-2/3s} = \frac{1}{3-2s}$ .

Ex: If  $X \sim \text{Bern}(p)$ ,  $P(X=0) = 1-p$ ,  $P(X=1) = p$  ( $0 < p \leq 1$ ),  $X$  has pgf  
 $E(s^X) = \sum_{k=0}^{\infty} P(X=k) s^k = (1-p)s^0 + ps^1 = 1-p+ps$

If  $X \sim \text{Bin}(n, p)$ , then  $X$  has pgf  $E(s^X) = (1-p+ps)^n$  since

① by def'n  $E(s^X) = \sum_{k=0}^n \binom{n}{k} p^k (1-p)^{n-k} s^k = \sum_{k=0}^n \binom{n}{k} (ps)^k (1-p)^{n-k}$

Binomial formula  $= (ps + (1-p))^n \checkmark$

② We can write  $X = X_1 + \dots + X_n$  where  $X_i$  indep.,  $X_i \sim \text{Bern}(p)$ .  
 Now, by our thm,  $X$  has pgf  $E(s^X) = (G(s))^n = (1-p+ps)^n$  where  $G(s) = 1-p+ps$  (pgf of  $\text{Bern}(p)$ )

Ex: (two-state experiment) Toss a biased coin, prob. of heads is  $1/5$ , tails is  $4/5$ , repeatedly 10 times. Assume successive tosses are indep. Let  $N \sim \text{Bin}(10, 1/5)$  be the nr of heads in the 10 tosses. Now, roll a fair die  $N$  times, count the nr of times 2 comes up, call this  $Y$ . Find the pgf of  $Y$ , and use it to find  $P(Y=2)$ .

Let  $X_i = \begin{cases} 1 & \text{if } i^{\text{th}} \text{ toss of die comes up } 2 \\ 0 & \text{if not} \end{cases}$ ,  $i=1, 2, \dots$   $P(X_i=1) = \frac{1}{6}$

Then  $Y = X_1 + \dots + X_N$ .  $N$  has pgf  $H(t) = (1 - \frac{1}{5} + \frac{1}{5}t)^{10} = (\frac{4}{5} + \frac{1}{5}t)^{10}$  b/c  $N \sim \text{Bin}(10, \frac{1}{5})$

The  $X_i$  have pgf  $G(s) = (1 - \frac{1}{6} + \frac{1}{6}s) = (\frac{5}{6} + \frac{1}{6}s)$  b/c  $X_i \sim \text{Bern}(\frac{1}{6})$

So,  $Y$  has pgf  $\phi(s) = H(G(s)) = H(\frac{5}{6} + \frac{1}{6}s) = (\frac{4}{5} + \frac{1}{5}(\frac{5}{6} + \frac{1}{6}s))^{10}$

$= (\frac{4}{5} + \frac{1}{6} + \frac{1}{30}s)^{10} = (\frac{29}{30} + \frac{1}{30}s)^{10} = \phi(s) \Rightarrow Y \sim \text{Bin}(10, \frac{1}{30})$ , so

$P(Y=2) = \binom{10}{2} (\frac{1}{30})^2 (\frac{29}{30})^8$  (or  $= \frac{\phi''(0)}{2!}$ )

Ex: Offspring dist.  $\text{Geom}(1/3)$ ,  $p_k = \frac{1}{3} (\frac{2}{3})^k$ ,  $k=0, 1, 2, \dots$   
 The pgf is  $G(s) = \frac{1}{3-2s} = G_1(s)$ .  $G_2(s) = G(G(s)) = \frac{1}{3-2G(s)} = \frac{1}{3 - \frac{2}{3-2s}}$   
 $\frac{3-2s}{3-2s} = \frac{3-2s}{9-6s-2} = \frac{3-2s}{7-6s}$ . Can check  $G_3(s) = G_2(G(s)) = \frac{3-2G(s)}{7-6G(s)} = \dots = \frac{7-6s}{15-14s}$

We know  $P(Z_0=0 | Z_0=1) = G(0) = 1/3$   
 $P(Z_2=0 | Z_0=1) = G_2(0) = 3/7$   
 $P(Z_3=0 | Z_0=1) = G_3(0) = 7/15$ .



Example:  $0 < p < 1$ .  $\underline{P} = \begin{matrix} & \begin{matrix} 1 & 2 & 3 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \end{matrix} & \begin{bmatrix} 0 & 1-p & p \\ p & 0 & 1-p \\ 1-p & p & 0 \end{bmatrix} \leftarrow \text{doubly stoch. matrix} \end{matrix}$

(a)  $\underline{P}$  regular b/c  $\underline{P}^2 = \begin{bmatrix} 0 & + & + \\ + & 0 & + \\ + & + & 0 \end{bmatrix} \begin{bmatrix} 0 & + & + \\ + & 0 & + \\ + & + & 0 \end{bmatrix} = \begin{bmatrix} + & + & + \\ + & + & + \\ + & + & + \end{bmatrix}$  is positive.

(b) Find stat. dist.  $\underline{\pi} = [\pi_1 \pi_2 \pi_3]$

Thm  $\Rightarrow$   $\underline{\pi}$  is unique.  $\underline{P}$  doubly stoch.  $\Rightarrow$   $\underline{\pi}$  uniform,  $\underline{\pi} = [\frac{1}{3} \frac{1}{3} \frac{1}{3}]$ .

(c) furthermore,  $\lim_{n \rightarrow \infty} p_{ij}^{(n)} = \frac{1}{3} \forall i, j \in \{1, 2, 3\}$ .  $\rightarrow$  did not have to compute  $\underline{P}^n$

Example:

$$\underline{P} = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \end{matrix} & \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1/6 & 1/6 & 1/6 & 1/2 \\ 1/5 & 2/5 & 1/5 & 1/5 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{matrix}$$

Find the equivalence classes for  $\underline{P}$ .

State 0:  $0 \leftrightarrow j$  for  $j=0$ ,  $C_1 = \{0\}$  is a communicating class  
 State 3:  $3 \leftrightarrow j$  for  $j=3$ ,  $C_2 = \{3\}$  is a communicating class

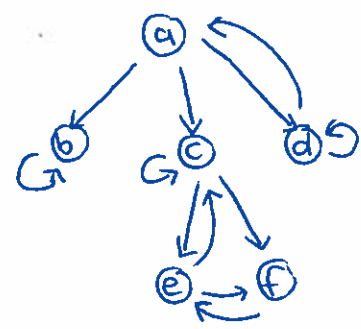
States 1, 2:  $1 \rightarrow j$  for all  $j$  so  $1 \leftrightarrow 2$   
 $2 \rightarrow j$  for all  $j$   $\rightarrow 0$  but  $0 \nrightarrow 1$  so  $0 \leftrightarrow 1$ , etc.  
 $\Rightarrow C_3 = \{1, 2\}$ .

Example:

$$\underline{P} = \begin{matrix} & \begin{matrix} a & b & c & d & e & f \end{matrix} \\ \begin{matrix} a \\ b \\ c \\ d \\ e \\ f \end{matrix} & \begin{bmatrix} 0 & 1/8 & 3/4 & 1/8 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1/3 & 0 & 1/3 & 1/3 \\ 1/3 & 0 & 0 & 2/3 & 0 & 0 \\ 0 & 0 & 1/4 & 0 & 0 & 3/4 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \end{matrix}$$

Find comm. classes; determine  $i \leftrightarrow j$  (?) for all  $i, j$ .

$i \leftrightarrow j$



$a \rightarrow \begin{cases} b \rightarrow b \\ c \rightarrow \begin{matrix} \text{frec} \\ \text{frec} \end{matrix} \rightarrow \begin{matrix} \text{frec} \\ \text{frec} \end{matrix} \\ d \rightarrow d \end{cases}$   
 $\Rightarrow a \rightarrow b, a \rightarrow c, a \rightarrow d, a \rightarrow e, a \rightarrow f$   
 $b \rightarrow b, c \rightarrow c, c \rightarrow e, c \rightarrow f$

c, e, f all communicate  
 $C_1 = \{c, e, f\}$  one class,  $C_2 = \{b\}$  one class,  $C_3 = \{a, d\}$  one class.  
 $\{a, d\} \rightarrow \{c, e, f\}$ , but  $\{c, e, f\} \not\rightarrow \{a, d\}$

Example:

$$\underline{P} = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & 4 & 5 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{matrix} & \begin{bmatrix} 0 & 1 & 2 & 3 & 4 & 5 \\ 0 & 1/10 & 0 & 0 & 0 & 1/10 \\ 0 & 0 & 1/3 & 0 & 1/3 & 1/3 \\ 1/3 & 0 & 0 & 2/3 & 0 & 0 \\ 0 & 0 & 1/4 & 0 & 0 & 3/4 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{matrix}$$

$i \leftrightarrow j$  & if  $P_{ij} > 0$   
 $0 \leftrightarrow 1 \leftrightarrow 5 \leftrightarrow 0 \leftrightarrow 2 \leftrightarrow 4 \leftrightarrow 5 \leftrightarrow 0$   
 $\leftrightarrow 3 \leftrightarrow 0$   
 $\overset{a_0}{0}, \overset{a_1}{1}, \overset{a_2}{5}, \overset{a_3}{0}, \overset{a_4}{2}, \overset{a_5}{4}, \overset{a_6}{5}, \overset{a_7}{0}, \overset{a_8}{3}, \overset{a_9}{0} \Rightarrow \underline{P}$  irred.

Ex:  $G(s) = \frac{1}{3-2s} = (3-2s)^{-1}$ ,  $G'(s) = -(3-2s)^{-2} (-2) = \frac{2}{(3-2s)^2}$ .

$\mu = G'(1) = \frac{2}{1} = 2 > 1$ , so  $e < 1$ . To find  $e$  set  $G(s) = s$ :

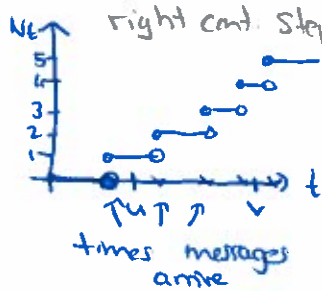
$\frac{1}{3-2s} = s \Leftrightarrow 1 = 3s - 2s^2 \Leftrightarrow 2s^2 - 3s + 1 = 0 \Leftrightarrow (s-1)(2s-1) = 0$

Roots are  $s=1, s=\frac{1}{2}$ , so  $e = \frac{1}{2}$ .

Ex: Turn on cellphone, call this time  $t=0$ , text messages come in.

Let  $N_t = \#$  of text messages that have arrived by time  $t$ .

[ $N_t$  counts events in  $[0, t]$   $\Rightarrow$  as  $t$  increases, the nr of events  $N_t$  increases]



$N_u = 1, N_v = 4$

The nr of messages that come in during the time interval  $[u, v] = N_v - N_u$  on an increment  $[0 \leq u < v]$  in the set  $t \mapsto N_t$ .

Ex: Supp.  $(N_t)_{t \geq 0}$  is a PP with rate  $\lambda = 0.3$ .

Find (a) the prob. no messages arrive in 1st 4 minutes

$\rightarrow P(N_4 = 0) = \frac{(4\lambda)^0}{0!} e^{-4\lambda} = e^{-4 \cdot 0.3} = e^{-1.2}$

$N_4 \sim \text{Pois}(4\lambda)$

(b) the prob. that 1 message arrived between times 2 and 3 given that 5 mess. arrived by time 2

$\rightarrow P(N_3 - N_2 = 1 \mid N_2 = 5) = P(N_3 - N_2 = 1)$

stat. incr.  $= P(N_1 = 1) = \frac{e^{-\lambda} \lambda}{1!} = e^{-\lambda} \lambda = e^{-0.3} (0.3)$

(indep. incr.  $P(A|B) = P(A)$  if  $A, B$  indep.)

(c) the prob. that 6 mess. are received in 1st ten minutes and exactly one of these was received in 1st 3 minutes.

$P(N_{10} = 6, N_3 = 1) = P(N_3 = 1, N_{10} = 6) \left[ \neq P(N_3 = 1) P(N_{10} = 6) \right]$

$= P(N_3 = 1, N_{10} - N_3 = 5) = P(N_3 = 1) P(N_{10} - N_3 = 5) = P(N_3 = 1)$

$\cdot P(N_7 = 5) = \frac{e^{-3\lambda} (3\lambda)^1}{1!} \cdot \frac{e^{-7\lambda} (7\lambda)^5}{5!}$

(d) the prob. that exactly 1 mess. is received in 1st 3 minutes given that exactly 6 mess. were received in 1st 10 minutes.

Example:

$$P = \begin{matrix} & \begin{matrix} a & b & c \end{matrix} \\ \begin{matrix} a \\ b \\ c \end{matrix} & \begin{bmatrix} 1/3 & 2/3 & 0 \\ 1 & 0 & 0 \\ 1/4 & 2/4 & 1/4 \end{bmatrix} \end{matrix}$$

Sum = 3/4



$a \leftrightarrow b, a \nrightarrow c, b \nrightarrow c$   
 $c \rightarrow a, c \rightarrow b$

Classes are  $\{a, b\}$  (closed) and  $\{c\}$  (open).

- Starting at either a or b, the chain is certain to return to a or b  $\rightarrow$  recurrent

- Starting at c, there is prob. 3/4 of never returning to c  $\rightarrow$  transient

$P(R_c < \infty | X_0 = c) = \frac{1}{4}$  c is transient

$P(R_a < \infty | X_0 = a) = \frac{1}{3} + \frac{2}{3} \cdot 1 = 1$  a is recurrent (b is too)  
 $[R_a = 1 \text{ or } R_a = 2]$

Example:

For same MC, we see the "realization" of the experiment

$X_0 = 1, X_1 = 1, X_2 = 3, X_3 = 3, X_4 = 2, X_5 = 3, X_6 = 1, X_7 = 2, \dots$   $R_1 = ?$

$\{n \geq 1 : X_n = 1\} = \{1, 6, \dots\} \rightarrow R_1 = 1, \{n \geq 0 : X_n = 1\} = \{0, 1, 6, \dots\} \Rightarrow H_1 = 0.$

$R_2 = 4, H_2 = 4 = R_2$

Example:

$P = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}$   $P^n = ?$

$P_{00}^n = P(X_n = 0 | X_0 = 0) = P(X_1 = 0, X_2 = 0, \dots, X_n = 0 | X_0 = 0) = P_{00} \cdot P_{00} \cdot \dots \cdot P_{00} = (0.4)^n$

$\Rightarrow P_{01}^n = 1 - (0.4)^n$   $P^n = \begin{bmatrix} (0.4)^n & 1 - (0.4)^n \\ 0 & 1 \end{bmatrix}$

$P_{11}^n = P(X_n = 1 | X_0 = 1) = P(X_1 = 1, X_2 = 1, \dots, X_n = 1 | X_0 = 1) = P_{11} \cdot \dots \cdot P_{11} = 1^n = 1$

$a = 0: \sum_{n=1}^{\infty} P_{aa}^n = \sum_{n=1}^{\infty} (0.4)^n < \infty$  geometric series  $\Rightarrow 0$  is ~~transient~~ transient

$a = 1: \sum_{n=1}^{\infty} P_{aa}^n = \sum_{n=1}^{\infty} 1 = \infty \Rightarrow 1$  is recurrent.

Ex 2 0 transient, 1 recurrent. 0, 1 are in different classes ( $P$  is not irreducible)

Example:

$$P = \begin{matrix} & \begin{matrix} a & b & c & d & e & f \end{matrix} \\ \begin{matrix} a \\ b \\ c \\ d \\ e \\ f \end{matrix} & \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0.9 & 0 & 0 & 0 & 0 & 0.1 \end{bmatrix} \end{matrix}$$

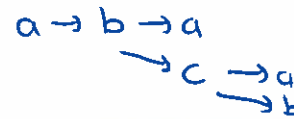
irreducible b/c  $a \rightarrow b \rightarrow c \rightarrow d \rightarrow e \rightarrow f \rightarrow a$

$P_{ff} > 0 \rightarrow P$  regular

$P^9$  not positive but  $P^{10}$  positive

Example:

$$P = \begin{matrix} & \begin{matrix} a & b & c \end{matrix} \\ \begin{matrix} a \\ b \\ c \end{matrix} & \begin{bmatrix} 0 & 1 & 0 \\ 1/2 & 0 & 1/2 \\ 1/2 & 1/2 & 0 \end{bmatrix} \end{matrix}$$



irreducible  $\checkmark$

$P_{ii} = 0 \forall i$

but:  $P$  regular.

regular  $\nRightarrow$  irred  $\& \exists i: P_{ii} > 0$  (only reg = irred)

Example: Supp. a MC has comm. classes  $C_1 = \{0, 1\}, C_2 = \{2, 3\}, C_3 = \{4, 5\}$ , supp.

also that  $C_1 \rightarrow C_2, C_2 \rightarrow C_3$ . What are the recurrent & transient states?

$C_1 \rightarrow C_2$  means  $i \rightarrow j$  for some  $i \in C_1, j \in C_2 \Rightarrow C_1$  open,  $C_2$  open. What about  $C_3$ ?

Supp  $C_3$  open  $\Rightarrow C_2 \rightarrow C_1$  or  $C_2 \rightarrow C_2$  but  $C_3 \nrightarrow C_1$  since  $C_1 \rightarrow C_3, C_1 \rightarrow C_2, C_2 \rightarrow C_3$

$$\rightarrow P(N_3=1 | N_{10}=6) = \frac{P(N_3=1, N_{10}=6)}{P(N_{10}=6)} \stackrel{\textcircled{c}}{=} \frac{e^{-3\lambda} (3\lambda)^1 e^{-2\lambda} (2\lambda)^5}{1! \cdot 5!} \quad [14]$$

$$= \dots = \binom{6}{1} \left(\frac{3}{10}\right)^1 \left(\frac{7}{10}\right)^5$$

↳ see HW

Binomial  $\binom{6}{1} \binom{3}{1} \binom{10}{10}$   $\textcircled{d}$   
 $P(X=1)$  where  $X \sim \text{Bin}\left(6, \frac{3}{10}\right)$

$\textcircled{e}$   $E(N_3 \cdot N_7)$  [  $\neq E N_3 \cdot E N_7$  ] (only  $N_3$  and  $N_7 - N_3$  are indep?)

$$= E(N_3 (N_7 - N_3) + N_3^2) = E(N_3(N_7 - N_3)) + E(N_3^2) = E(N_3) E(N_7 - N_3) + E(N_3^2)$$

$$= E N_3 \cdot E(N_4) + E(N_3^2) = 3\lambda \cdot 4\lambda + 3\lambda + \beta\lambda^2$$

$P(N_7 - N_3 = \dots)$   
 $= P(N_4 = \dots)$

[  $X \sim \text{Pois } \lambda \Rightarrow E(X) = \lambda, \text{Var}(X) = \lambda = E(X^2) - (E(X))^2$   
 $\Rightarrow E(X^2) = \text{Var}(X) + (E(X))^2$  ]

Ex: Supp  $(N_t)_{t \geq 0}$  PP, rate  $\lambda = 0.3$ .

$\textcircled{a}$  Find the expected time of the arrival of the 3rd message  
 - difficult to counter just using  $(N_t)$   
 $\hookrightarrow = E(S_3) = \frac{3}{\lambda} = \frac{3}{.3} = 10$

$\textcircled{b}$  Find the prob the 3rd mess. arrived between 10 and 15.  
 $\rightarrow P(10 < S_3 < 15) = \int_{10}^{15} f_3(k) dk = \int_{10}^{15} \frac{\lambda^3 x^2}{2!} e^{-\lambda x} dx = \dots$  ↑ by parts twice

Ex: -  $h^2 = o(h)$  as  $h \rightarrow 0$ :  $\lim_{h \rightarrow 0} \frac{h^2}{h} = \lim_{h \rightarrow 0} h = 0$

-  $\sqrt{h} = o(h)$  as  $h \rightarrow 0$ ?  $\lim_{h \rightarrow 0} \frac{\sqrt{h}}{h} = \lim_{h \rightarrow 0} \frac{1}{\sqrt{h}} \neq 0$ .

-  $\sin h \neq o(h)$  as  $h \rightarrow 0$ :  $\frac{\sin h}{h} \rightarrow 1$  as  $h \rightarrow 0$ .

-  $\cos h = 1 + o(h)$  as  $h \rightarrow 0$ :  $\lim_{h \rightarrow 0} \frac{\cos h - 1}{h} \stackrel{\text{Hoppital's rule}}{=} \lim_{h \rightarrow 0} \frac{-\sin h}{1} = 0 \checkmark$

-  $e^{2h} = 1 + 2h + o(h)$  as  $h \rightarrow 0$ :  $\lim_{h \rightarrow 0} \frac{e^{2h} - (1+2h)}{h} \stackrel{\downarrow}{=} \lim_{h \rightarrow 0} \frac{2e^{2h} - 2}{1} = 0 \checkmark$

Ex: Consider births at a local hospital, assume the prob. a given birth is male to be  $p_m = .48$ , the prob. " " is female " "  $p_f = .52$ .

Assume the nbs over time is a rate  $\lambda = 2$  PP, and successive births are indep. of one another and the PP  $(N_t)_{t \geq 0}$

Def  $N_t^m = \#$  of male births by time  $t$  (each  $\lambda p_m$ ),  $N_t^f = \#$  ... female  
 Thm  $\Rightarrow (N_t^m)_{t \geq 0}$  is PP, rate  $\lambda p_m = 2(.48)$ ,  $(N_t^f)_{t \geq 0}$ : PP rate  $\lambda p_f = 2(.52)$

and the two processes are indep  
 Find Prob. at least one male & no females born during a 3 hour period

$$P(N_3^m \geq 1, N_3^f = 0) \stackrel{\text{indep}}{=} P(N_3^m \geq 1) P(N_3^f = 0) = (1 - P(N_3^m = 0)) P(N_3^f = 0)$$

$$= (1 - e^{-3\lambda p_m - (3\lambda p_m)^0}) e^{-3\lambda p_f (3\lambda p_f)^0}$$

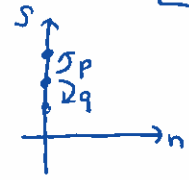
Example 3.13 Simple One-dimensional random walk

↳ jumps are either +1 or -1

State space: {all integers} = {0, ±1, ±2, ...}

0 < p < 1 fixed param., q = 1 - p.

$$P := \begin{cases} P_{i,i+1} = p & \forall i \\ P_{i,i-1} = q & \forall i \\ P_{ij} = 0 & \text{if } |j-i| \neq 1 \end{cases}$$



Fact: P is irreducible

Thm: All states are recurrent if p = 1/2. All states are transient if p ≠ 1/2.

- Intuitive argument for p = 2/3: there is a drift upwards, so standing at a state the MC may never return.

- We will show this using the  $\sum_{n=1}^{\infty} p_{ii}^{(n)}$  criteria.

It suffices to check if  $\sum_{n=1}^{\infty} p_{00}^{(2n)}$  converges or diverges. Want a formula for  $p_{00}^{(2n)}$ .

$p_{00}^{(n)} = 0$  for all odd n. [from 0 the walk can revisit 0 in an even nrof steps]

$$p_{00}^{(2n)} = P(X_{2n} = 0 | X_0 = 0) = \binom{2n}{n} p^n q^n = \frac{(2n)!}{n!n!} (pq)^n$$

nrof +1 (up) steps must equal the nrof of down (-1) steps must equal n (2n steps in total) → n up steps n down steps  
 (choose n positions for +1's →  $\binom{2n}{n}$  ways to do this; per. for -1's → 1 way) any such "path" has prob.  $p^n q^n$   
 nrof such paths =  $\binom{2n}{n}$

Stirling's formula →  $p_{00}^{(2n)} \sim \frac{(pq)^n}{\sqrt{\pi n}}$

$$\frac{(2n)!}{n!n!} (pq)^n \sim \frac{(2n)^{2n} e^{-2n} \sqrt{2\pi(2n)}}{n^{2n} e^{-2n} \sqrt{2\pi n} \sqrt{2\pi n}} (pq)^n = \frac{\sqrt{\pi n}}{4^n (pq)^n} = \frac{1}{\sqrt{\pi n}}$$

$$\rightarrow \sum_{n=0}^{\infty} p_{00}^{(2n)} \begin{cases} \approx \sum_{n=1}^{\infty} \frac{1}{\sqrt{\pi n}} = \infty & \text{if } p = \frac{1}{2} \\ \approx \sum_{n=1}^{\infty} \frac{(4p(1-p))^n}{\sqrt{\pi n}} < \infty & \text{if } p \neq \frac{1}{2} \end{cases}$$

- Recall that a finite irred. MC has all states recurrent
- this simple random walk ex. is irred but all states are transient if p ≠ 1/2.

Example: If in addition P is doubly stochastic, then  $\mu_j = \# \text{ of states, } V_j$ .  
 ↳ uniform stat. distr.

$$P = \begin{matrix} & \begin{matrix} 1 & 2 & 3 & 4 & 5 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{matrix} & \begin{bmatrix} 0 & 1/2 & 0 & 0 & 1/2 \\ 1/2 & 0 & 1/2 & 0 & 0 \\ 0 & 1/2 & 0 & 1/2 & 0 \\ 0 & 0 & 1/2 & 0 & 1/2 \\ 1/2 & 0 & 0 & 1/2 & 0 \end{bmatrix} \end{matrix}$$

S = {1, 2, ..., 5} doubly stoch. matrix ⇒  $\pi_j = 1/5, \mu_j = 5$

Example: Ruin probability

N > 0 fixed (target for quitting), S = {0, 1, ..., N}  $P_{i,i+1} = p, P_{i,i-1} = q$

Ruin event is {hit 0 before N} = {H\_0 < H\_N} = {H\_0 < a}  $P_{00} = 1, P_{NN} = 1$   
 $H_a = \min \{n \geq 0 | X_n = a\}$   $[H_N = \infty]$

Let  $x_k = P(H_0 < \infty | X_0 = k), k = 0, 1, 2, \dots, N. x_0 = 1, x_N = 0.$

Claim: For  $1 \leq k \leq N-1, x_k = p x_{k+1} + q x_{k-1}$

Sketch: Restrict to  $x_0 = k, 2 \leq k \leq N-2 (x_1 \neq 0/N)$

$$x_k = P(H_0 < \infty | X_0 = k) = \sum_{j \in S} P(H_0 < \infty, X_1 = j | X_0 = k) = P(H_0 < \infty, X_1 = k+1 | X_0 = k) + P(H_0 < \infty, X_1 = k-1 | X_0 = k) = P(H_0 < \infty | X_1 = k+1, X_0 = k) P(X_1 = k+1 | X_0 = k) + P(H_0 < \infty | X_1 = k-1, X_0 = k) P(X_1 = k-1 | X_0 = k)$$

$$= p P(H_0 < \infty | X_1 = k+1) + q P(H_0 < \infty | X_1 = k-1) \stackrel{\text{time-hom.}}{=} p P(H_0 < \infty | X_0 = k+1) + q P(H_0 < \infty | X_0 = k-1)$$

Ex:  $S = \{a, b\}$    $\underline{P} = \begin{bmatrix} a & b \\ 1 & 0 \end{bmatrix}$  embedded discrete time MC

Ex:  $S = \{a, b, c\}$  generator:  $\underline{Q} = \begin{bmatrix} a & b & c \\ -q_{ab} - q_{ac} & q_{ab} & q_{ac} \\ q_{ba} & -q_{ba} - q_{bc} & q_{bc} \\ q_{ca} & q_{cb} & -(q_{ca} + q_{cb}) \end{bmatrix}$

Ex: 2 states   $\underline{Q} = \begin{bmatrix} -\lambda & \mu \\ \lambda & -\mu \end{bmatrix}$

(FE)  $P_{11}'(t) = -q_{11} P_{11}(t) + P_{12}(t) q_{21} = -\lambda P_{11}(t) + \mu P_{12}(t)$

$\underline{P}(t) = \begin{bmatrix} P_{11}(t) & P_{12}(t) \\ P_{21}(t) & P_{22}(t) \end{bmatrix}$

(BE)  $P_{11}'(t) = \sum_{k=1}^2 q_{1k} P_{k1}(t) = q_{12} P_{21}(t) + q_{11} P_{11}(t) = -\lambda P_{11}(t) + \mu P_{21}(t)$

In (FF) can we  $P_{11}(t) + P_{12}(t) = 1$   
 $\rightarrow P_{11}'(t) = -\lambda P_{11}(t) + \mu P_{12}(t) = -\lambda P_{11}(t) + \mu(1 - P_{11}(t))$   
 $= P_{11}(t)(-\lambda + \mu) + \mu$

$P_{11}(0) = 1$

Let  $y = y(t) = P_{11}(t) \rightarrow y' = -(\lambda + \mu)y + \mu$   $y' + (\lambda + \mu)y = \mu, y(0) = 1$   
 1<sup>st</sup> order, linear, const. coeff. diff. eqn.

Sol'n: If  $\mu = 0$ :  $y = C_1 e^{-(\lambda + \mu)t} + C_2, C_1, C_2$  const.

$y' = -C_1(\lambda + \mu)e^{-(\lambda + \mu)t} + 0 \Rightarrow y + (\lambda + \mu)y = -C_1(\lambda + \mu)e^{-(\lambda + \mu)t} + (\lambda + \mu)(C_1 e^{-(\lambda + \mu)t} + C_2)$   
 $+ C_2] = (\lambda + \mu)C_2 \stackrel{!}{=} \mu \Rightarrow C_2 = \frac{\mu}{\lambda + \mu} \Rightarrow y = C_1 e^{-(\lambda + \mu)t} + \frac{\mu}{\lambda + \mu}$

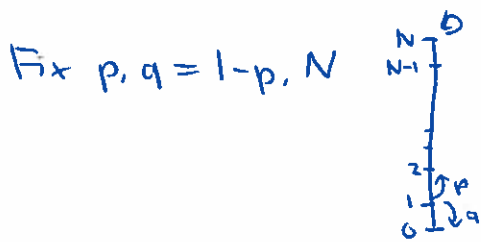
Set  $t=0, y(0) = C_1 \cdot 1 + \frac{\mu}{\lambda + \mu} \stackrel{!}{=} 1 \Rightarrow C_1 = 1 - \frac{\mu}{\lambda + \mu} = \frac{\lambda}{\lambda + \mu}$

$\Rightarrow P_{11}(t) = \frac{\lambda}{\lambda + \mu} e^{-(\lambda + \mu)t} + \frac{\mu}{\lambda + \mu} \Rightarrow P_{12} = -\frac{\lambda}{\lambda + \mu} e^{-(\lambda + \mu)t} + \frac{\lambda}{\lambda + \mu}$  ( $P_{11}(t) + P_{12}(t) = 1$ )  
 $\underline{P}(t) = \frac{1}{\lambda + \mu} \begin{bmatrix} \lambda e^{-(\lambda + \mu)t} + \mu & \lambda - \lambda e^{-(\lambda + \mu)t} \\ \mu - \mu e^{-(\lambda + \mu)t} & \lambda + \mu e^{-(\lambda + \mu)t} \end{bmatrix}$  Note  $\lim_{t \rightarrow 0} \underline{P}(t) = \begin{bmatrix} \frac{\lambda}{\lambda + \mu} & \frac{\mu}{\lambda + \mu} \\ \frac{\mu}{\lambda + \mu} & \frac{\lambda}{\lambda + \mu} \end{bmatrix} = \underline{P}(0)$

Ex:  $\underline{Q} = \begin{bmatrix} -\lambda & \mu \\ \lambda & -\mu \end{bmatrix}, \pi_1 = \frac{\mu}{\lambda + \mu}, \pi_2 = \frac{\lambda}{\lambda + \mu}$  (limiting dist.)  
 Can check:  $\underline{\pi} \underline{P}(t) = \underline{\pi} \quad \forall t \geq 0$

Ex: 7.14 (Eat, play, sleep) Baby 3 states: eat (e), sleep (s), p (play).  
 eats an average for  $\frac{1}{2}$  hr, plays an av. for 1<sup>hr</sup>, sleeps on av. 3 hrs.  
 After eating, 50% chance of s or p. After playing, 50% chance of e or s.  
 After sleeping, always p. What proportion of the day does the baby spend  $S^2$  (hrs)  
 (X<sub>t</sub>) CTMC, X<sub>t</sub> = state of baby at time t, either e, s, p.  
 Want  $\underline{\pi}$ , so we need  $\underline{Q}$

# Gambler's Ruin



$$\begin{aligned}
 P_{00} &= P_{NN} = 1 \\
 P_{i,i+1} &= p, \quad 0 < i < N \\
 P_{i,i-1} &= q, \quad 0 < i < N \\
 P_{ij} &= 0 \text{ otherwise}
 \end{aligned}$$

1<sup>st</sup> step analysis eqns:

$$\begin{aligned}
 P(\text{Ruin} \mid X_0 = i) &= P(H_0 < \infty \mid X_0 = i) \\
 &= u(i) \\
 &\uparrow \\
 &\text{get to } 0 \text{ before } N \\
 &\text{ever get to } 0 \\
 &\{H_0 < \infty\}
 \end{aligned}$$

Take  $2 \leq i \leq N-2$ , then  $P_{i0} = 0$ .

$$\Rightarrow u(i) = \sum_{j=0}^N P_{ij} u(j) = P_{i,i+1} u(i+1) + P_{i,i-1} u(i-1) = pu(i+1) + qu(i-1)$$

$$\Rightarrow u(i) = pu(i+1) + qu(i-1), \quad 2 \leq i \leq N-2$$

$$\underline{i=1}: u(1) = P_{10} + P_{12} u(2) \quad u(2) = q + pu(2) = pu(2) + qu(0) \quad \checkmark$$

$$\underline{i=N-1}: u(N-1) = P_{N-1,0} + P_{N-1,N} u(N) + P_{N-1,N-2} u(N-2) = 0 + pu(N) + qu(N-2) \quad \checkmark$$

$\Rightarrow$  We get  $u(0) = 1, u(N) = 0$ ,  $u(i) = pu(i+1) + qu(i-1), 1 \leq i \leq N$ .  
 difference eqn, solved in Probl. 9 on DE handout.

Consider  $E(\text{duration of game} \mid X_0 = i) = \min\{R_0, R_N\} \stackrel{\text{def}}{=} T, i \neq 0 \text{ or } N$ .

Put  $w(i) = E(T \mid X_0 = i), w(0) = w(N) = 0$ .

By 1<sup>st</sup> step analysis,  $w(i) = 1 + \sum_{j \neq 0, j \neq N} P_{ij} w(j) = 1 + P_{i,i+1} w(i+1) + P_{i,i-1} w(i-1) = 1 + pw(i+1) + qw(i-1)$ .

Set  $p = q = \frac{1}{2}$ .  $w(i) = 1 + \frac{1}{2}w(i+1) + \frac{1}{2}w(i-1), 0 < i < N$ .  
 $w(0) = w(N) = 0$ .  
 $\hookrightarrow$  DE, Problem 8 on DE handout

Ex: period:

$$P = \begin{matrix} & 0 & 1 & 2 \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} 0 & 1 & 0 \\ 113 & 0 & 213 \\ 0 & 1 & 0 \end{bmatrix} \end{matrix}$$

Find periods of each state.

$$P^2 = \begin{matrix} & 0 & 1 & 2 & 2 \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} 113 & 0 & 213 \\ 0 & 1 & 0 \\ 113 & 0 & 213 \end{bmatrix} \end{matrix}, \quad P^3 = \begin{matrix} & 0 & 1 & 0 \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} 113 & 0 & 213 \\ 0 & 1 & 0 \end{bmatrix} \end{matrix} = P \Rightarrow P^n = \begin{matrix} & 0 & 1 & 0 \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} 113 & 0 & 213 \\ 0 & 1 & 0 \\ 113 & 0 & 213 \end{bmatrix} \end{matrix} \begin{matrix} n \text{ odd} \\ n \text{ even} \end{matrix}$$

$$d(0) = \text{g.c.d.} \{n \geq 1 \mid P_{00}^n > 0\} = \text{g.c.d.} \{2, 4, 6, \dots\} = \text{g.c.d.} \{2, 4, 6, \dots\} = 2$$

$$d(1) = \text{g.c.d.} \{2, 4, 6, \dots\} = 2$$

Ex: Simple random walk on  $S = \{0, 1, 2, \dots\}$  with reflection at 0.



Prop: This chain is irred., has period 2, and recurrent if  $p > \frac{1}{2}$ , null recurrent if  $p = \frac{1}{2}$ , and pos recurrent if  $p < \frac{1}{2}$ , and

We know  $q_e, q_p, q_s$

Assuming times spent in the states

$q_e = \text{param. of holding time } T_e = \frac{1}{1/2} = 2$  are expon. rv's.

$q_p = \frac{1}{1} = 1$

$q_s = \frac{1}{3}$

(expected value of an exp. rv. with param  $\lambda$  is  $\frac{1}{\lambda}$ )

Know  $\tilde{P}$ , embedded chain matrix (for  $Y_n$ ):  
[always 0 on diagonal]

$$\tilde{P} = \begin{matrix} & \begin{matrix} e & p & s \end{matrix} \\ \begin{matrix} e \\ p \\ s \end{matrix} & \begin{bmatrix} 0 & 1/2 & 1/2 \\ 1/2 & 0 & 1/2 \\ 0 & 1 & 0 \end{bmatrix} \end{matrix}$$

Recall  $\hat{P}_{ij} = \frac{q_{ij}}{q_i} \ (i \neq j) \Rightarrow q_{ij} = q_i \hat{P}_{ij}$

$$\rightarrow Q = \begin{matrix} & \begin{matrix} e & p & s \end{matrix} \\ \begin{matrix} e \\ p \\ s \end{matrix} & \begin{bmatrix} -2 & 1 & 1 \\ 1/2 & -1 & 1/2 \\ 0 & 1/3 & -1/3 \end{bmatrix} \end{matrix}$$

$\Rightarrow \pi_s = \frac{9}{14}$  (prop. of time spent sleeping)

Solve  $\pi Q = 0 = [0 \ 0 \ 0]$

$$\Rightarrow \pi = \left[ \frac{1}{14} \quad \frac{4}{14} \quad \frac{9}{14} \right]$$

$= [0_e \ \pi_p \ \pi_s]$