南方科技大学
SOUTHERN UNIVERSITY OF SCIENCE AND TECHNOLOGY

SUSTech
Southern University of Science and Technology

Project 1

Information Exposure Maximization

Outline

- Overview
- Problem Description
- IEM Example

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- **Overview**
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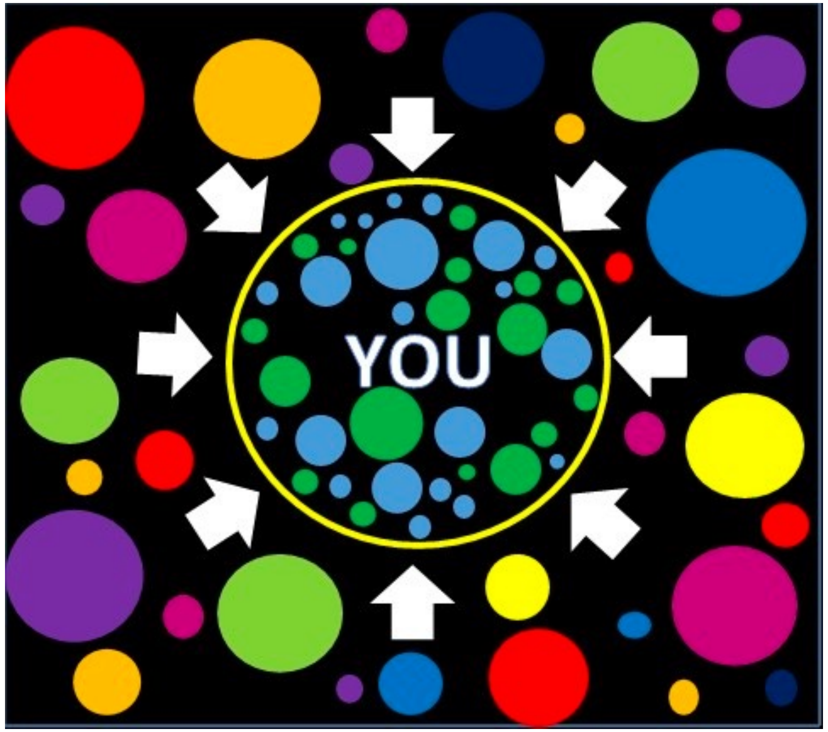
- IEM Example

Overview

Information Exposure Maximization (IEM) is an important algorithmic problem that is proposed to solve the <u>echo chamber effect</u> on social media.

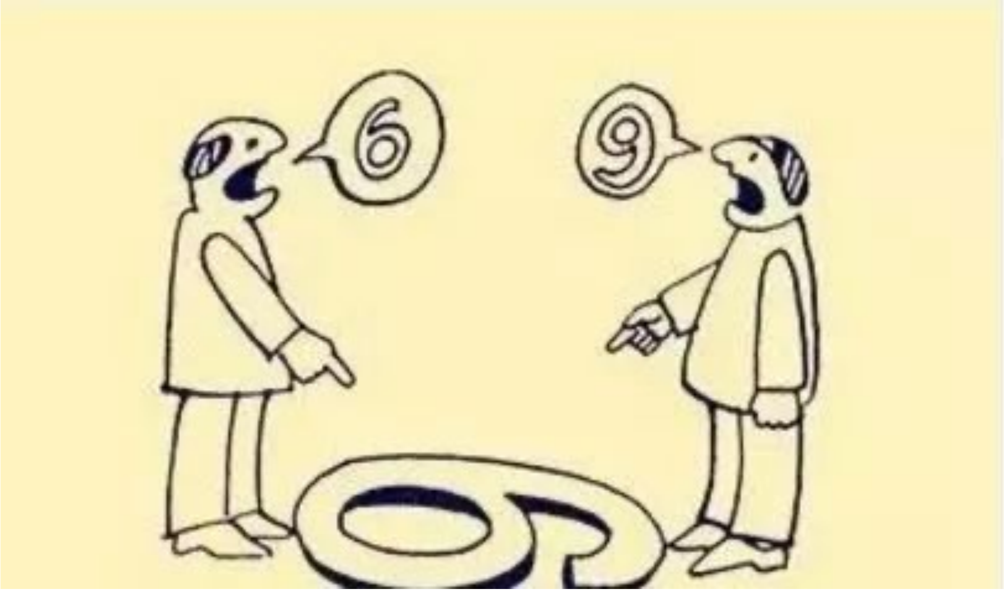


Users tend to gather in groups whose members think alike, and that polarisation is greater when content feeds cannot be easily tweaked.

[M. Cinelli et al. PNAS 2021]

Overview

Assume that there are two viewpoints in a social network, the IEM problem is **to select two campaigns**, each containing a set of users who hold one of these viewpoints, to maximize the expected number of users that are **either reached by both campaigns** or **remain oblivious to both campaigns**.



Overview

TASK: **Two search algorithms** to solve the IEM problem

- One heuristic algorithm
- One evolutionary algorithm or one simulated annealing algorithm

Grading Rules

- Project report
- Code evaluation (15 points)
  - Objective evaluation (2.0 points)
  - Heuristic algorithm (6.5 points)
  - Evolutionary algorithm or simulated annealing algorithm (6.5 points)

Outline

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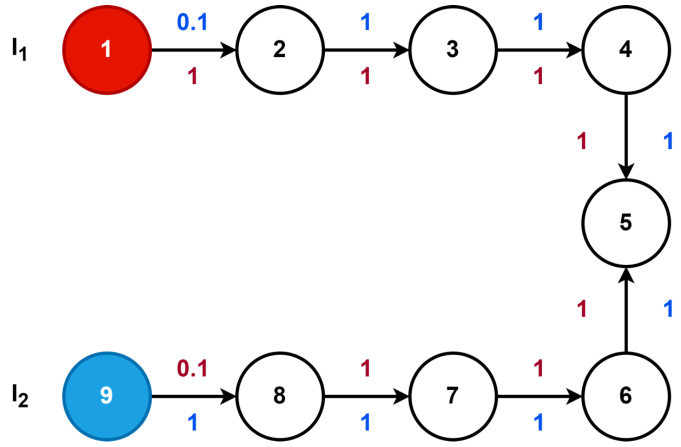
- **Problem Description**
- IEM Example

Assumption

The following information is available

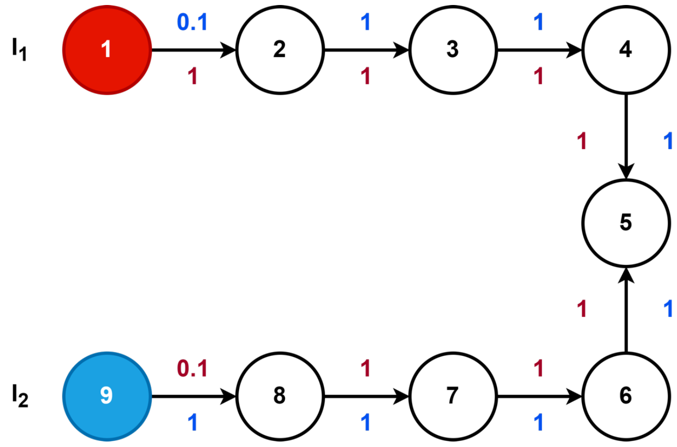
- A social network $G = (V, E)$ with two campaigns
- Two seed sets
  - each support one of the two viewpoints



Assumption

The following information is available

- A social network $G = (V, E)$ with two campaigns
- Two seed sets
  - each support one of the two viewpoints
- Heterogeneous propagation
  - two viewpoints are propagated independently of each other
- Two functions $p: E \rightarrow [0,1]$
  - associate probability $p_{(u,v)}$ with edge (u, v) capturing the influence u exerts over v



Assumption

The following information is available

- A social network $G = (V, E)$ with two campaigns
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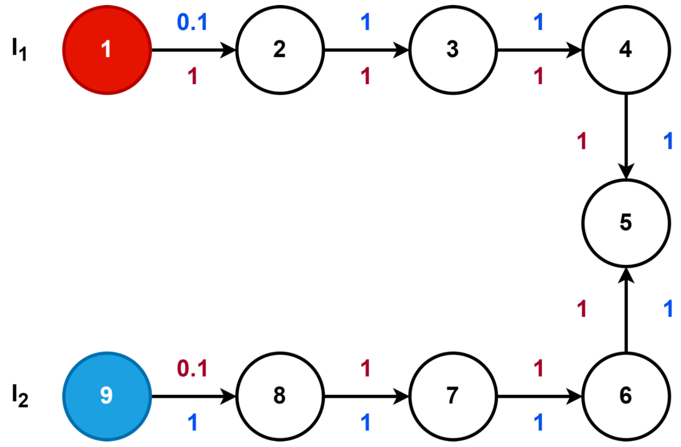
- Heterogeneous propagation
  - two viewpoints are propagated independently of each other
- Two functions $p: E \rightarrow [0,1]$
  - associate probability $p_{(u,v)}$ with edge (u, v) capturing the influence u exerts over v
- A diffusion model
  - describe how influence propagates to a node from its neighbors



Influence Diffusion of Each Campaign

The famous Independent Cascade (IC) model is used.

- Each node $v \in V$ has two possible states, ***inactive*** and ***active***
  - *active*: adopts new information being propagated through the network
  - *inactive*: has not adopted new information yet
    - Ever been attempted to be activated but NOT
    - Never been attempted to be activated
  - Can ONLY switch from *inactive* to *active*

Influence Diffusion of Each Campaign

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Exposed Node Set

Influence Diffusion of Each Campaign

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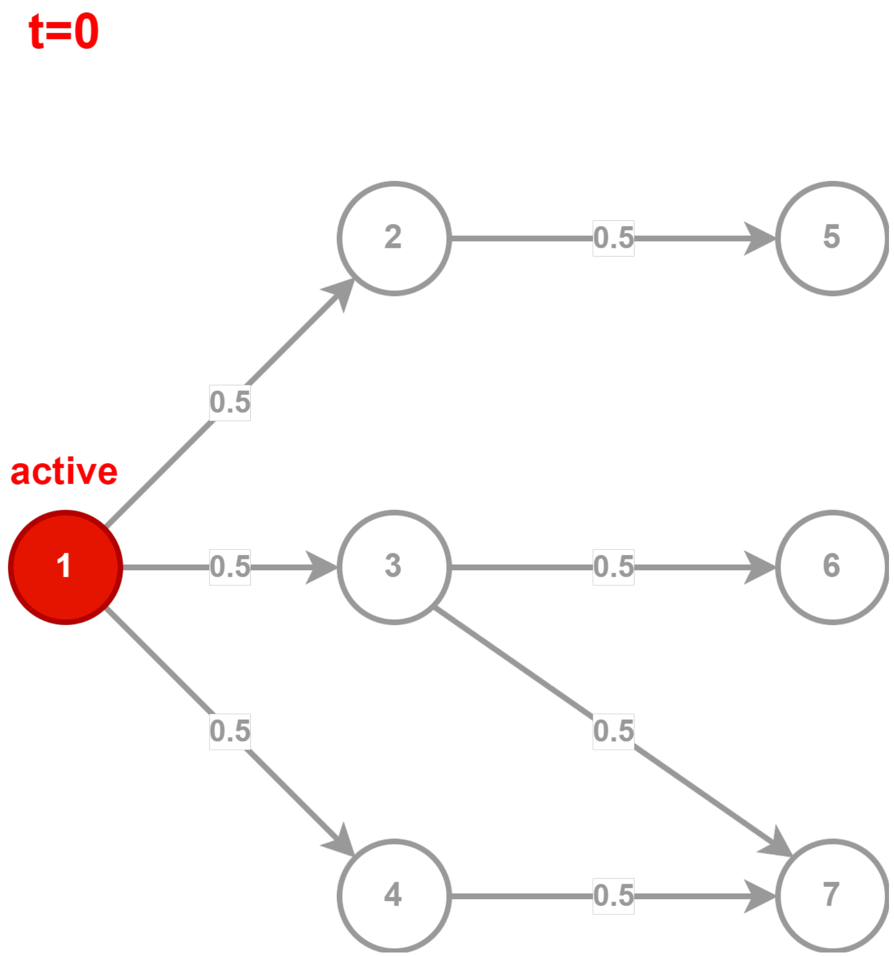
Information proceeds in discrete time steps, with $t = 0,1,2,\cdots$

- Let U be the set of **active** nodes in time 0
- Let $r(U)$ be the **FINAL exposed node set**

Influence Diffusion of Each Campaign (Case)

- Seed set $U = \{1\}$

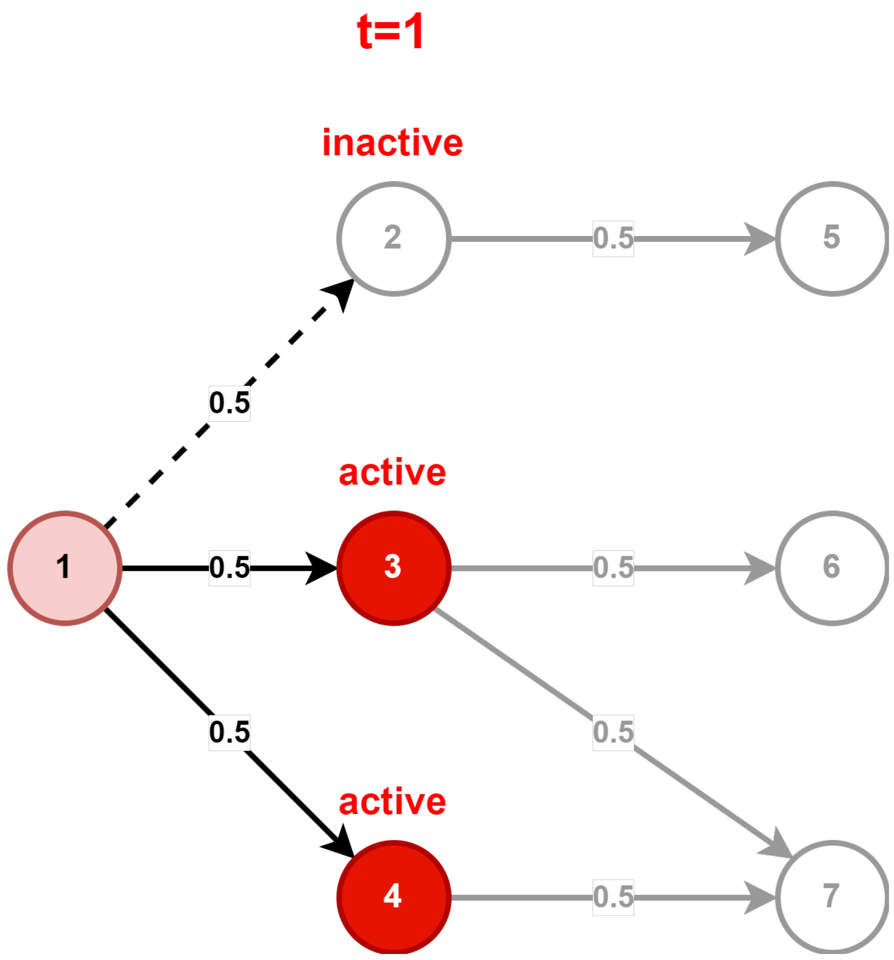
- Time step $t = 0$
  - Active node set $\{1\}$
  - Exposed node set $\{1\}$



Influence Diffusion of Each Campaign (Case)

- Seed set $U = \{1\}$

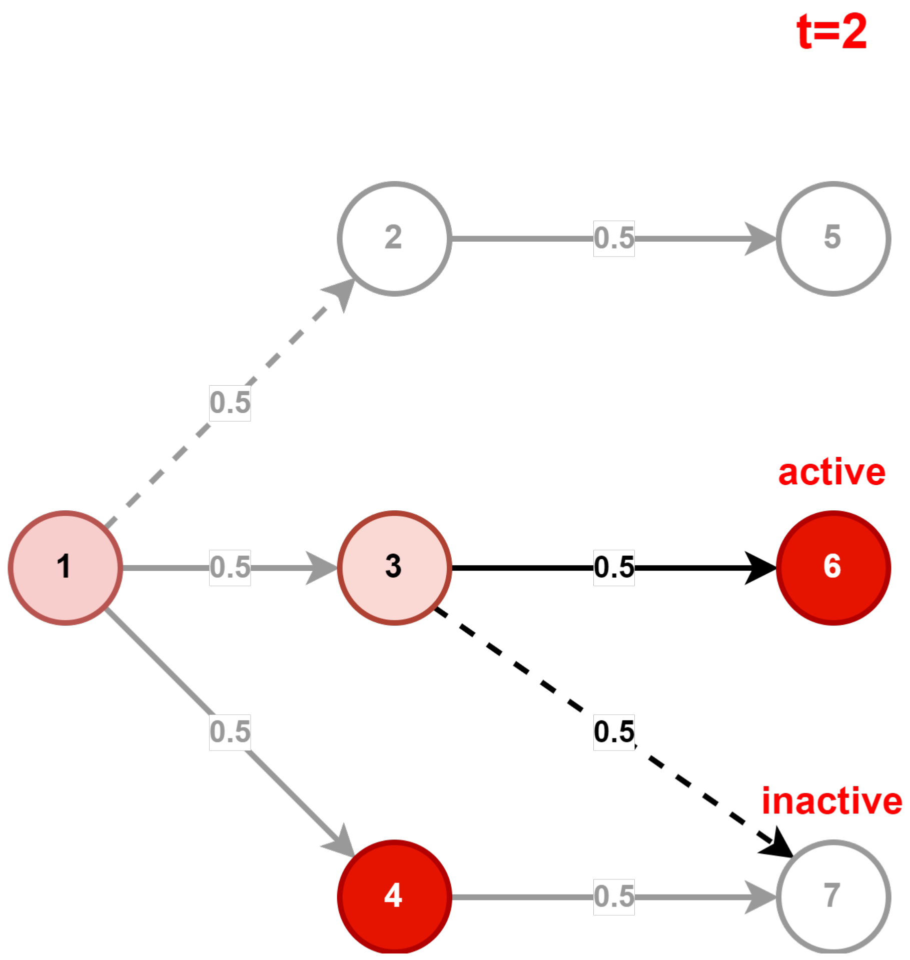
- Time step $t = 1$
  - Active node set $\{1, 3, 4\}$
  - Exposed node set $\{1, 2, 3, 4\}$



Influence Diffusion of Each Campaign (Case)

- Seed set $U = \{1\}$

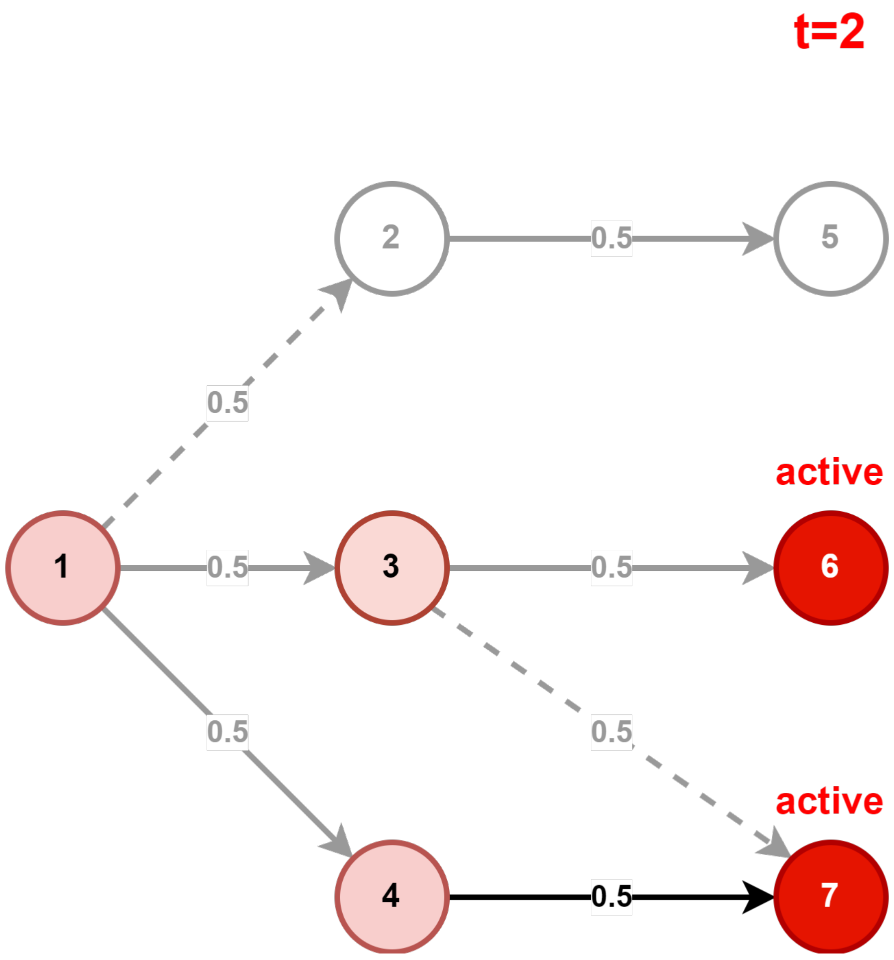
- Time step $t = 2$
  - Active node set $\{1, 3, 4, 6\}$
  - Exposed node set $\{1, 2, 3, 4, 6, 7\}$



Influence Diffusion of Each Campaign (Case)

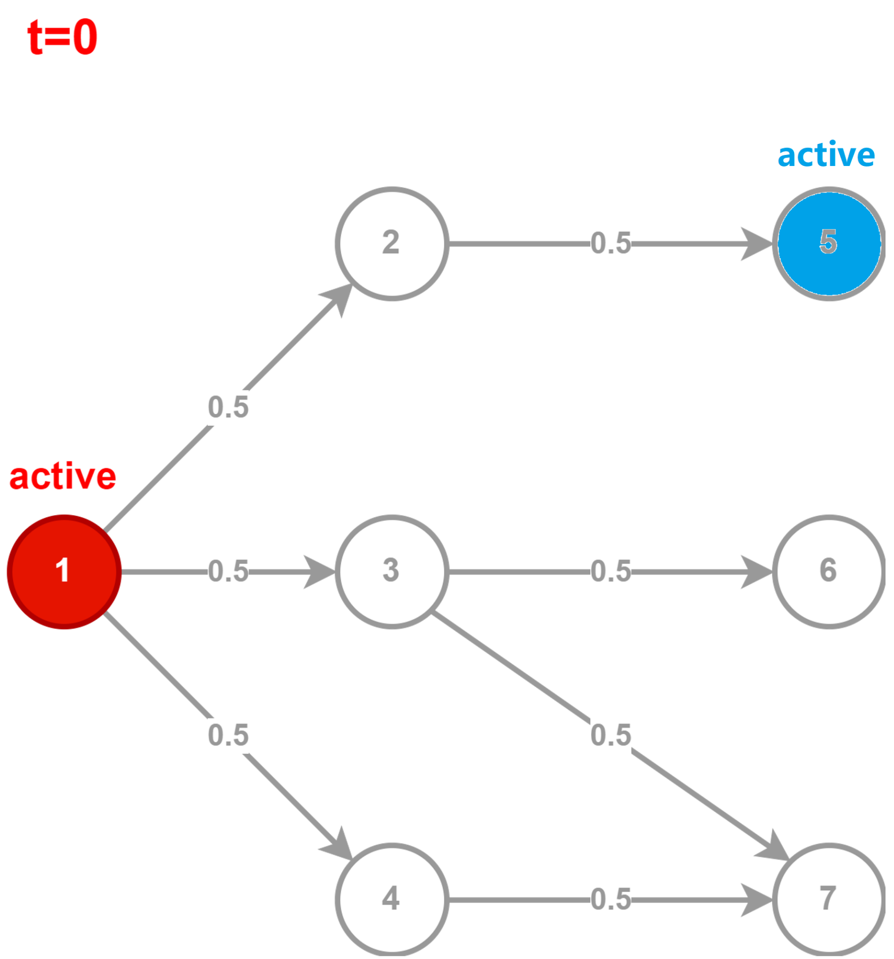
- Seed set $U = \{1\}$

- Time step $t = 2$
  - Active node set $\{1, 3, 4, 6, 7\}$
  - Exposed node set $\{1, 2, 3, 4, 6, 7\}$



Influence Exposure of Two Campaigns (Case)

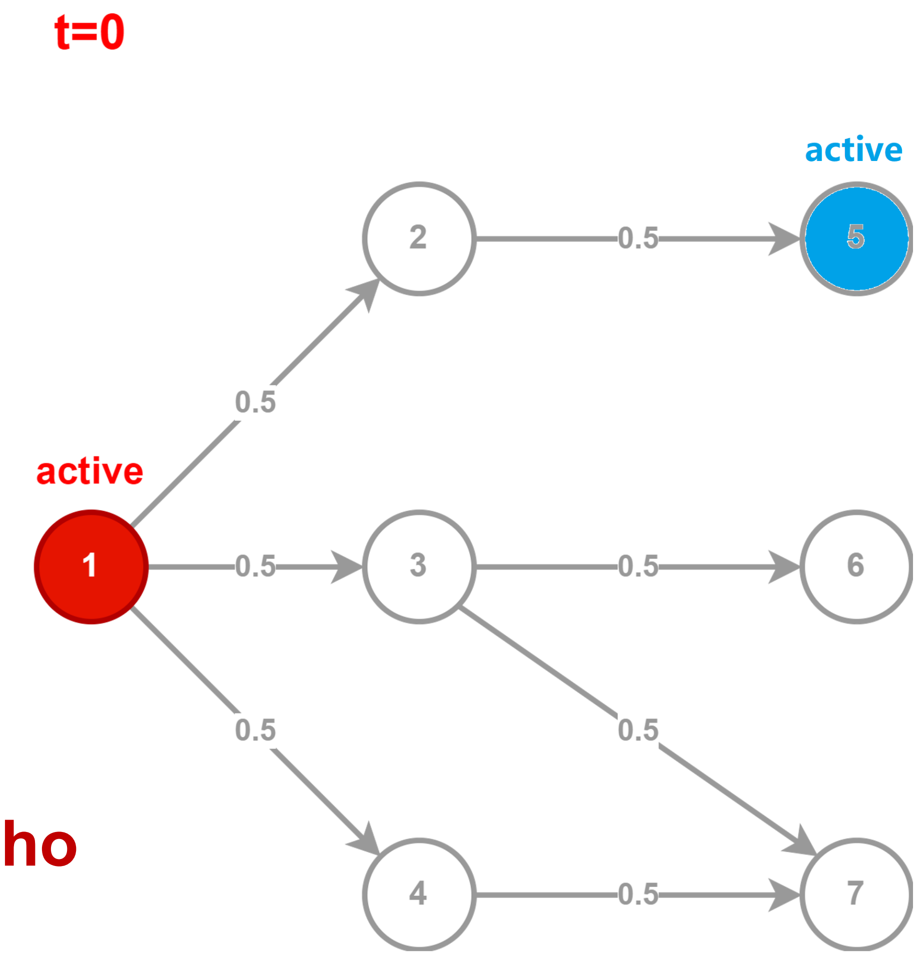
- Seed set $U_1 = \{1\}$
  - Exposed node set $\{1, 2, 3, 4, 6, 7\}$
- Seed set $U_2 = \{5\}$
  - Exposed node set $\{5\}$



Influence Exposure of Two Campaigns (Case)

- Seed set $U_1 = \{1\}$
  - Exposed node set $\{1, 2, 3, 4, 6, 7\}$
- Seed set $U_2 = \{5\}$
  - Exposed node set $\{5\}$

NO node can break through the echo chamber in this propagation



Balanced Seed Set

Campaign c_i, $i \in \{1,2\}$

- Seed set $U_i = I_i \cup S_i$
  - Initial seed set $I_i \subseteq V$: available
  - Balanced seed set $S_i \subseteq V$: **to be found**

Balanced Information Exposure

The expected number of nodes that are either **reached by both campaigns** or **remain oblivious to both campaigns**

$$A \vartriangle B = (A \setminus B) \cup (B \setminus A)$$

$$\Phi(S_1, S_2) = \mathbb{E}\left[\left|V \setminus \left(r_1(I_1 \cup S_1) \vartriangle r_2(I_2 \cup S_2)\right)\right|\right]$$

Both are **random variables** determined by the stochastic process of the diffusion model and their diffusion probabilities

Problem Description

Given a social network $G = (V, E)$, two initial seed sets I_1 and I_2, and a budget k.

The IEM is **to find two balanced seed sets S_1 and S_2**, where $|S_1| + |S_2| \leq k$, and **maximize the balanced information exposure**, i.e.,

$$\max \Phi(S_1, S_2) = \max \mathbb{E}\left[\left|V \setminus \left(r_1(I_1 \cup S_1) \vartriangle r_2(I_2 \cup S_2)\right)\right|\right]$$

$$\text{s.t.} \quad |S_1| + |S_2| \leq k$$

$$S_1, S_2 \subseteq V$$

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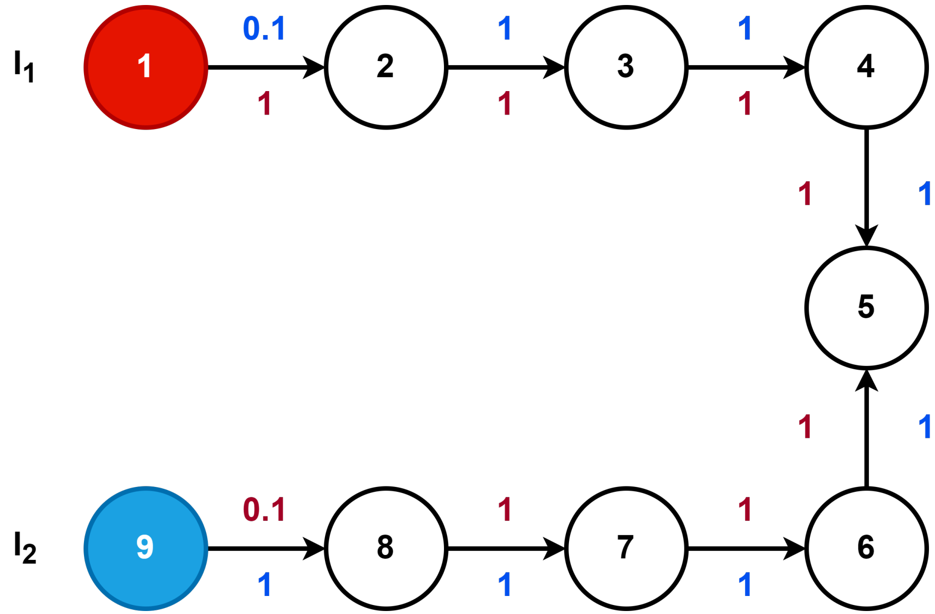
IEM Example

Campaigns c_1 (Red), c_2 (blue)

- Initial Seed Set $I_1 = \{1\}, I_2 = \{9\}$
- Balanced Seed Set:
  - Solution 1: $S_1 = \{8\}, S_2 = \{2\}$
  - Solution 2: $S_1 = \{9\}, S_2 = \{1\}$

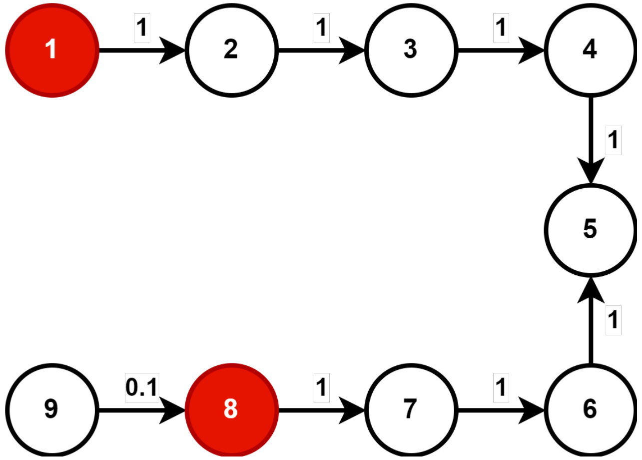


IEM Solution 1

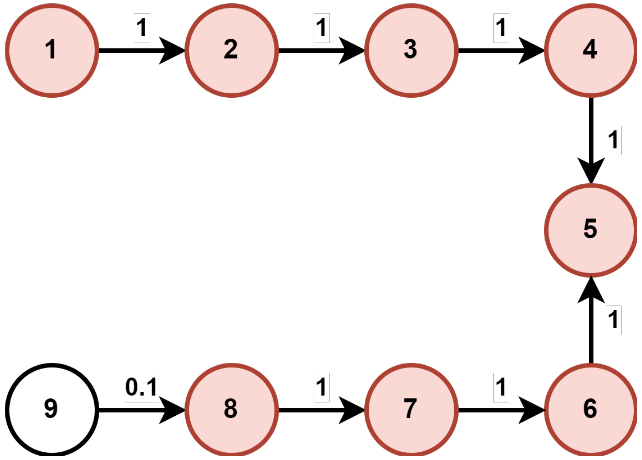
Campaigns c_1

- Initial Seed Set $I_1 = \{1\}$
- Balanced Seed Set $S_1 = \{8\}$

  - Exposed Node Set $\{1, 2, 3, 4, 5, 6, 7, 8\}$



$t = 0$



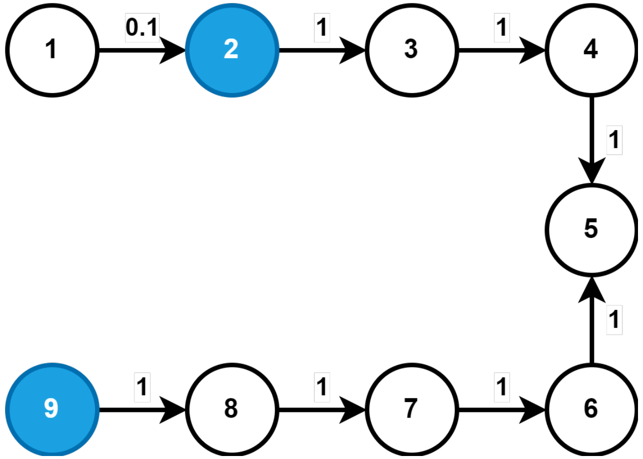
$t = 4$

IEM Solution 1

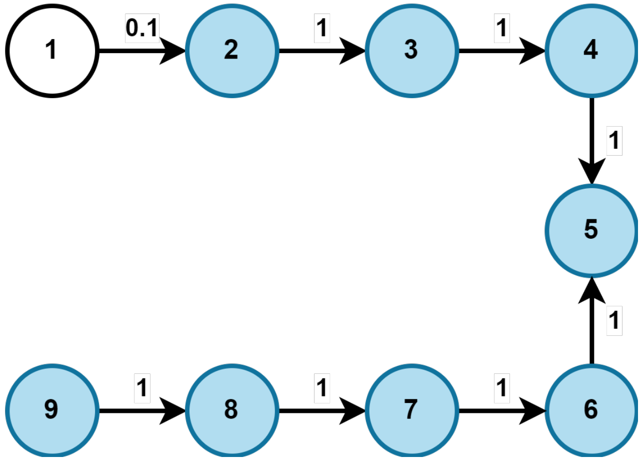
Campaigns c_2

- Initial Seed Set $I_2 = \{9\}$
- Balanced Seed Set $S_2 = \{2\}$

  - Exposed Node Set $\{2, 3, 4, 5, 6, 7, 8, 9\}$



$t = 0$



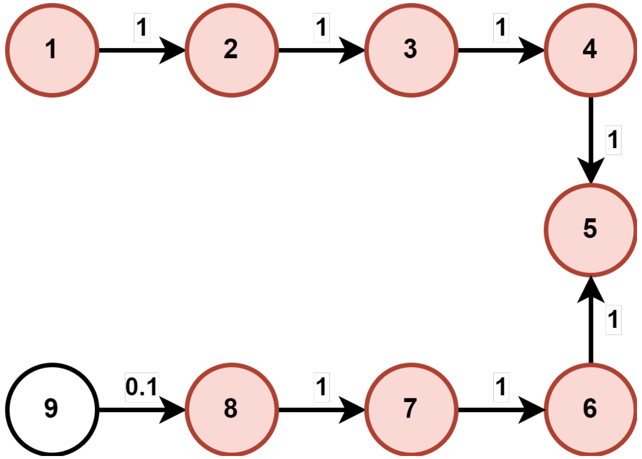
$t = 4$

IEM Solution 1

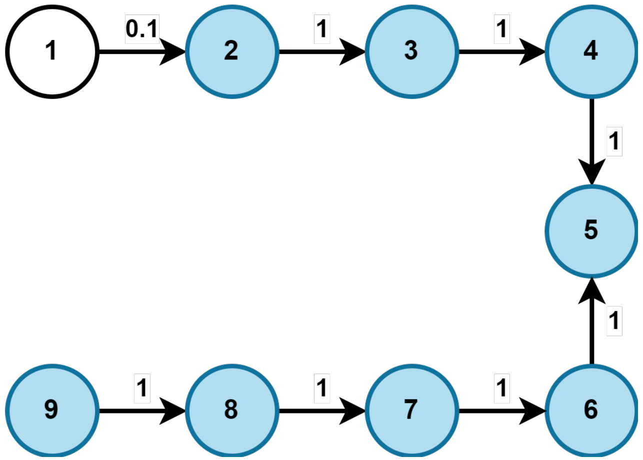
Balanced Exposed Node

- Initial Seed Set $I_1 = \{1\}, I_2 = \{9\}$
- Balanced Seed Set $S_1 = \{8\}, S_2 = \{2\}$

- $\Phi(S_1, S_2) = \left|V \setminus \left(r_1(I_1 \cup S_1) \triangle r_2(I_2 \cup S_2)\right)\right| = |\{2,3,4,5,6,7,8\}| = 7$



$\boldsymbol{r_1} = \{\mathbf{1,2,3,4,5,6,7,8}\}$

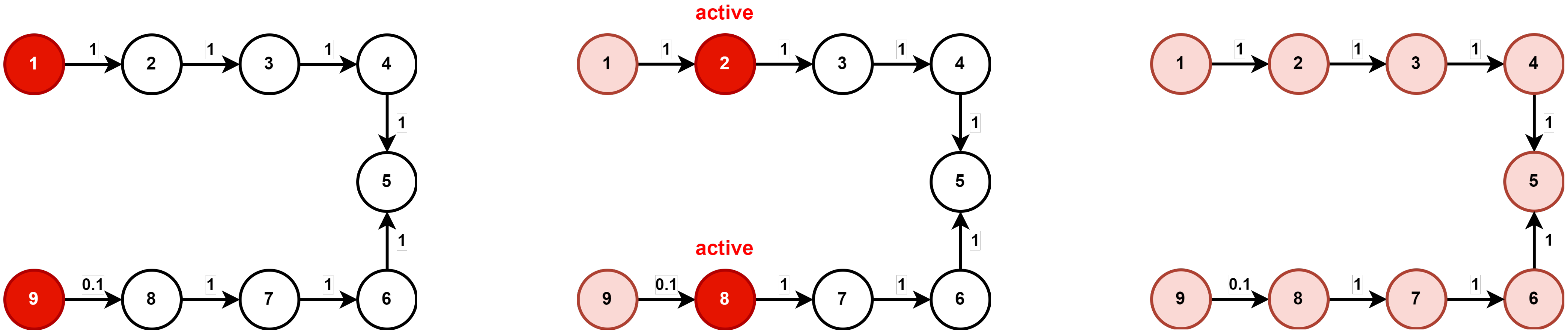


$\boldsymbol{r_2} = \{\mathbf{2,3,4,5,6,7,8,9}\}$

IEM Solution 2

Campaigns c_1

- Initial Seed Set $I_1 = \{1\}$
- Balanced Seed Set $S_1 = \{9\}$
- Case 1: node 8 activate with probability 0.1
  - Exposed Node Set $\{1, 2, 3, 4, 5, 6, 7, 8, 9\}$

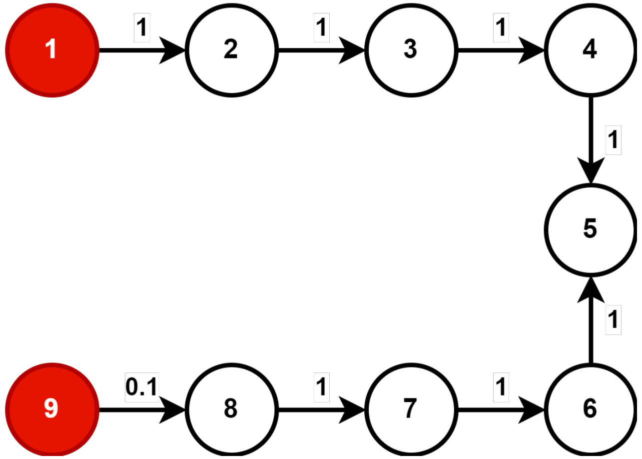


$t = 0$ $\quad$ $t = 1$ $\quad$ $t = 4$

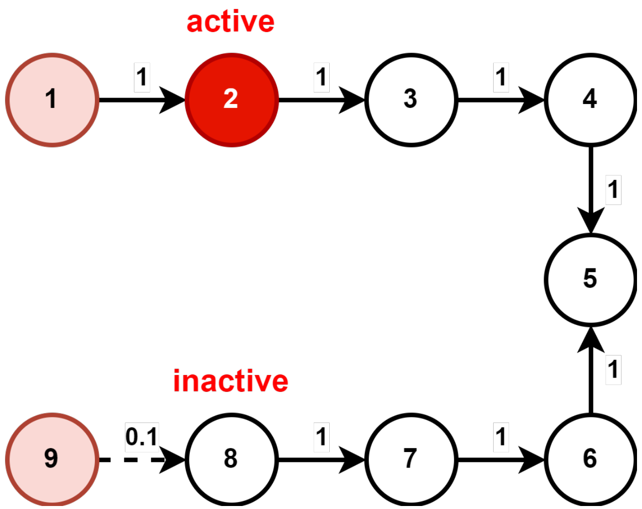
IEM Solution 2

Campaigns c_1

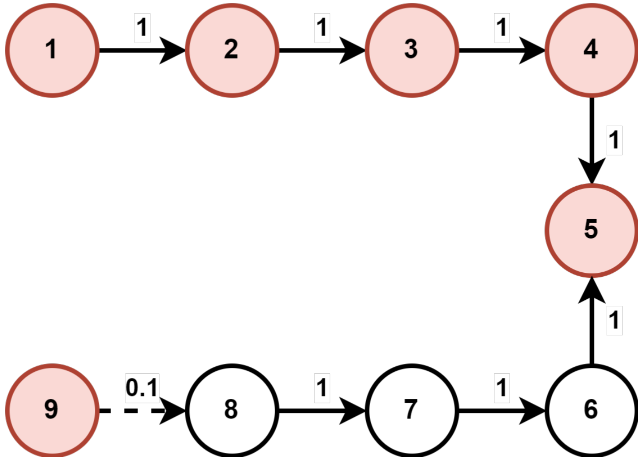
- Initial Seed Set $I_1 = \{1\}$
- Balanced Seed Set $S_1 = \{9\}$
- Case 2: node 8 inactivate with probability 0.9
    - Exposed Node Set $\{1, 2, 3, 4, 5, 8, 9\}$



$t = 0$



$t = 1$

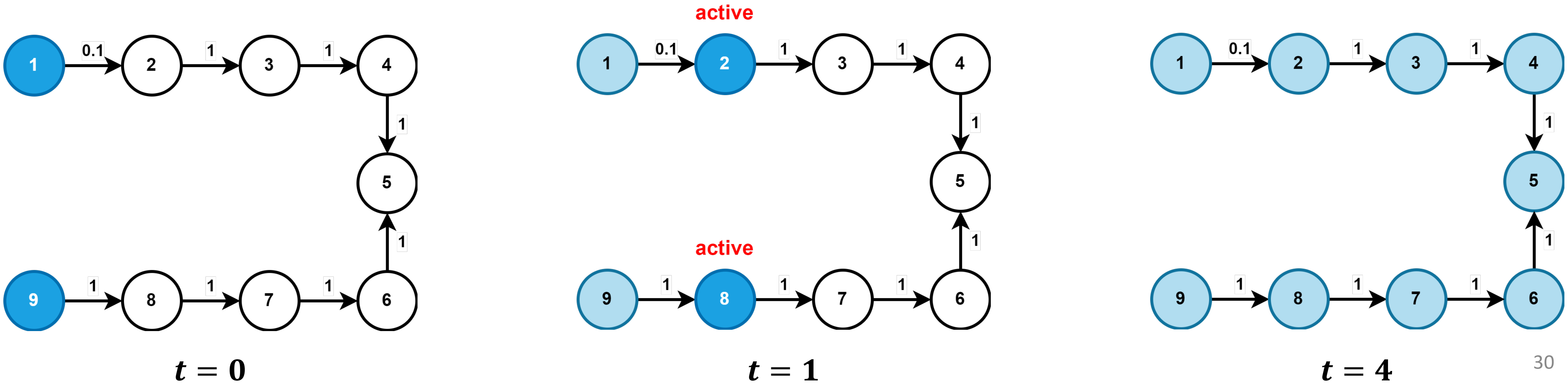


$t = 4$

IEM Solution 2

Campaigns c_2

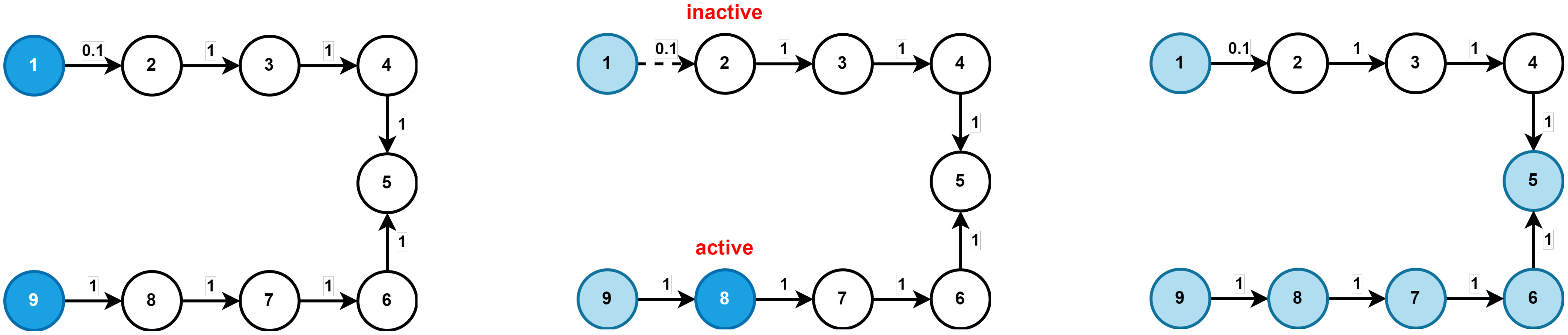
- Initial Seed Set $I_2 = \{9\}$
- Balanced Seed Set $S_2 = \{1\}$
- Case 1: node 2 activate with probability 0.1
    - Exposed Node Set $\{1, 2, 3, 4, 5, 6, 7, 8, 9\}$



IEM Solution 2

Campaigns c_2

- Initial Seed Set $I_2 = \{9\}$
- Balanced Seed Set $S_2 = \{1\}$
- Case 2: node 2 inactivate with probability 0.9
  - Exposed Node Set $\{1, 2, 5, 6, 7, 8, 9\}$

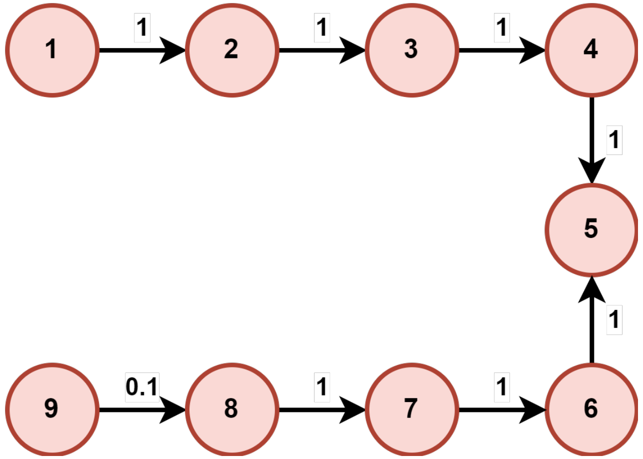


$t = 0$ $t = 1$ $t = 4$

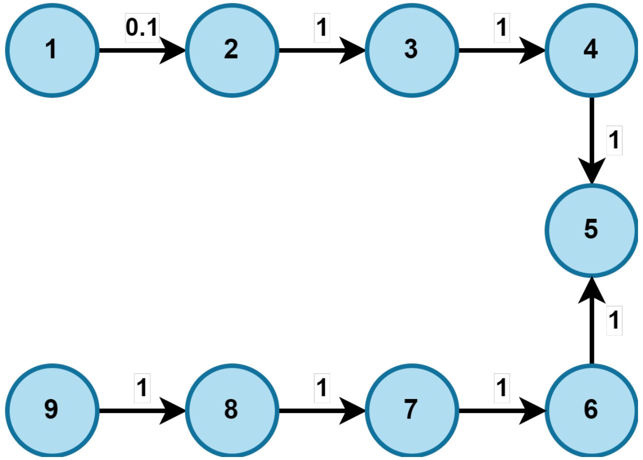
IEM Solution 2

Balanced Exposed Node

- Initial Seed Set $I_1 = \{1\}, I_2 = \{9\}$
- Balanced Seed Set $S_1 = \{9\}, S_2 = \{1\}$
  - Probability $p^{(1)} = p_1 \times p_2 = 0.01$
  - $\Phi^{(1)}(S_1, S_2) = \left|V \setminus \left(r_1(I_1 \cup S_1) \,\triangle\, r_2(I_2 \cup S_2)\right)\right| = |\{1,2,3,4,5,6,7,8,9\}| = 9$



$\boldsymbol{p_1 = 0.1, r_1 = \{1,2,3,4,5,6,7,8,9\}}$



$\boldsymbol{p_2 = 0.1, r_2 = \{1,2,3,4,5,6,7,8,9\}}$

IEM Solution 2

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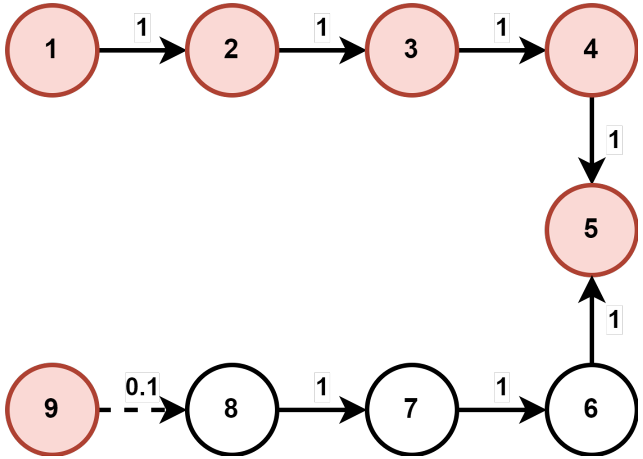
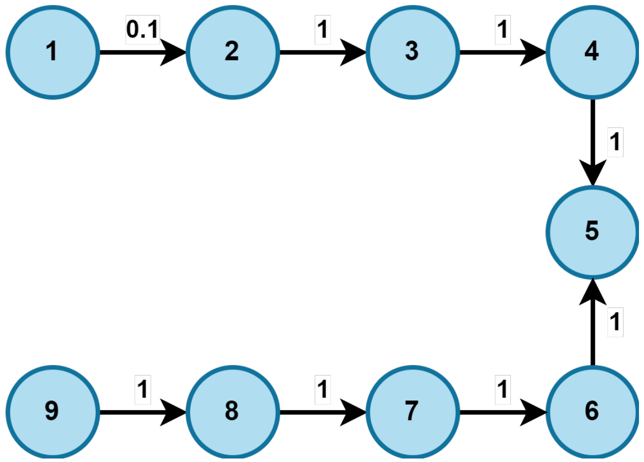
Balanced Exposed Node

- Initial Seed Set $I_1 = \{1\}, I_2 = \{9\}$
- Balanced Seed Set $S_1 = \{9\}, S_2 = \{1\}$
  - Probability $p^{(2)} = p_1 \times p_2 = 0.09$
  - $\Phi^{(2)}(S_1, S_2) = \left|V \setminus \left(r_1(I_1 \cup S_1) \bigtriangleup r_2(I_2 \cup S_2)\right)\right| = |\{1, 2, 3, 4, 5, 8, 9\}| = 7$



$\boldsymbol{p_1 = 0.9, r_1 = \{1, 2, 3, 4, 5, 8, 9\}}$

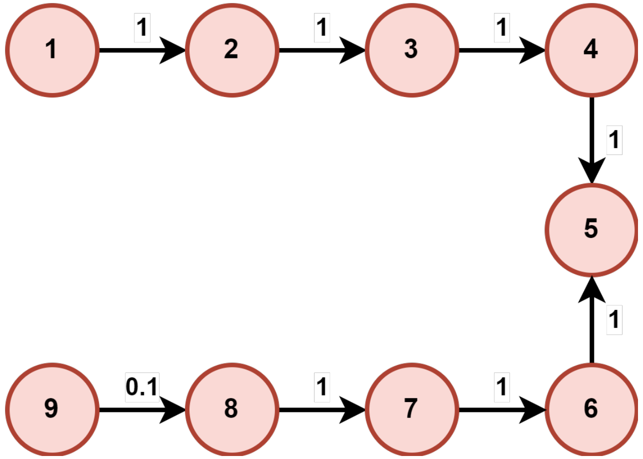


$\boldsymbol{p_2 = 0.1, r_2 = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}}$

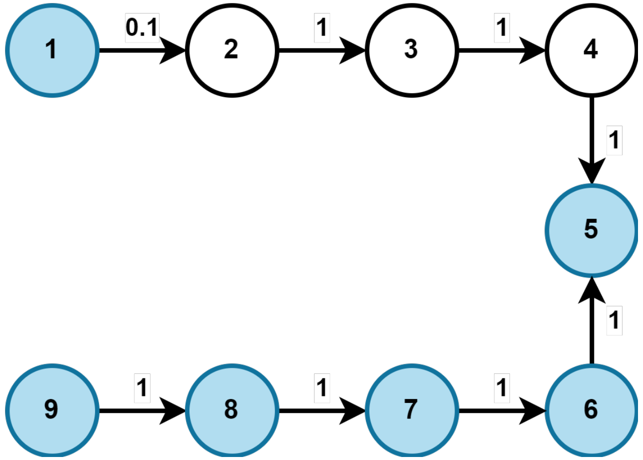
IEM Solution 2

Balanced Exposed Node

- Initial Seed Set $I_1 = \{1\}, I_2 = \{9\}$
- Balanced Seed Set $S_1 = \{9\}, S_2 = \{1\}$
  - Probability $p^{(3)} = p_1 \times p_2 = 0.09$
  - $\Phi^{(3)}(S_1, S_2) = \left|V \setminus \left(r_1(I_1 \cup S_1) \,\Delta\, r_2(I_2 \cup S_2)\right)\right| = |\{1,2,5,6,7,8,9\}| = 7$



$\boldsymbol{p_1 = 0.1, r_1 = \{1,2,3,4,5,6,7,8,9\}}$

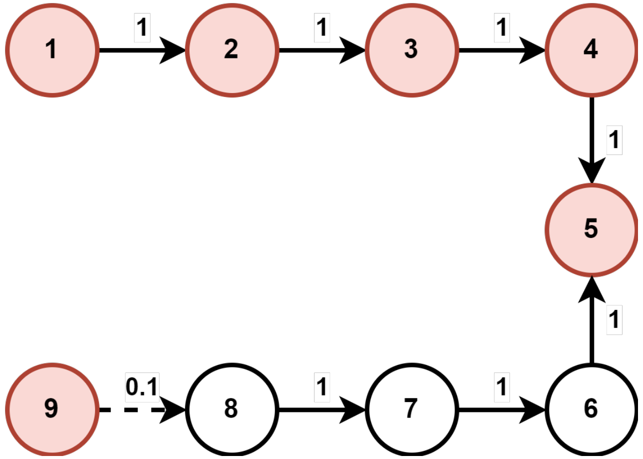


$\boldsymbol{p_2 = 0.9, r_2 = \{1,2,5,6,7,8,9\}}$

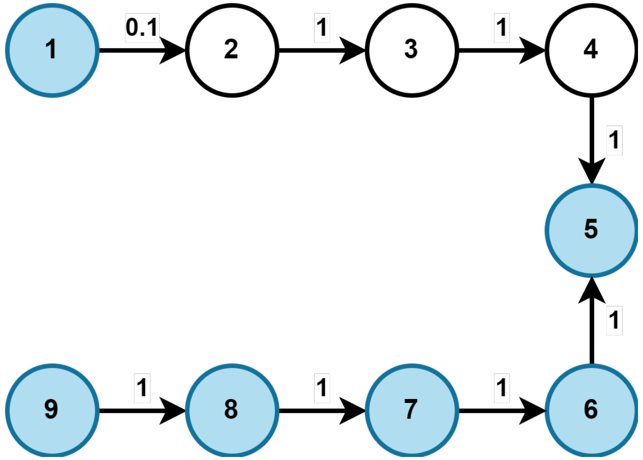
IEM Solution 2

Balanced Exposed Node

- Initial Seed Set $I_1 = \{1\}, I_2 = \{9\}$
- Balanced Seed Set $S_1 = \{9\}, S_2 = \{1\}$
  - Probability $p^{(4)} = p_1 \times p_2 = 0.81$
  - $\Phi^{(4)}(S_1, S_2) = \left|V \setminus \left(r_1(I_1 \cup S_1) \triangle r_2(I_2 \cup S_2)\right)\right| = |\{1,2,5,8,9\}| = 5$



$\boldsymbol{p_1 = 0.9, r_1 = \{1,2,3,4,5,8,9\}}$



$\boldsymbol{p_2 = 0.9, r_2 = \{1,2,5,6,7,8,9\}}$

IEM Solution 2

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Balanced Exposed Node

- Initial Seed Set $I_1 = \{1\}, I_2 = \{9\}$
- Balanced Seed Set $S_1 = \{9\}, S_2 = \{1\}$

$$\Phi(S_1, S_2) = \mathbb{E}\left[\left|V \setminus \left(r_1(I_1 \cup S_1) \triangle r_2(I_2 \cup S_2)\right)\right|\right] = \sum_{i=1}^{4} p^{(i)} \times \Phi^{(i)}(S_1, S_2)$$

$$= 0.01\times 9 + 0.09\times 7 + 0.09\times 7 + 0.81\times 5 = 5.4$$

Project1: Information Exposure Maximization

- Information Exposure Maximization is computationally complex
  - Computing the balanced information exposure for a given solution is NP-hard.
  - Finding an optimal solution of IEM is NP-hard.
- Three tasks
  - An objective estimator
  - Two search algorithms

Thank you!

For more information, please refer to **Project1.PDF**