

Markov Chains

- Bernoulli * Poisson \longrightarrow memoryless
- future does not depend on past

- Markov:
- Future depends on past.
- Can be predicted by what happened in the past

Markov: Effect of the past on future

Summarized by a state

- state takes on finite # of values.

- changes according to probabilities

that don't ~~change over time~~. depend on the time of change.

Discrete Time Markov Chains

- State changes at certain discrete time instants.
indexed by n .

State $X_n \in S$

- $S =$ finite set of states, called State Space.

- Markov chain described by Transition Probabilities P_{ij}

- P_{ij} : Whenever state is i , probability P_{ij} ~~is~~
next state is j .

$$P_{ij} = P(X_{n+1} = j \mid X_n = i) \quad i, j \in S$$

- Assume Markov property:

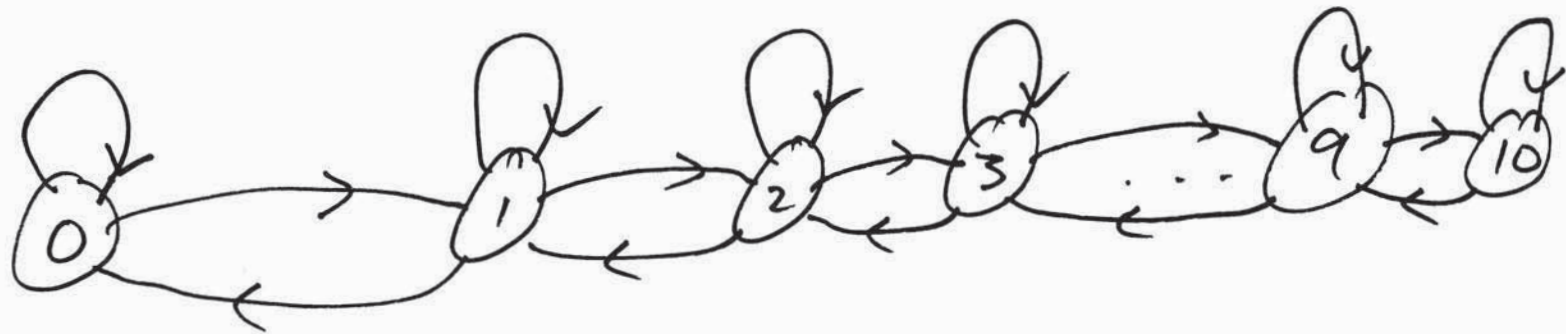
$$P(X_{n+1} = j \mid X_n = i, X_{n-1} = i_{n-1}, \dots, X_0 = i_0) = P(X_{n+1} = j \mid X_n = i) = P_{ij}$$

$\forall n$, \forall states $i, j \in S$
and all possible sequences i_0, \dots, i_{n-1}

In words: - Transition prob. P_{ij} applies whenever state i is reached, no matter HOW state i was reached.

- X_{n+1} only depends on past through X_n .

$$\sum_{j=1}^m P_{ij} = 1 \quad \forall i$$



Transition Probability Matrix

$$\begin{bmatrix} P_{11} & P_{12} & \dots & P_{1m} \\ P_{21} & P_{22} & \dots & P_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \dots & P_{mm} \end{bmatrix}$$

~~it's~~
 ith row, jth
 column : P_{ij}

Also known as Transition probability graph.

Example: Student either up to date in each week or behind. (2 states).

If up to date in a given week, then up to date next week with prob 0.8, and behind 0.2.

If behind in a given week, then prob of up to date next week is 0.6, behind is 0.4.

~~$P_{11} = 0.8$~~ P_{12} state 1 = up to date
 state 2 = behind.

$$P_{11} = 0.8$$

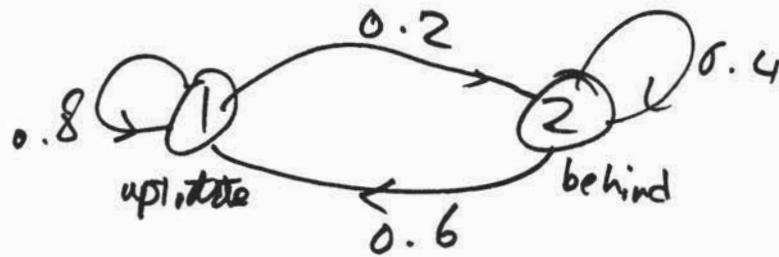
$$P_{12} = 0.2$$

$$P_{21} = 0.6$$

$$P_{22} = 0.4$$

Transition Prob matrix

$$\begin{bmatrix} 0.8 & 0.2 \\ 0.6 & 0.4 \end{bmatrix}$$

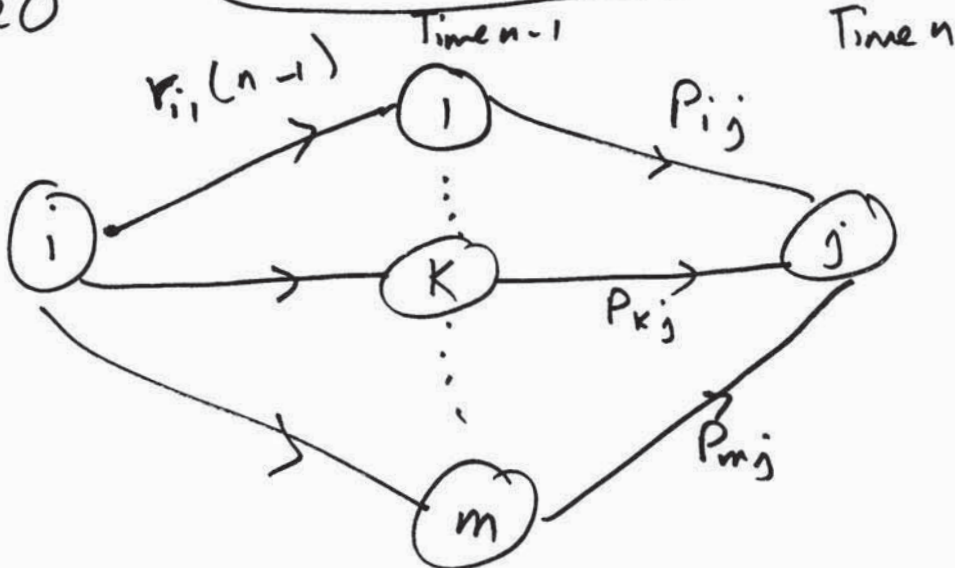


~~Probability of a state~~

n-step Transition Probabilities

$$r_{ij}(n) = P(X_n = j \mid X_0 = i) ??$$

Time 0



Apply ~~the~~ Chapman-Kolmogorov Eqn:

$$r_{ij}(n) = \sum_{k=1}^m r_{ik}(n-1) P_{kj} \quad \forall n > 1$$

$\forall i, j$

Need initial conditions: $r_{ij}(1) = P_{ij}$

n-step Transition prob. matrix =
 $r_{ij}(n)$ is i th row, j th column.

	U	B
U	0.8	0.2
B	0.6	0.4

$r_{ij}(1)$

0.76	0.24
0.72	0.28

$r_{ij}(2)$

0.752	0.248
0.744	0.256

$r_{ij}(3)$

.75	.249
.748	.256

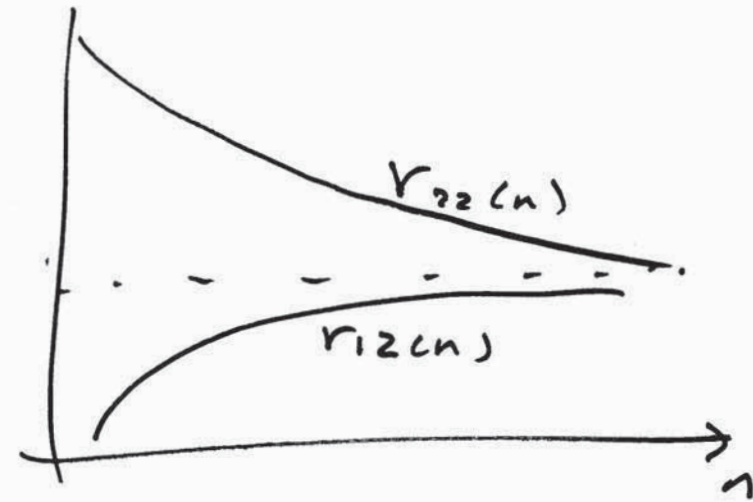
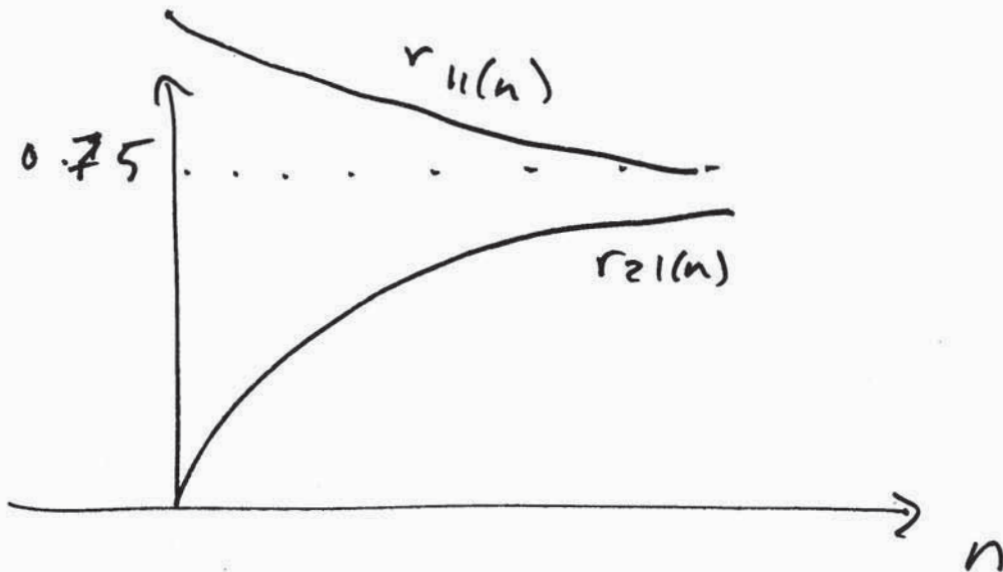
$r_{ij}(4)$

.7501	.2499
.7498	.2502

$r_{ij}(5)$

Observe: $r_{ij}(n)$ converges to a limit as $n \rightarrow \infty$
 Independent of initial state

Conclusions: Each state has a steady state probability of being occupied at times far into the future.



Ex fly moves along a straight line in unit increments

- one unit left with prob 0.3
- " " right " " 0.3
- stays in place " " 0.4

- Two Spiders in position 1 and m

- Fly starts in a position between 1 and m.

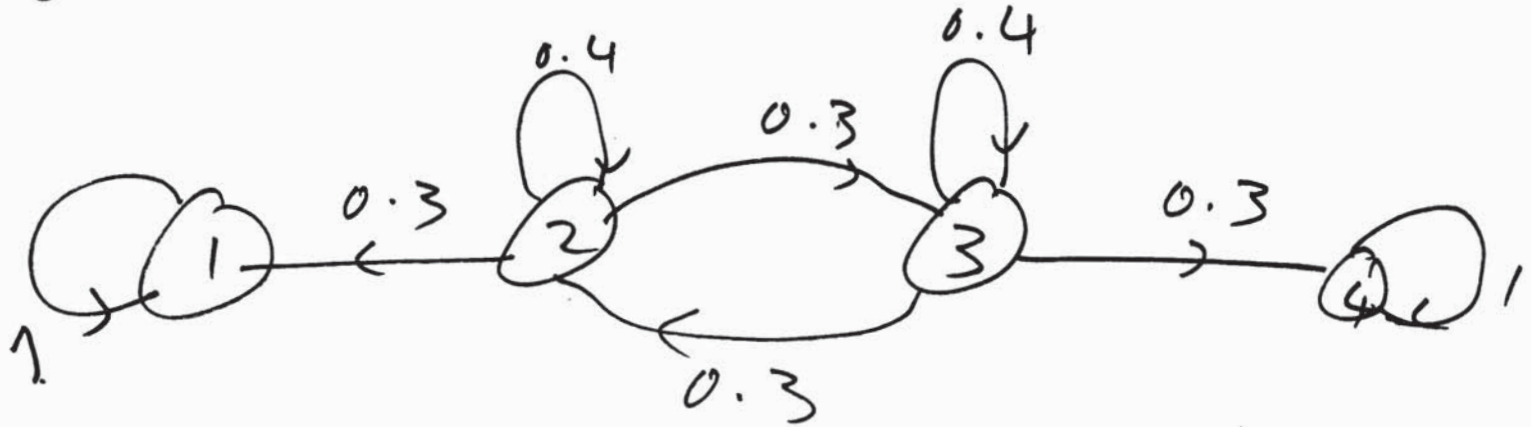
$$P_{ii} = 1$$

$$P_{mm} = 1.$$

$$P_{ij} = \begin{cases} 0.3 & \text{if } j = i-1 \\ 0.4 & \text{if } i = j \end{cases}$$

$$j = i-1 \quad \text{or} \quad j = i+1$$

Suppose:
 $m = 4$



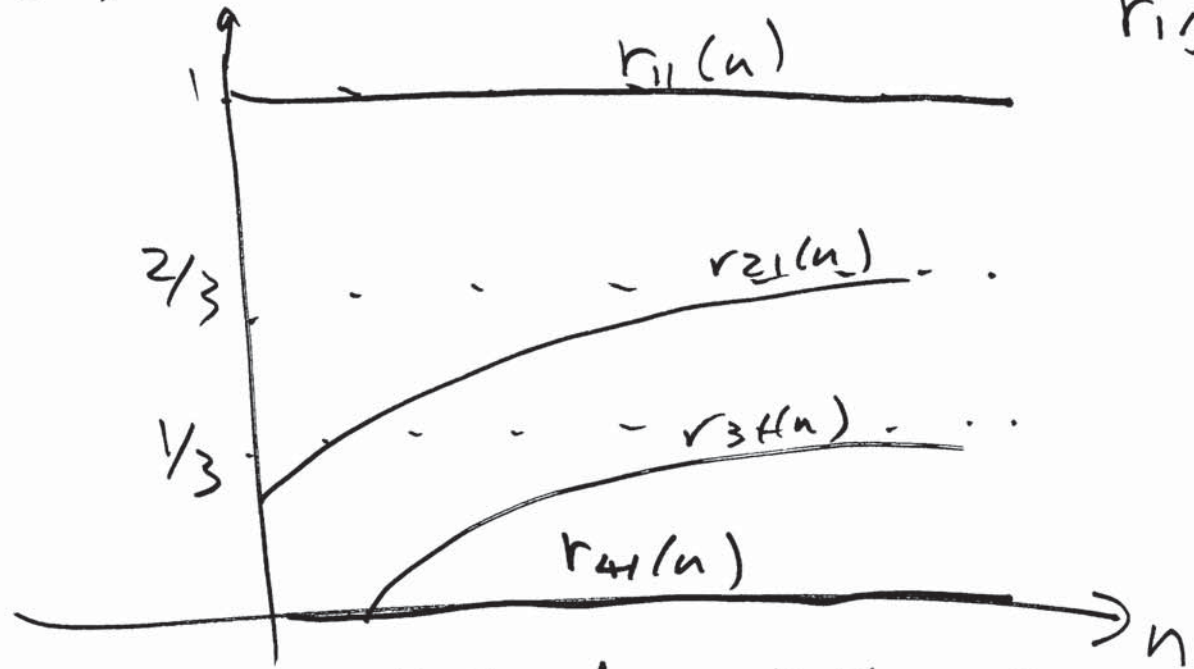
What is $r_{ij}(n)$ as $n \rightarrow \infty$

	1	2	3	4
1	1	0	0	0
2	0.3	0.4	0.3	0
3	0	0.3	0.4	0.3
4	0	0	0	0

1	0	0	0
$\frac{2}{3}$	0	0	$\frac{1}{3}$
$\frac{1}{3}$	0	0	$\frac{2}{3}$
0	0	0	1

$r_{ij}(1)$

$r_{ij}(\infty)$



prob of reaching state 1 starting from state i

observation: - limit $\lim_{n \rightarrow \infty}$ depends on the initial state

- "Absorbing" states: once reached only repeated.
states i and u absorbing.

- Idea: Classify states based on long term frequency they are visited.

- Define Accessible:
state j is accessible from state i
if $\exists n$ s.t. $r_{ij}(n) > 0$

$A(i)$: set of accessible states from i

Recurrent & Transient States

Recurrent: state ~~i~~ i is recurrent if starting from i and from wherever you can go there is a way of returning to i .

Aliter Def.: i is recurrent if $\forall j$ that is accessible from i , i is also accessible from j .

If not recurrent \rightarrow Then Transient

~~If a recurrent state is visited once, it is going to be visited ∞ times.~~

Aliter Def of Transient
 i is transient if $\exists j \in A(i)$ s.t. i is not accessible from j .

\Rightarrow

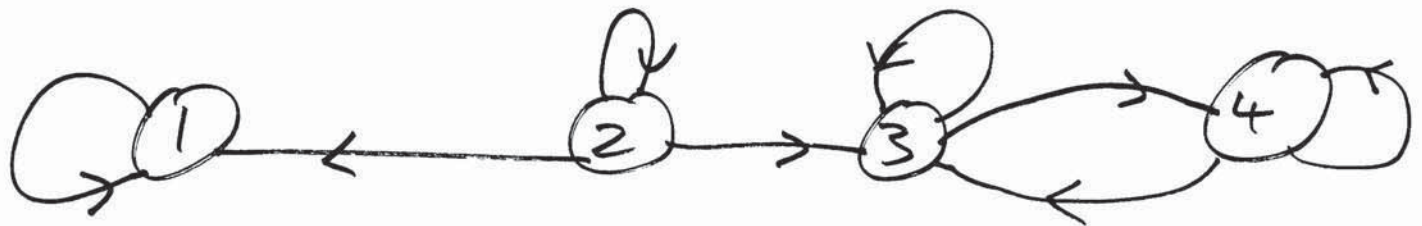
Can show:

① If a recurrent state is visited once, it is going to be visited ∞ many times.

② A Transient state will ^{only} be visited finite # of times.

if i is transient $P(X_n = i) \rightarrow 0$ as $n \rightarrow \infty$

Ex



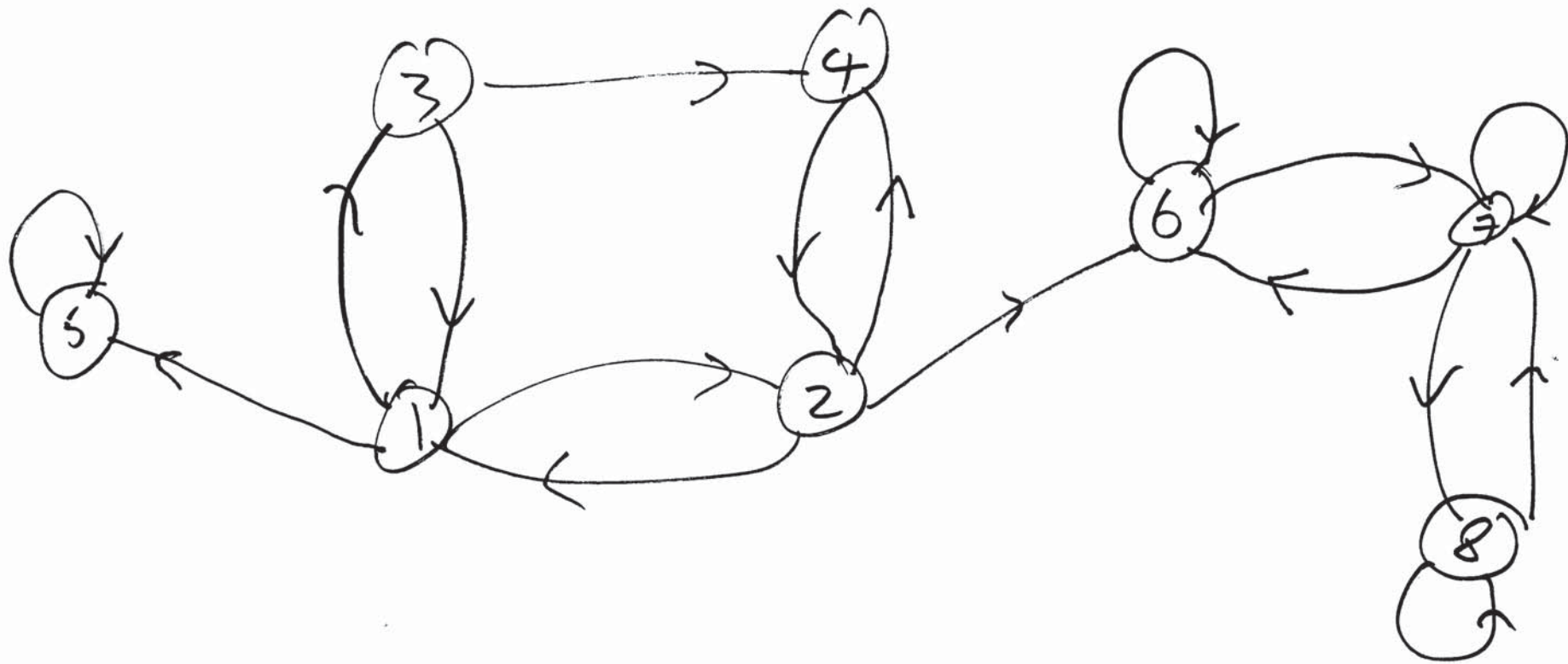
Which states are Transient which ones recurrent

1 = recurrent : only 1 is accessible from 1

2 = Transient

3 & 4 : recurrent.

How about This.



Recurrent Class

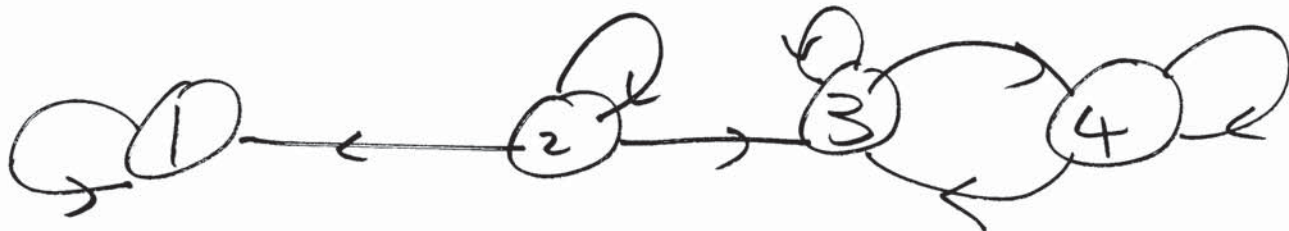
- Collection of recurrent states that communicate with each other and with no other state.

- If i is recurrent, $A(i)$ forms a recurrent class.

\Rightarrow states in $A(i)$ are all accessible from each other And no state outside of $A(i)$ is accessible from them.

- For a recurrent state i
we have $A(i) = A(j) \quad \forall j \in A(i)$

Example



What are recurrent classes?

A : ① is recurrent class
3,4 is " " "

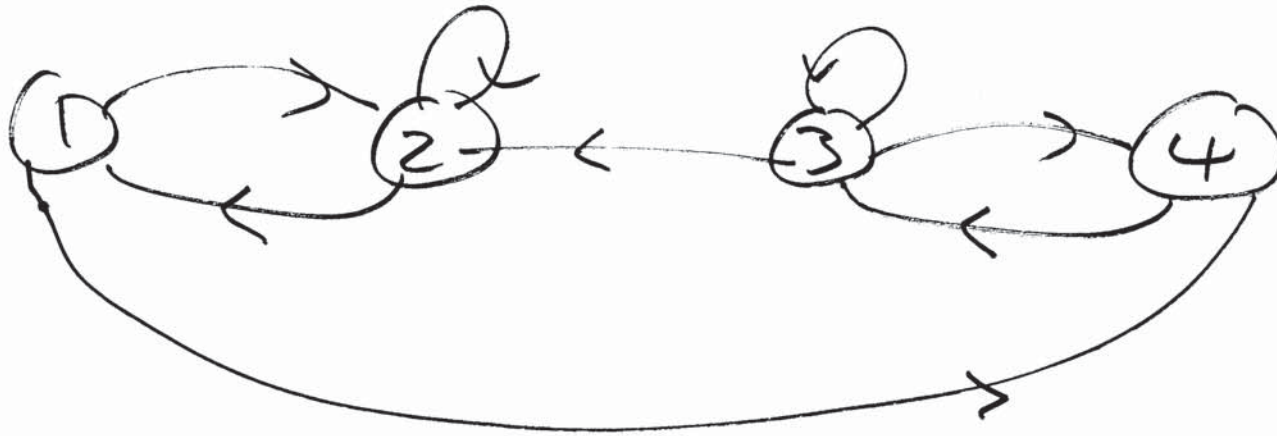
Markov Chain Decompositions

1. A M.C. can be decomposed into 2 or more recurrent classes plus possibly some transient states.
2. A recurrent state is accessible from all states in its class but is not from recurrent states in other classes.
3. A transient state is not accessible from any recurrent state.
4. At least one, maybe more, recurrent states are accessible from a given transient state.

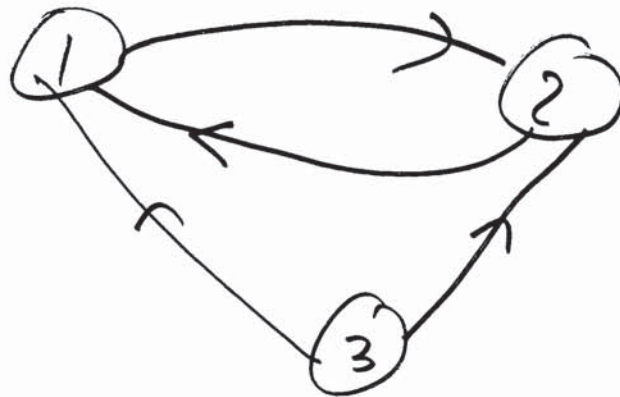
EX

~~State transition diagram of a Markov chain~~

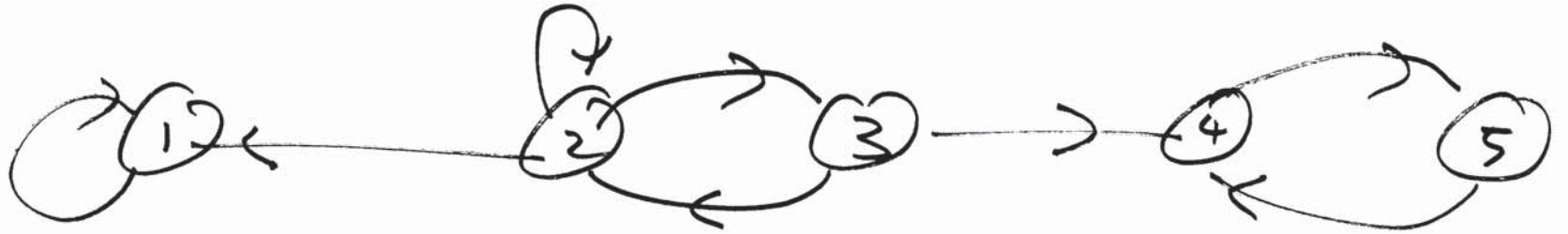
How many recurrent classes?
How many transient?



①



A: 1 recurrent class: (1 2 2)
1 transient state (3)



Two classes of recurrent states.

- class 1: state 2

- " 2: 4, 5

- Two transient states: 1, 3