Lecture 8: Random Processes, Part II

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EE210: Probability and Introductory Random Processes
KAIST EE

MONTH DAY, 2021

Roadmap

- Basics on Random Process
- Bernoulli Process
- Poisson Process
- Use of Bernoulli and Poisson Processes
- Markov Chain
  - Definition, Transition Probability Matrix, State Transition Diagram
  - Classification of States
  - Steady-state Behaviors and Stationary Distribution
  - Transient Behaviors

- Assume discrete times $n = 1, 2, \ldots$

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  - Markov chain
  - One of the most popular random processes in engineering

Example: Machine Failure, Repair, and Replacement

- A machine: working or broken down on a given day.
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- What will happen at $(n+1)$-th day depends only on what happens at n-th day?

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  Thus, for any $n \geq 0$, we introduce a simple notation p_{ij}

  $$p_{ij} \triangleq \mathbb{P}(X_{n+1} = j | X_n = i)$$

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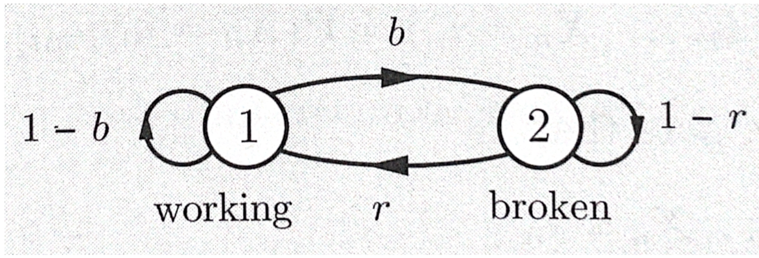
- Transition probability matrix

$$\begin{bmatrix} 1 - b & b \\ r & 1 - r \end{bmatrix}$$

- State transition diagram



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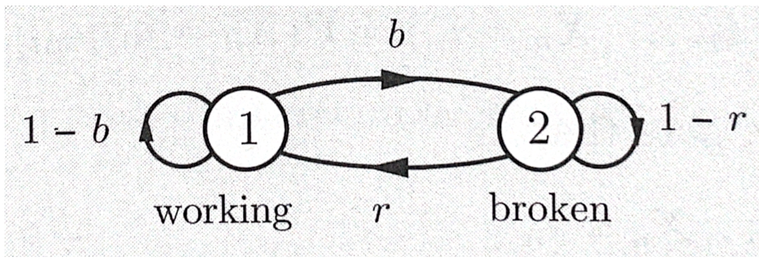

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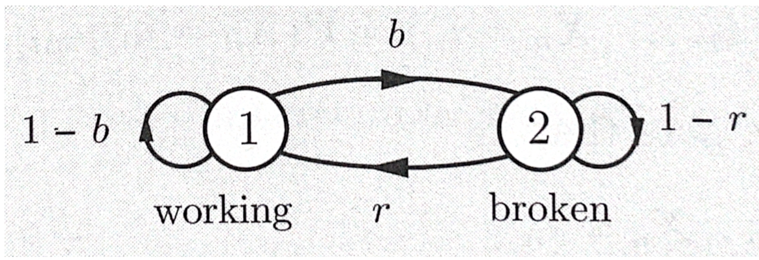

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- $\sum_{j=}^{m} p_{ij} = 1$ (for each row i, the column sum $= 1$)

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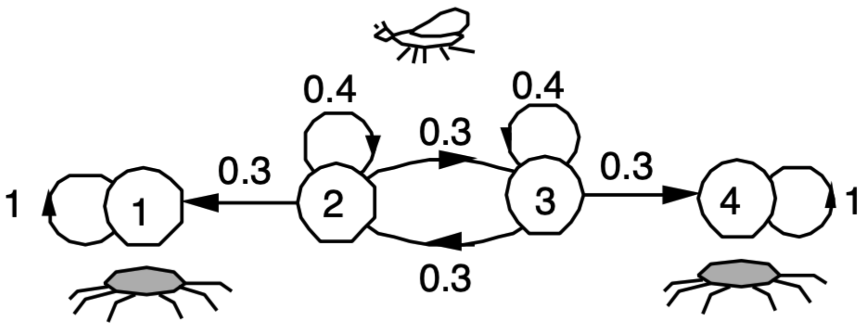

	1	2	3	4
1	1.0	0	0	0
2	0.3	0.4	0.3	0
3	0	0.3	0.4	0.3
4	0	0	0	1.0

p_{ij}

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&= p_{i_{n-1} i_n} \cdot \mathbb{P}\Big(X_0 = i_0, X_1 = i_1, \ldots, X_{n-1} = i_{n-1}\Big) = \mathbb{P}(X_0 = i_0) \cdot p_{i_0 i_1} \cdot p_{i_1 i_2} \cdots p_{i_{n-1} i_n}
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$$\mathbb{P}(X_0 = 2, X_1 = 2, X_2 = 2, X_3 = 3, X_4 = 4) = \mathbb{P}(X_0 = 2) p_{22} p_{22} p_{23} p_{34} = \mathbb{P}(X_0 = 2)(0.4)^2(0.3)^2$$

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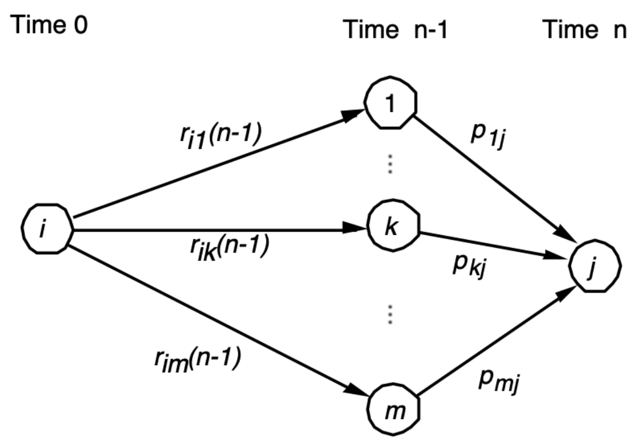

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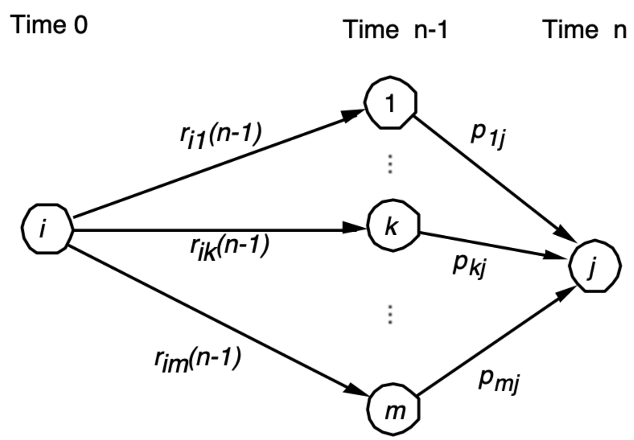

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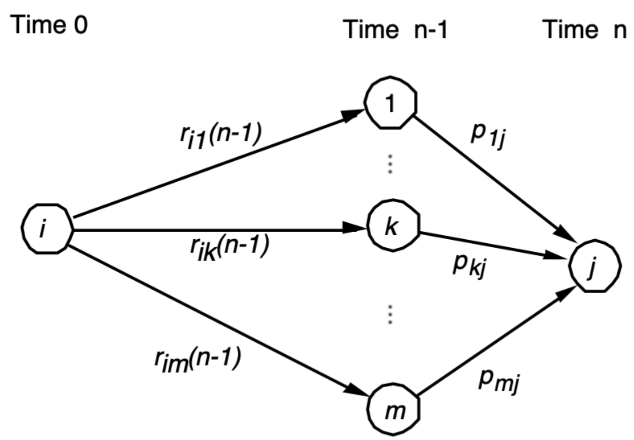
$$= \sum_{k=1}^{m} r_{ik}(n-1) p_{kj}$$



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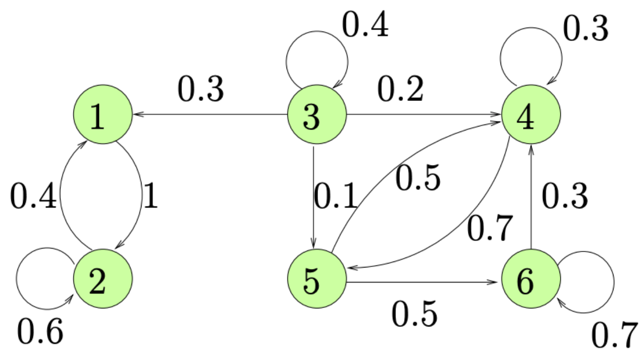

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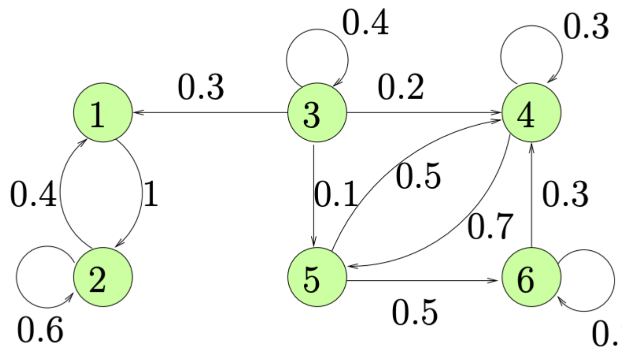

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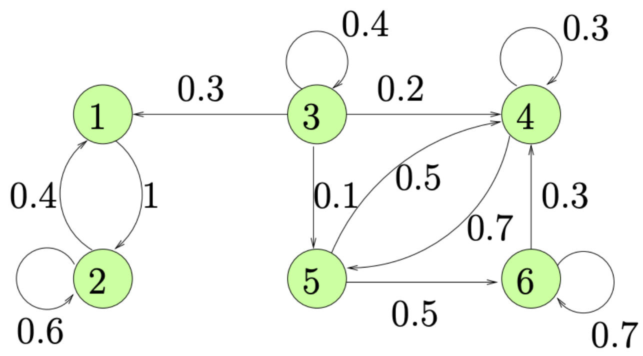

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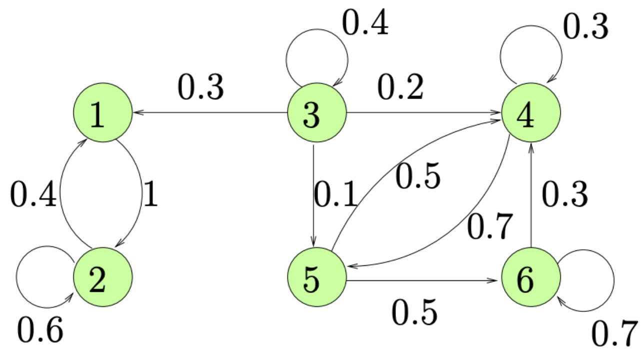

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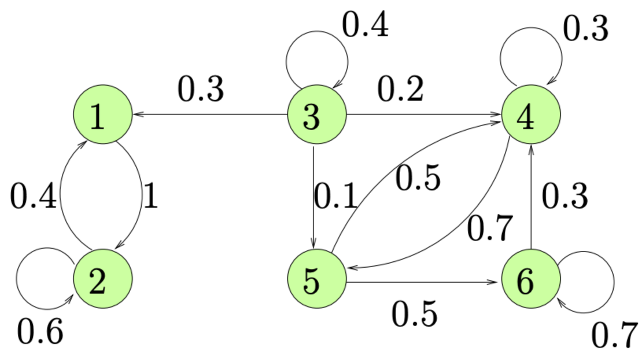

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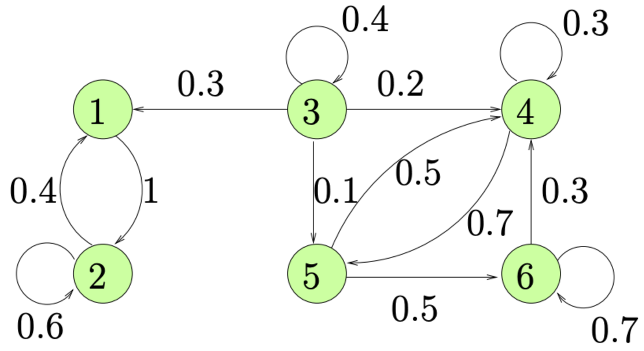

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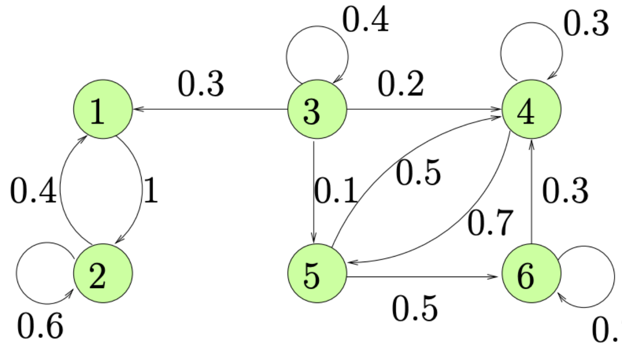

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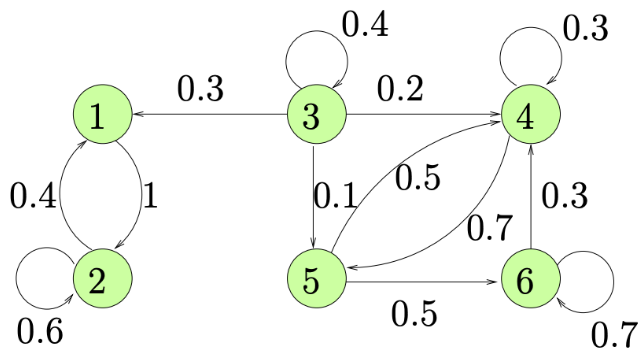

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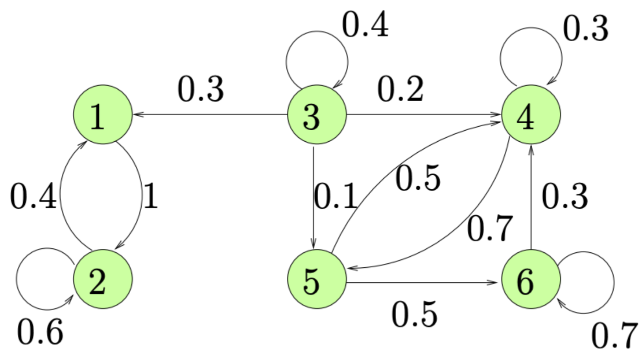

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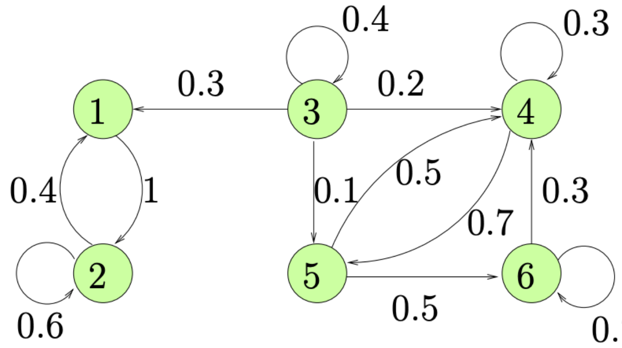

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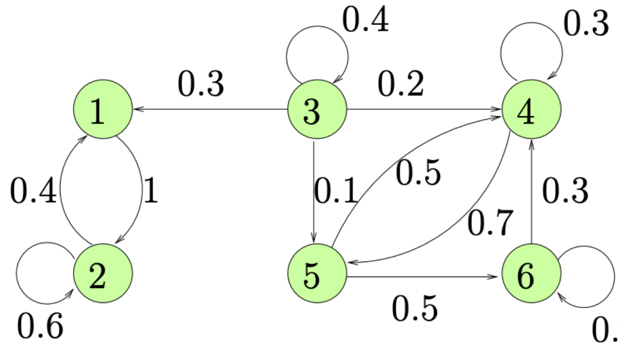

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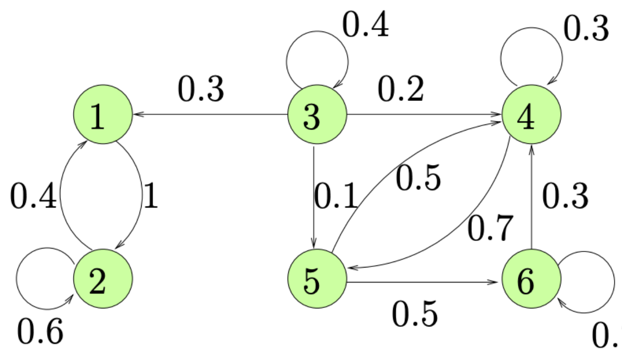

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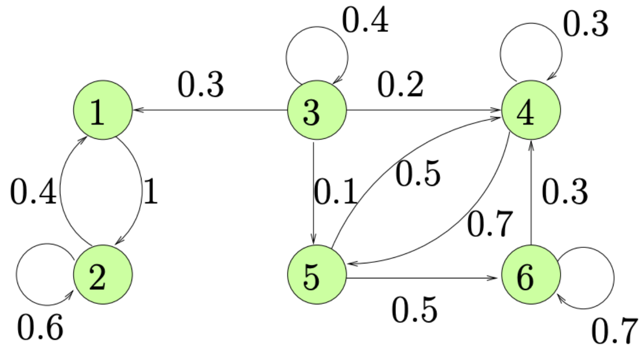

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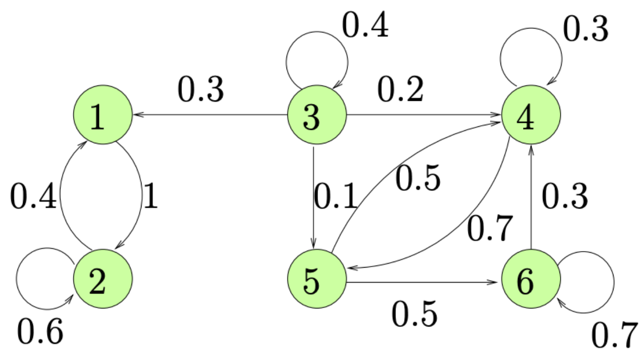

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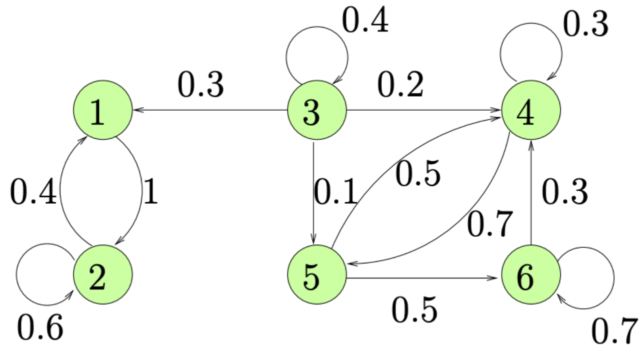

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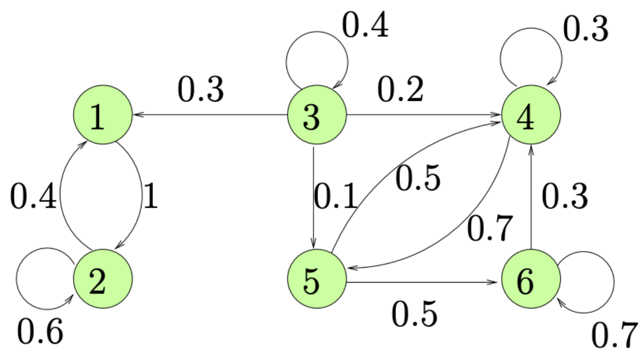

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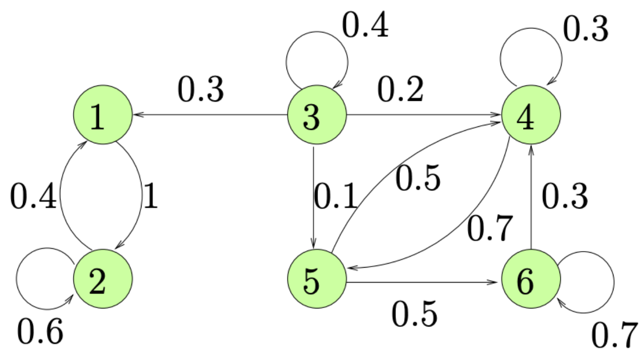

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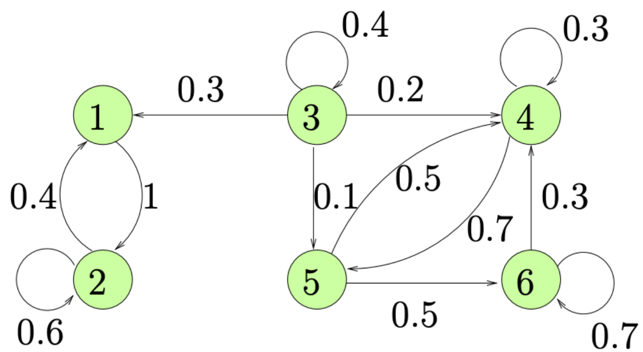

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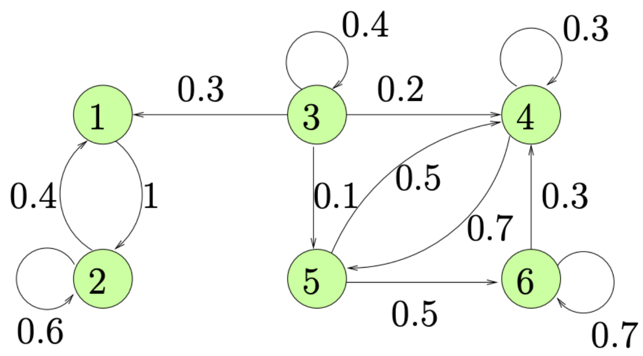

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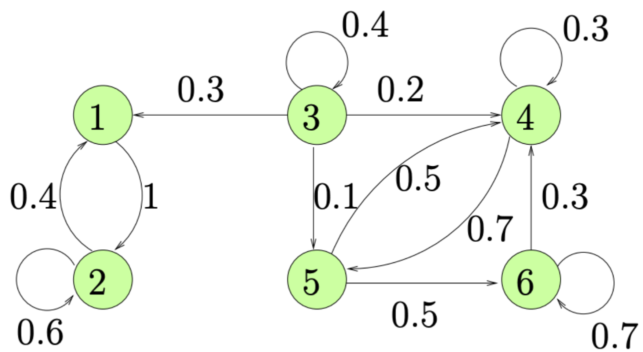

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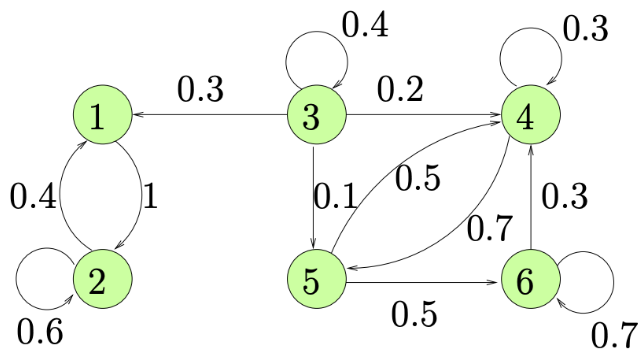

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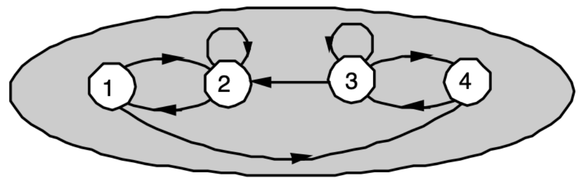
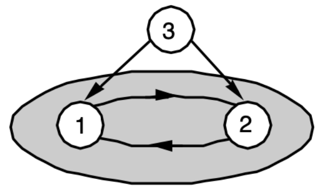
  - 2 is recurrent? Yes. 3 is recurrent? No.
  - If we start from a recurrent state i, then there is always some probability of returning to i. It means that, given enough time, it is certain that it returns to i.

Classification of States (2)

- A set of recurrent states which communicate with each other form a class.



Single class of recurrent states



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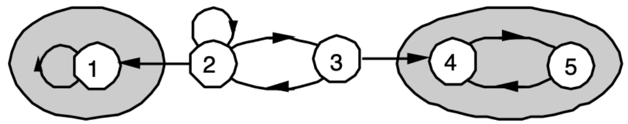

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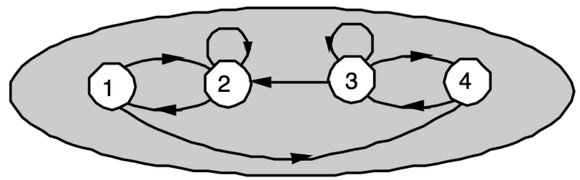

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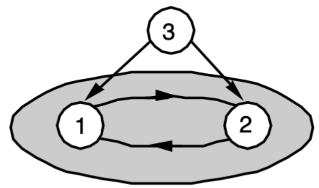

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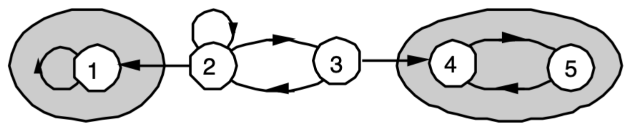

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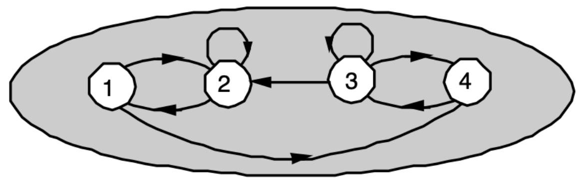

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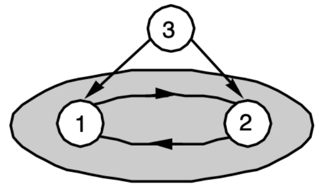

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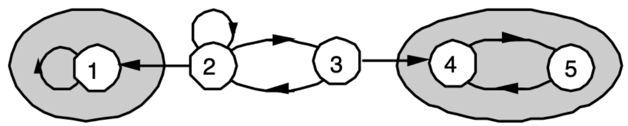

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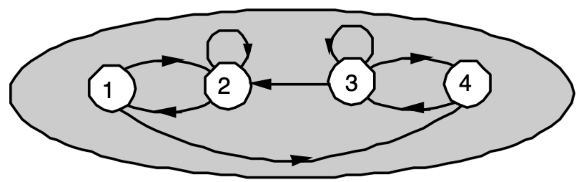

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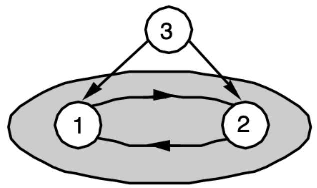

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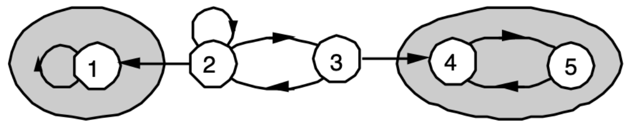

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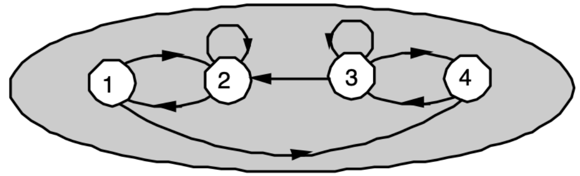

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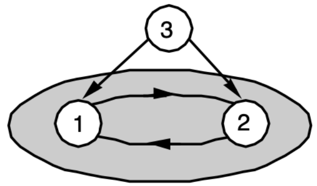

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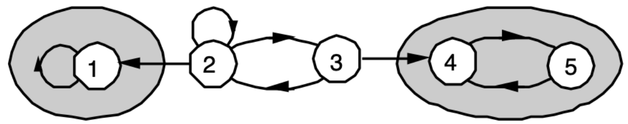

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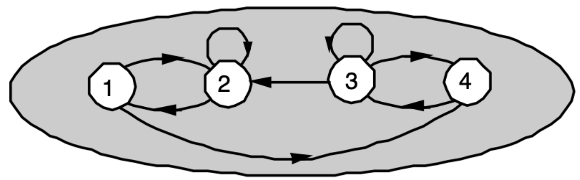

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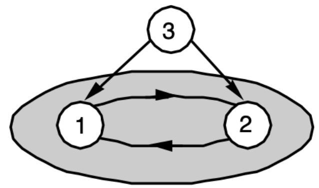

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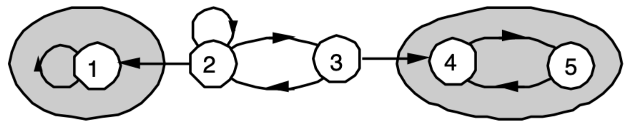

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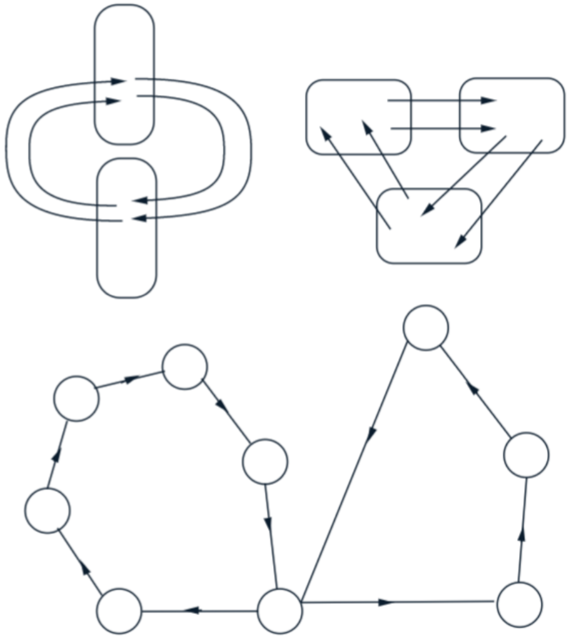
Periodicity



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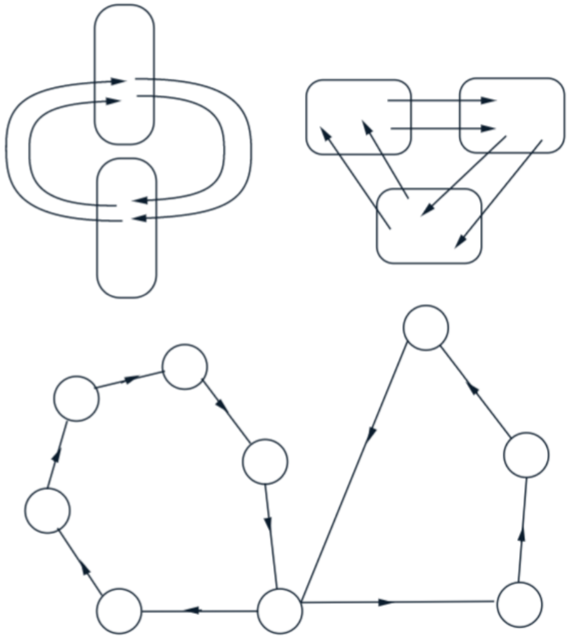

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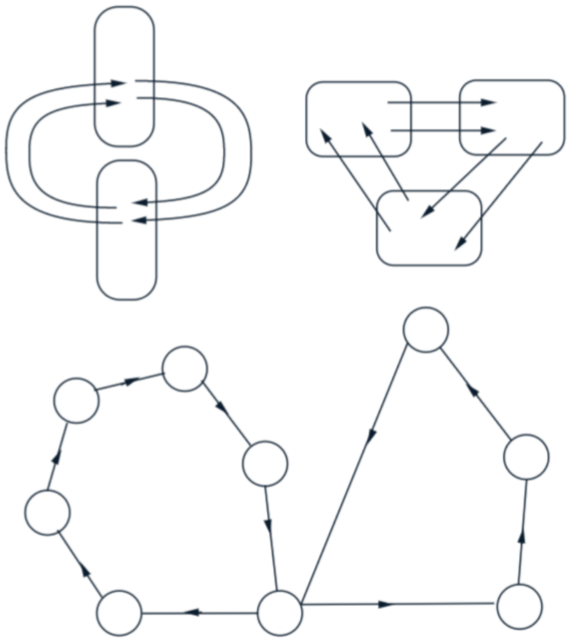
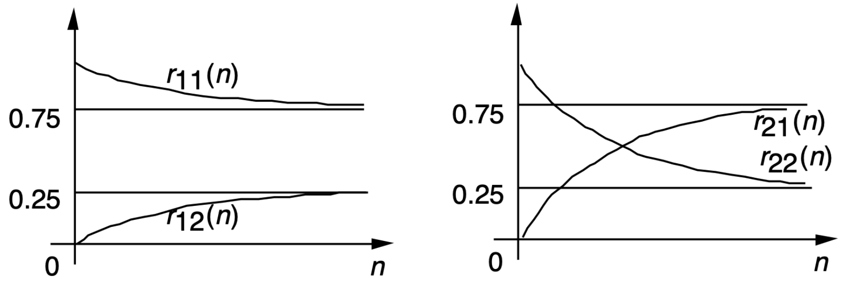


Roadmap

- Basics on Random Process
- Bernoulli Process
- Poisson Process
- Use of Bernoulli and Poisson Processes
- Markov Chain
  - Definition, Transition Probability Matrix, State Transition Diagram
  - Classification of States
  - Steady-state Behaviors and Stationary Distribution
  - Transient Behaviors

n-step transition prob.: $r_{ij}(n)$ for large n



n-step transition probabilities as a function of the number n of transitions

	UpD	B
UpD	0.8	0.2
B	0.6	0.4

$r_{ij}(1)$

.76	.24
.72	.28

$r_{ij}(2)$

.752	.248
.744	.256

$r_{ij}(3)$

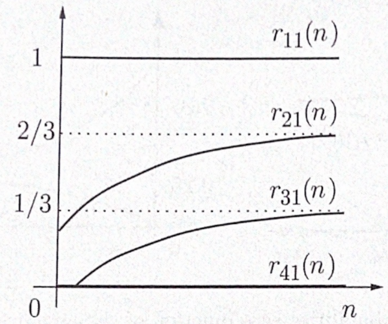
.7504	.2496
.7488	.2512

$r_{ij}(4)$

.7501	.2499
.7498	.2502

$r_{ij}(5)$

Sequence of n-step transition probability matrices



n-step transition probabilities into state 1

	1	2	3	4
1	1.0	0	0	0
2	0.3	0.4	0.3	0
3	0	0.3	0.4	0.3
4	0	0	0	1.0

$r_{ij}(1)$

1.0	0	0	0
.42	.25	.24	.09
.09	.24	.25	.42
0	0	0	1.0

$r_{ij}(2)$

1.0	0	0	0
.50	.17	.17	.16
.16	.17	.17	.50
0	0	0	1.0

$r_{ij}(3)$

1.0	0	0	0
.55	.12	.12	.21
.21	.12	.12	.55
0	0	0	1.0

$r_{ij}(4)$

....

1.0	0	0	0
2/3	0	0	1/3
1/3	0	0	2/3
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$r_{ij}(\infty)$

Sequence of transition probability matrices

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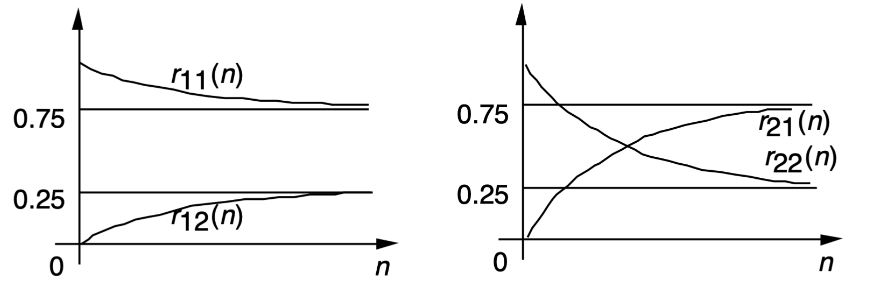
- Convergence irrespective of the starting state



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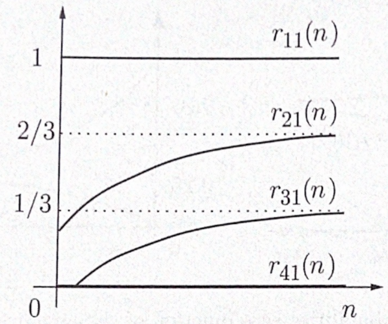

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.42	.25	.24	.09
.09	.24	.25	.42
0	0	0	1.0

$r_{ij}(3)$

1.0	0	0	0
.50	.17	.17	.16
.16	.17	.17	.50
0	0	0	1.0

$r_{ij}(4)$

1.0	0	0	0
.55	.12	.12	.21
.21	.12	.12	.55
0	0	0	1.0

....

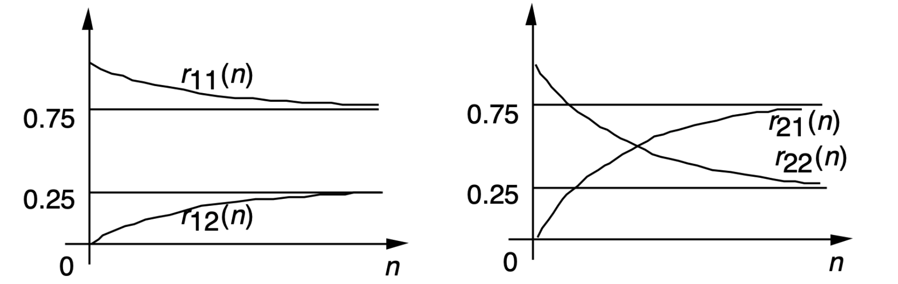
$r_{ij}(\infty)$

1.0	0	0	0
2/3	0	0	1/3
1/3	0	0	2/3
0	0	0	1.0

Sequence of transition probability matrices

n-step transition prob.: $r_{ij}(n)$ for large n

- Convergence irrespective of the starting state



n-step transition probabilities as a function of the number n of transitions

$r_{ij}(1)$

	UpD	B
UpD	0.8	0.2
B	0.6	0.4

$r_{ij}(2)$

.76	.24
.72	.28

$r_{ij}(3)$

.752	.248
.744	.256

$r_{ij}(4)$

.7504	.2496
.7488	.2512

$r_{ij}(5)$

.7501	.2499
.7498	.2502

Sequence of n-step transition probability matrices

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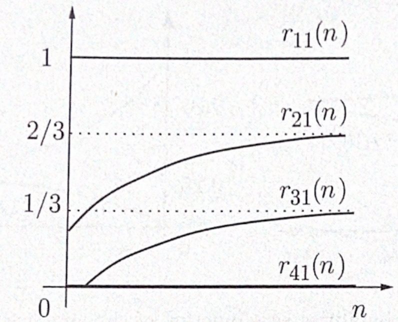

n-step transition probabilities into state 1

$r_{ij}(1)$

	1	2	3	4
1	1.0	0	0	0
2	0.3	0.4	0.3	0
3	0	0.3	0.4	0.3
4	0	0	0	1.0

$r_{ij}(2)$

1.0	0	0	0
.42	.25	.24	.09
.09	.24	.25	.42
0	0	0	1.0

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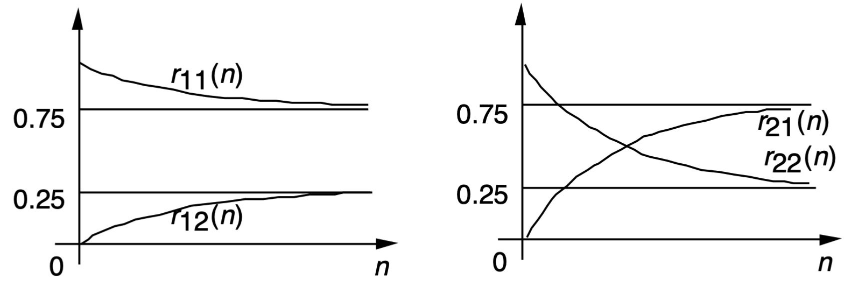

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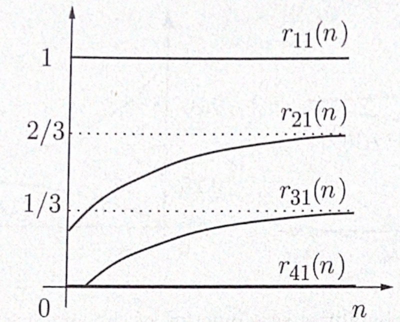

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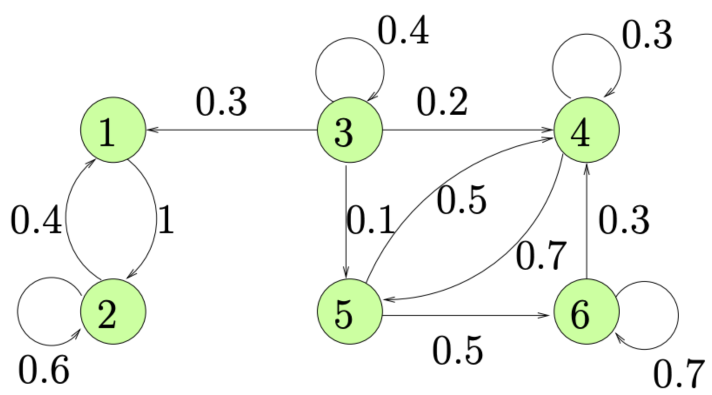
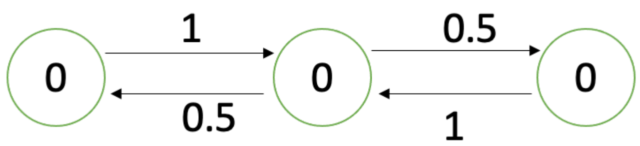
Sequence of transition probability matrices

(Q) Under what conditions, convergence occurs? If so, how does it depend on the starting state?

Steady-state behavior

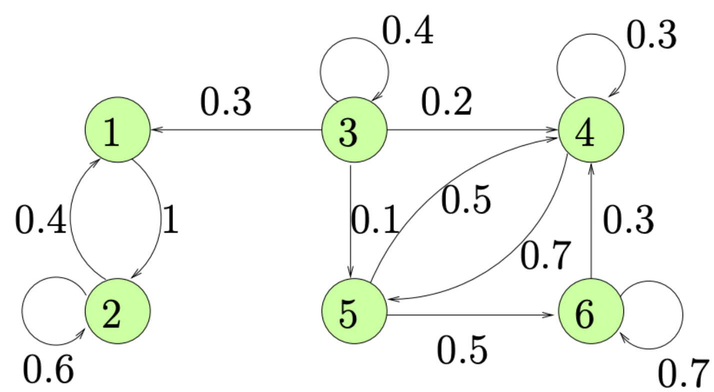
- $r_{ij}(n) \xrightarrow{n\to\infty} \pi_j$, for some $\pi_j \leq 1$?

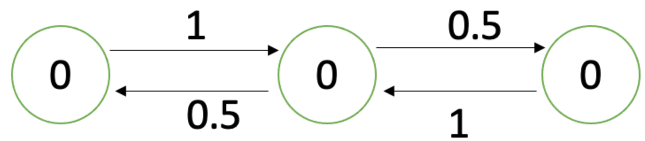




Steady-state behavior

- $r_{ij}(n) \xrightarrow{n \to \infty} \pi_j$, for some $\pi_j \leq 1$?
- Convergence occurs, independent of the starting state, if:





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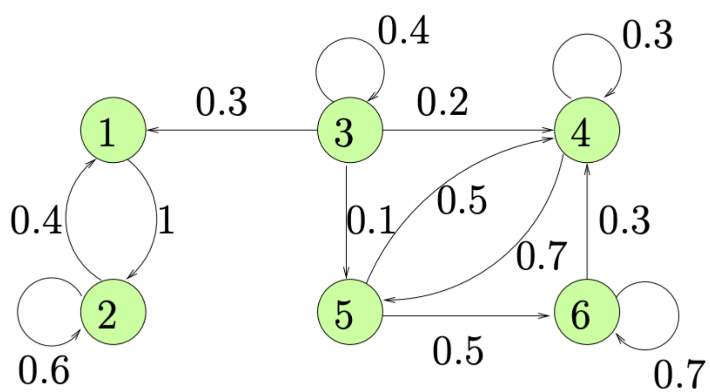
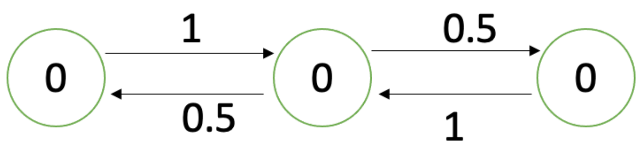
- $r_{ij}(n) \xrightarrow{n\to\infty} \pi_j$, for some $\pi_j \leq 1$?
- Convergence occurs, independent of the starting state, if:

  C1. Only a single recurrent class





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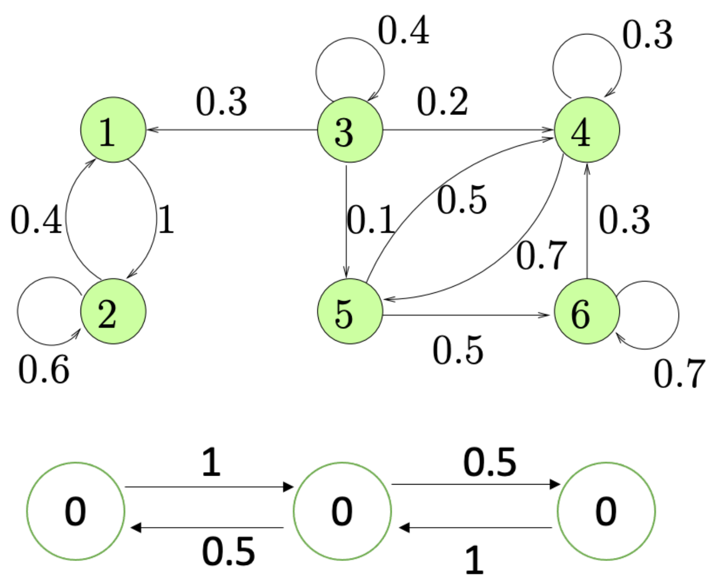
C1. For the case of multiple recurrent classes, one stays at the class including the starting state.



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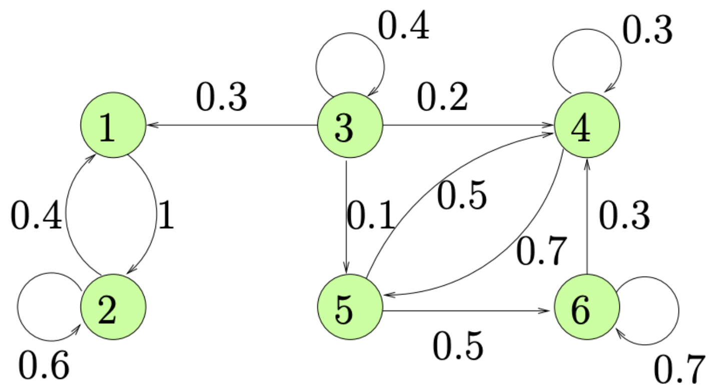

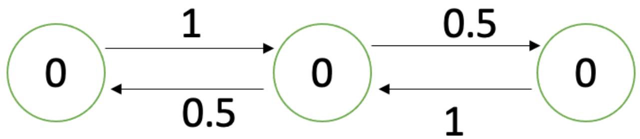

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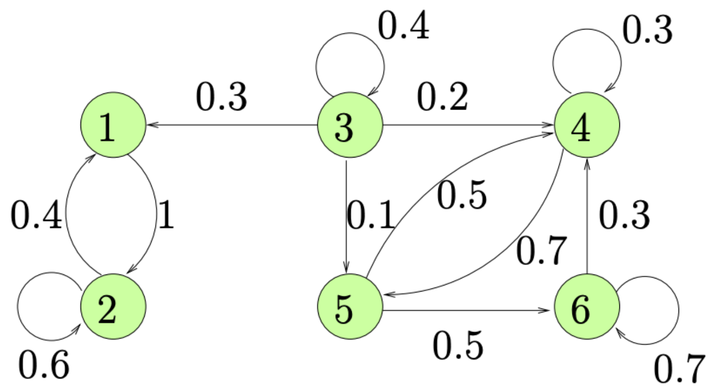
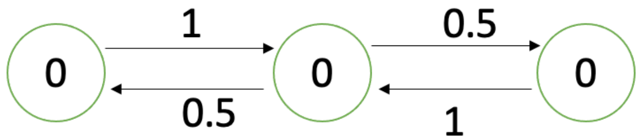
C2. Divergent behavior for periodic recurrent classes.





Balance Equation

- If $r_{ij}(n) \xrightarrow{n\to\infty} \pi_j$, for some $\pi_j \leq 1$,

$$r_{ij}(n) = \sum_{k=1}^{m} r_{ik}(n-1)p_{kj} \Longrightarrow$$

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- Normalization equation

$$\sum_{i=1}^{m} \pi_i = 1$$

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- Normalization equation

$$\sum_{i=1}^{m} \pi_i = 1$$

- Balance equation + Normalization equation $\Longrightarrow$ Finding the steady-state probabilities $\{\pi_i\}$.

Example

- A two-state MC with:

$$p_{11} = 0.8, \quad p_{12} = 0.2,$$
$$p_{21} = 0.6, \quad p_{22} = 0.4.$$

- Balance equation:

$$\pi_1 = \pi_1 p_{11} + \pi_2 p_{21}$$
$$\pi_2 = \pi_2 p_{22} + \pi_1 p_{12}$$

- Normalization equation: $\pi_1 + \pi_2 = 1$
- The stationary distribution is: $\pi_1 = 0.25$, $\pi_2 = 0.75$.

Stationary Distribution

Stationary Distribution

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  - Then, $\mathbb{P}(X_n = j) = \pi_j$, for all n and j.

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KAIST EE

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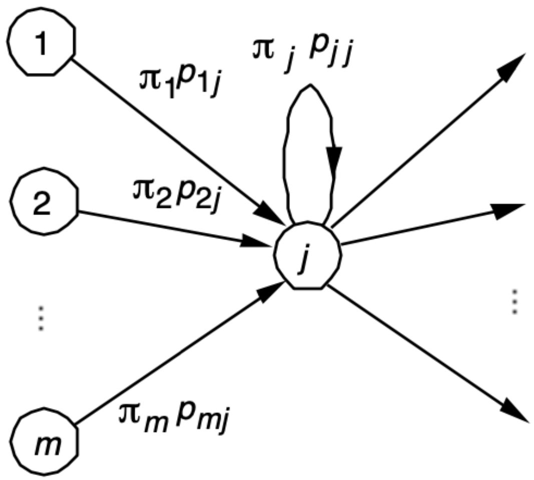
  - If the initial state is chosen according to $\{\pi_j\}$, the state at any future time will have the same distribution (i.e., the distribution does not change over time).
- We say that "the limiting distribution is equal to to the stationary distribution"

Long-term Frequency Interpretation

- π_j: the long-term expected fraction of time that the state is equal to j.



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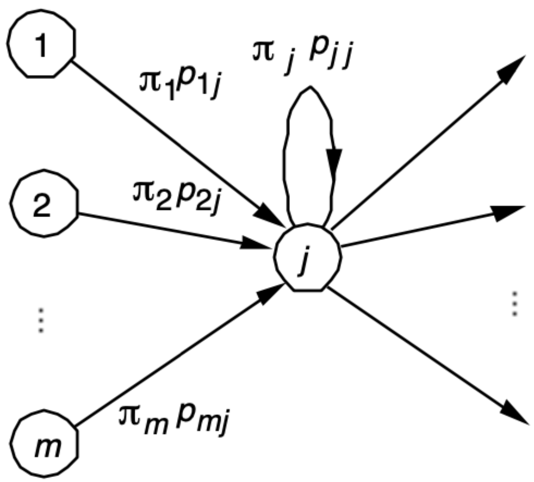
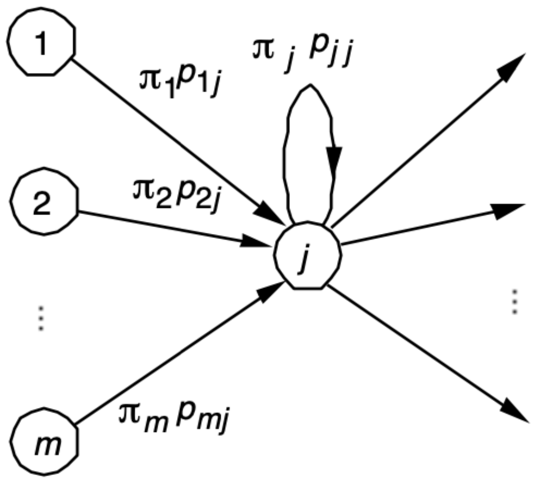


Long-term Frequency Interpretation

- π_j: the long-term expected fraction of time that the state is equal to j.
- Balance equation: $\sum_{k=1}^{m} \pi_k p_{kj} = \pi_j$ means:
  - The expected frequency π_j of visits to j is equal to the sum of the expected frequencies $\pi_k p_{kj}$ of transitions that lead to j.



Roadmap

- Basics on Random Process
- Bernoulli Process
- Poisson Process
- Use of Bernoulli and Poisson Processes
- Markov Chain
    - Definition, Transition Probability Matrix, State Transition Diagram
    - Classification of States
    - Steady-state Behaviors and Stationary Distribution
    - Transient Behaviors

Absorption Probability

- Definition. A state k is absorbing, if $p_{kk} = 1$, and $p_{kj} = 0$ for all $j \neq k$.

[0] The notation a_i should have dependence on s, but we omit it for simplicity.

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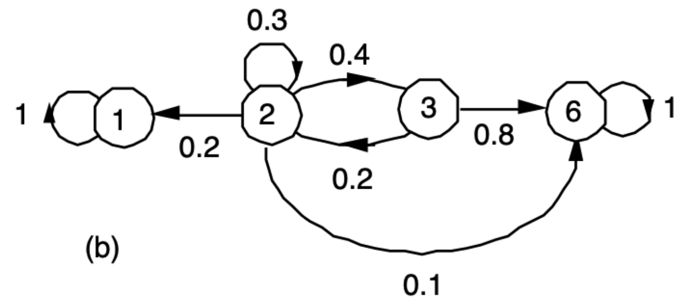
  $a_3 = 0.2a_2 + 0.8a_6$



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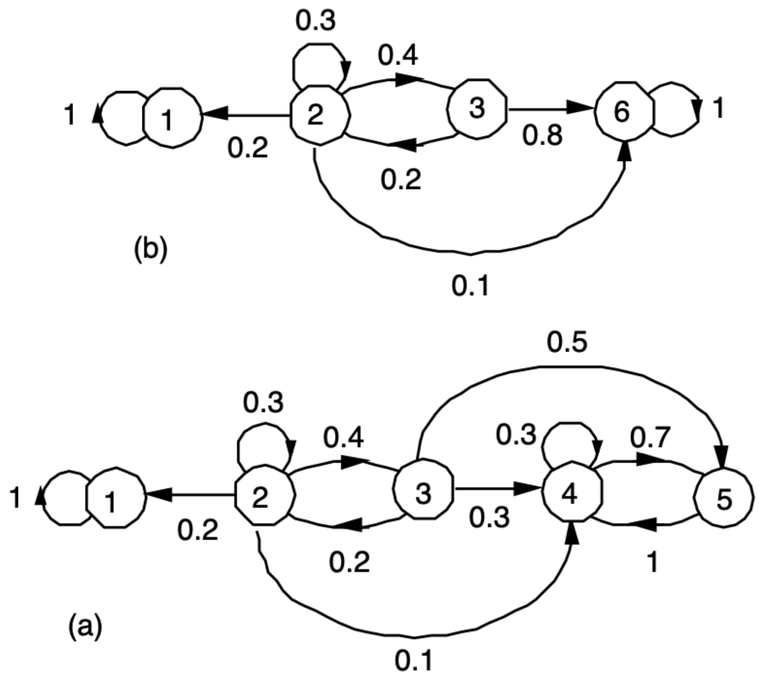

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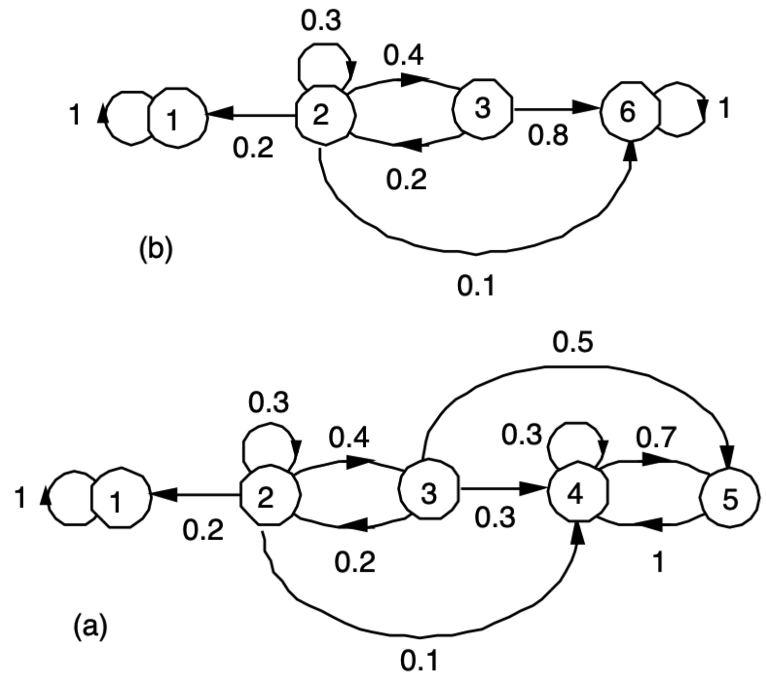

(Q) What if there are some non-absorbing recurrent state?

- Convert it into the one only with absorbing recurrent states (from (a) to (b)).

---

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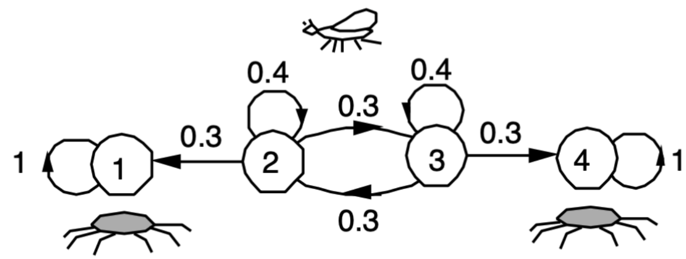
Expected Time to Any Absorbing State

(Q) Starting from a transient state i, expected number of transitions μ_i until absorption to any absorbing state?



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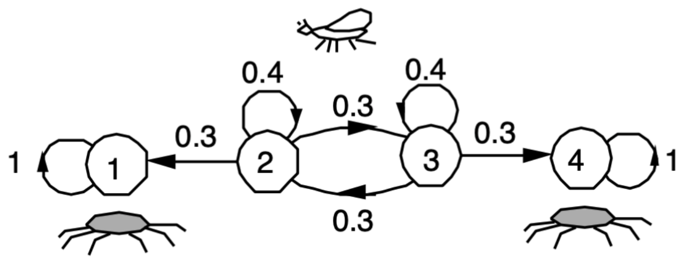

- Spider-fly example

$$\mu_1 = \mu_4 = 0 \quad \text{(for recurrent states)}$$

$$\mu_2 = 1 + 0.4\mu_2 + 0.3\mu_3, \quad \mu_3 = 1 + 0.3\mu_2 + 0.4\mu_3 \quad \text{(for transient states)}$$

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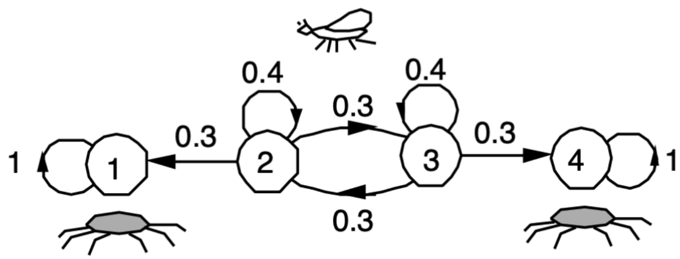

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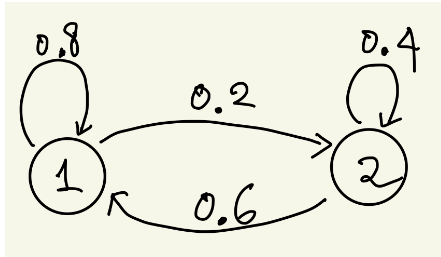
- For generalized description, please see the textbook (pp. 367).

Expected time to a particular recurrent state s

- Assume a single recurrent class



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Expected time to a particular recurrent state s

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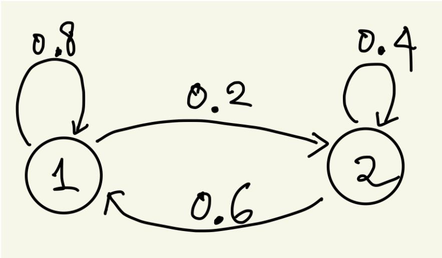
(Q) First passage time. Starting from a i, expected number of transitions t_i to reach s for the first time?



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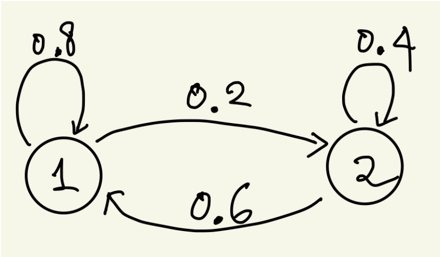

- Mean first passage time from 2 to 1

$$t_1 = 0$$

$$t_2 = 1 + p_{21} t_1 + p_{22} t_2 = 1 + 0.4 t_2 \Longrightarrow t_2 = 5/3$$

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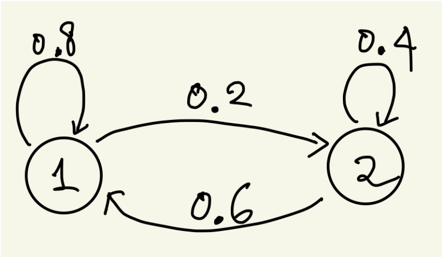
Expected time to a particular recurrent state s

- Assume a single recurrent class

(Q) First passage time. Starting from a i, expected number of transitions t_i to reach s for the first time?

(Q) First recurrence time. Starting from a s, expected number of transitions $t_s^\star$ to reach s for the first time?



- Mean first passage time from 2 to 1

$$t_1 = 0$$

$$t_2 = 1 + p_{21} t_1 + p_{22} t_2 = 1 + 0.4 t_2 \Longrightarrow t_2 = 5/3$$

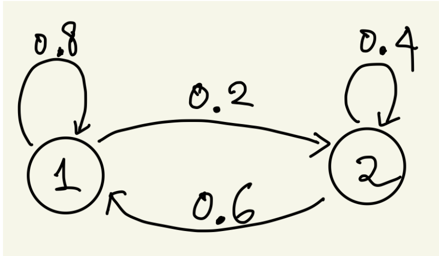
[0] The notation t_i should have the dependence on s, but we omit it for simplicity.

Expected time to a particular recurrent state s

- Assume a single recurrent class

(Q) First passage time. Starting from a i, expected number of transitions t_i to reach s for the first time?

(Q) First recurrence time. Starting from a s, expected number of transitions $t_s^\star$ to reach s for the first time?



- Mean first passage time from 2 to 1

$$t_1 = 0$$
$$t_2 = 1 + p_{21}t_1 + p_{22}t_2 = 1 + 0.4t_2 \Longrightarrow t_2 = 5/3$$

- Mean first recurrence time from 1 to 1

$$t_1^\star = 1 + p_{11}t_1 + p_{12}t_2 = 1 + 0 + 0.2\frac{5}{3} = \frac{4}{3}$$

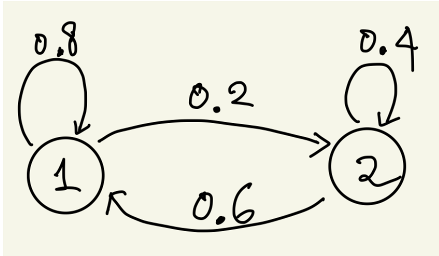
[0] The notation t_i should have the dependence on s, but we omit it for simplicity.

Expected time to a particular recurrent state s

- Assume a single recurrent class

(Q) First passage time. Starting from a i, expected number of transitions t_i to reach s for the first time?

(Q) First recurrence time. Starting from a s, expected number of transitions $t_s^\star$ to reach s for the first time?



- Mean first passage time from 2 to 1

$$t_1 = 0$$

$$t_2 = 1 + p_{21}t_1 + p_{22}t_2 = 1 + 0.4t_2 \implies t_2 = 5/3$$

- Mean first recurrence time from 1 to 1

$$t_1^\star = 1 + p_{11}t_1 + p_{12}t_2 = 1 + 0 + 0.2\frac{5}{3} = \frac{4}{3}$$

- For generalized description, please see the textbook (pp. 368)

[0]The notation t_i should have the dependence on s, but we omit it for simplicity.

Questions?

1) Why do you think Markov chain (MC) is important?
2) What is the Markov property and its meaning? What's the key difference of MC from Bernoulli processes?
3) What are the limiting distribution and the stationary distribution of MCs?
4) How are you going to compute the stationary distribution, if you are given a transition probability matrix?
5) What are recurrent and transient states in MC?