

03/01/04 What happens in the long run
 if I start in a state $i \in T$,
 (Lawler Sec. 1.3)

Sometimes helpful (not mandatory) to
 write the transition matrix for
 a reducible MC in canonical form,

$$\begin{array}{l}
 \text{recurrent} \\
 \text{transient}
 \end{array}
 \begin{array}{l}
 T^c \\
 T
 \end{array}
 \left\{ \begin{array}{l}
 T^c \\
 T
 \end{array} \right.
 \left[\begin{array}{cc}
 \bar{P} & 0 \\
 S & Q
 \end{array} \right] = P$$

Arrange recurrent states to group them
 by communication classes so then
 \bar{P} will be block diagonal

$$\bar{P} = \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_M \end{array} \left[\begin{array}{cccc}
 \bar{P}^{(1)} & 0 & 0 & 0 \\
 0 & \bar{P}^{(2)} & 0 & 0 \\
 0 & 0 & \ddots & 0 \\
 0 & 0 & 0 & \bar{P}^{(M)}
 \end{array} \right]$$

Question: If I start at $i \in T$,
then what is the first state
 $j \in T^c$ that I reach?

This is important because it tells
us what recurrent class we end
up in, which in turn describes
the long term properties.

$$\text{Let } U_{ij} = \text{Prob}(X_{\tau} = j \mid X_0 = i)$$

for $i \in T, j \in T^c$

where τ is the time at which
the MC first leave transient states,

$$\tau = \min \{n \in \mathbb{Z}_{\geq 0} : X_n \notin T\}$$

To calculate U_{ij} , we will use
first-step analysis

- study + break down the MC dynamics
based on what happens at first step.

$$U_{ij} = \text{Prob}(X_T = j \mid X_0 = i)$$

$$= \sum_{k \in S} \text{Prob}(X_T = j \text{ and } X_1 = k \mid X_0 = i)$$

$$\text{Prob}(A \text{ and } B \mid C) = \text{Prob}(A \mid B \text{ and } C) \times \text{Prob}(B \mid C)$$

$$= \sum_{k \in S} \frac{\text{Prob}(X_T = j \mid X_1 = k \text{ and } X_0 = i)}{\text{Prob}(X_1 = k \mid X_0 = i)}$$

$$= \sum_{k \in S} \text{Prob}(X_T = j \mid X_1 = k) \text{Prob}(X_1 = k \mid X_0 = i)$$

What do these factors look like for various k ?

$$\text{Suppose } k \in T^c \text{ and } k \neq j \Rightarrow T=1$$

$$\Rightarrow \text{Prob}(X_T = j \mid X_1 = k) = 0$$

$$\text{Suppose } k = j \Rightarrow T=1 \text{ (since } j \in T^c)$$

$$\text{Prob}(X_T = j \mid X_1 = k) = 1$$

$$\text{Suppose } k \in T, \text{ then } \text{Prob}(X_T = j \mid X_1 = k) = U_{kj}$$

Combining these facts

$$U_{ij} = P_{ij} + \sum_{k \in T} P_{ik} U_{kj} \quad \text{for } i \in T, j \in T^c$$

This can be also be written

$$U_{ij} = S_{ij} + \sum_{k \in T} Q_{ik} U_{kj}$$

where Q, S are the submatrices of P ,

$$U = S + Q U \quad \text{as matrices,}$$

$$(I - Q) U = S$$

$$U = (I - Q)^{-1} S$$

But is $I - Q$ really invertible? Yes,

$$(I - Q)^{-1} = \sum_{n=0}^{\infty} Q^n \quad \text{if RHS exists,}$$

~~Q^n~~ "Resolvent"

$$(Q^n)_{ij} = \text{Prob}(X_n = j | X_0 = i) \text{ decreases geometrically with } n,$$

This implies in particular $Q^n \rightarrow 0$ as $n \rightarrow \infty$
and so all ev's λ of Q must
satisfy $|\lambda| < 1$,

$$\Rightarrow (I - Q)^{-1} \text{ exists}$$

The formula $U = (I - Q)^{-1} S$ has an
intuitive meaning

$$U = (I - Q)^{-1} S = \sum_{n=0}^{\infty} Q^n S$$

~~$$= \sum_{n=0}^{\infty} \text{Prob}(X_{\tau} = j \text{ and } \tau = n)$$~~

$$U_{ij} = \sum_{n=0}^{\infty} (Q^n S)_{ij}$$

$$(Q^n S)_{ij} = \text{Prob}(X_{\tau} = j \text{ and } \tau = n+1 \mid X_0 = i)$$

Birth-death chains

$$P = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & \dots & N \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ \vdots \\ N \end{matrix} & \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ q_1 & r_1 & p_1 & 0 & \dots & 0 \\ 0 & q_2 & r_2 & p_2 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & \dots & \dots & \dots & q_{N-1} & r_{N-1} & p_{N-1} \\ 0 & 0 & 0 & \dots & 0 & 0 & 1 \end{bmatrix} \end{matrix}$$

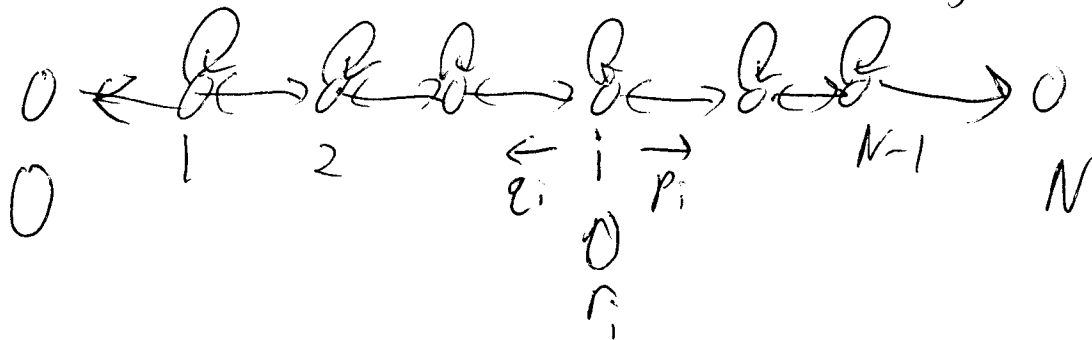
$$q_i + r_i + p_i = 1$$

q_i = prob for left move from i

p_i = prob for right " "

r_i = prob for no move " "

The states 0 and N: absorbing



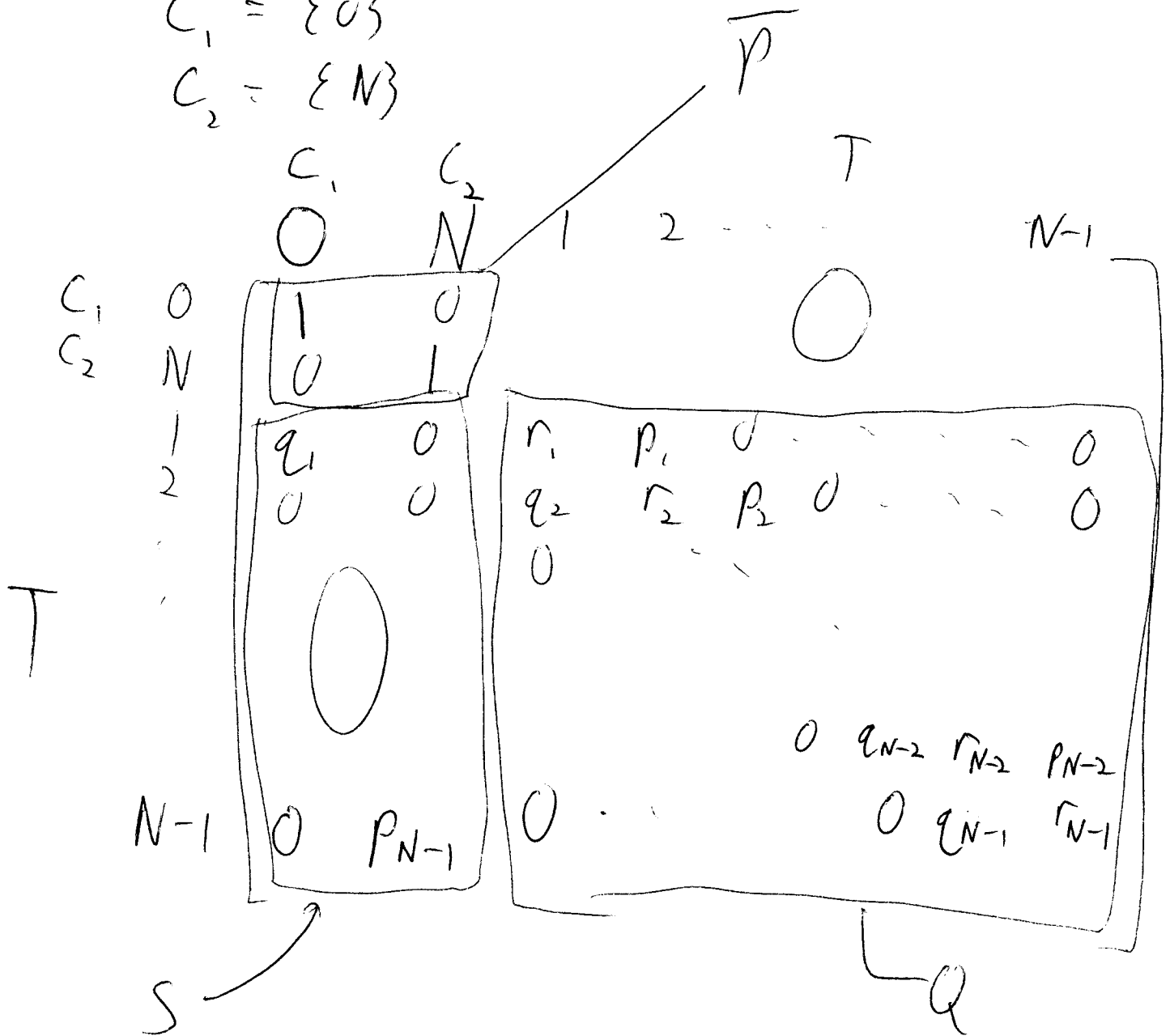
Starting in state i , what's the prob I eventually wind up in state 0 (or in state N)

Canonical form (not necessary)

$T = \{1, \dots, N-1\}$

$C_1 = \{0\}$

$C_2 = \{N\}$



$U = (I - d)^{-1} S$... hard to explicit formulas

$$U_{ij} = \text{Prob}(X_{\tau} = j \mid X_0 = i) \quad \text{where}$$

τ is first time at which ~~use~~
 $X_n \notin \{1, \dots, N-1\}$

$$U_{ij} = P_{ij} + \sum_{k=1}^{N-1} P_{ik} U_{kj} \quad \begin{array}{l} 1 \leq i \leq N-1 \\ j=0 \text{ or } j=N \end{array}$$

Solve by hand.

For $2 \leq i \leq N-2$

$$U_{ij} = q_i U_{i-1,j} + r_i U_{ij} + p_i U_{i+1,j}$$

Intuitive meaning!

Can also use this eqn for all $1 \leq i \leq N-1$
 if I set (define)

$$U_{00} = 1, \quad U_{0N} = 0, \quad U_{N0} = 0, \quad U_{NN} = 1$$

This is now a system of linear
 difference eqns w/ BCs.

- techniques: bare hands

~~or~~ generating functions (esp. if recursive)

Bender tors zug Ch. 2 or 3

Because $r_i = 1 - p_i - q_i$

$$q_i (U_{i-1,j} - U_{ij}) + p_i (U_{i+1,j} - U_{ij}) = 0$$

Define $V_{ij} = U_{ij} - U_{i-1,j}$ for $1 \leq i \leq N$

$$-q_i V_{ij} + p_i V_{i+1,j} = 0$$

$$V_{i+1,j} = \frac{q_i}{p_i} V_{ij}$$

$$V_{i,j} = \left(\prod_{1 \leq k \leq i-1} \frac{q_k}{p_k} \right) V_{1,j}$$

$$\gamma_i = \prod_{1 \leq k \leq i-1} \frac{q_k}{p_k}$$

Get $V_{1,j}$ from using BC's,

$$\sum_{i=1}^N V_{ij} = \cancel{0} \quad U_{Nj} - U_{0j} = \delta_{Nj} - \delta_{0j}$$

$$\left(\sum_{k=1}^N \gamma_k \right) V_{1j} = \delta_{Nj} - \delta_{0j}$$

$$V_{1j} = \frac{\delta_{Nj} - \delta_{0j}}{\sum_{k=1}^N \gamma_k}$$

$$V_{ij} = \gamma_i \frac{(\delta_{Nj} - \delta_{0j})}{\sum_{k=1}^N \gamma_k}$$

$$U_{ij} = \sum_{k=1}^i V_{kj} + U_{0j}$$

~~Wrong~~

$$U_{i0} = \text{Prob}(X_T = 0 | X_0 = i) = \frac{\sum_{k'=i+1}^N \gamma_{k'}}{\sum_{k=1}^N \gamma_k}$$

$$U_{iN} = \text{Prob}(X_T = N | X_0 = i) = \frac{\sum_{k'=1}^i \gamma_{k'}}{\sum_{k=1}^N \gamma_k}$$

where $\gamma_i = \prod_{1 \leq k \leq i-1} \frac{q_k}{p_k}$

These techniques can also be used to answer

$$\text{Prob}(X_T \in C_k \mid X_0 = i) \quad \text{for } i \in T$$

C_k is a recurrent class

Could add up probabilities for each state in C_k or...

write a condensed MC where

C_k is collapsed into 1 state,

Another observation: ... later

Another question of interest:

Suppose there is a function f associated to MC.

How does $\sum_{i=1}^N f(X_i)$ behave for?

☺

Examples: income
deaths

productivity, N

For large N , $\frac{1}{N} \sum_{i=1}^N f(X_i)$ behaves like?

→ first figure out the probabilities that you wind up in the various recurrent classes

→ given you end up in a recurrent class C_k ,

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N f(X_i) = \sum_{j \in S} \pi_j^{(k)} f(j) \quad \text{w/ prob 1}$$

stat dist. assoc.
to class C_k .

(Karlin & Taylor Ch. 3)

HW 2 can be turned in on
Wed March 17,