

The background features a network diagram with white human icons connected by thin lines, set against a light gray background. The icons are arranged in a grid-like pattern, with lines connecting them to form a network structure.

A Budgeted Framework to Model a Multi-round Competitive Influence Maximization Problem

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Outline

- ❑ Models of influence
 - Linear Threshold
 - Independent Cascade
- ❑ Influence maximization problem Algorithm
- ❑ Competitive Influence maximization problem
- ❑ Our Approach
- ❑ Experiments
 - Data and setting
 - Results

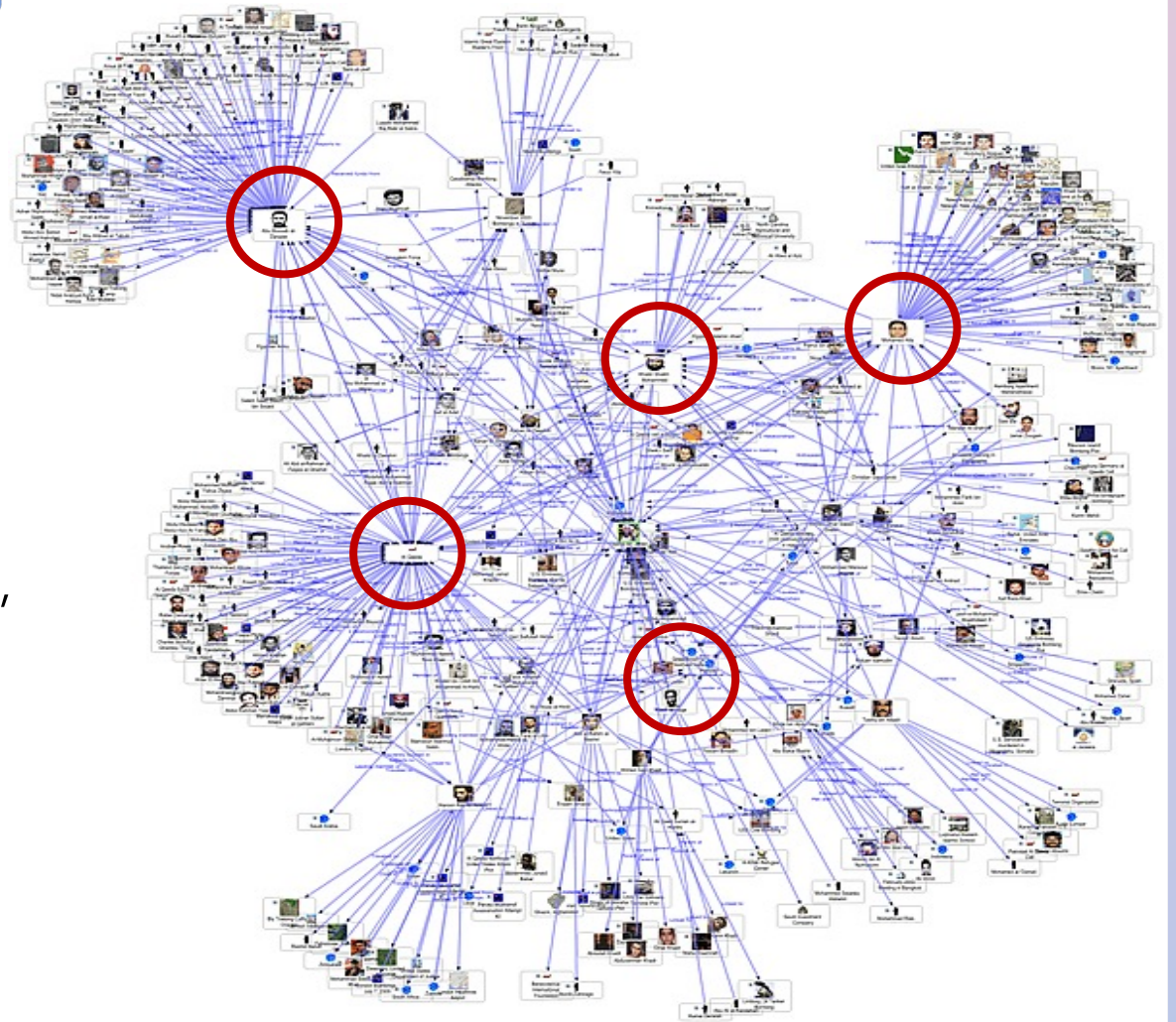


What is Social Influence?

- Social network plays a fundamental role as a medium for the spread of **INFLUENCE** among its members
 - Opinions, ideas, information, innovation...
- **Nodes:** Social actors (individuals or organizations)
- **Links:** Social relations
- Social influence occurs when one's opinions, emotions, or behaviors are affected by others, intentionally or unintentionally.
- Influential persons often have many friends.

Influential Persons

- Number of friends: Node degree
- Famous persons
- Betweenness centrality
- Direct Marketing takes the “word-of-mouth” effects to significantly increase profits



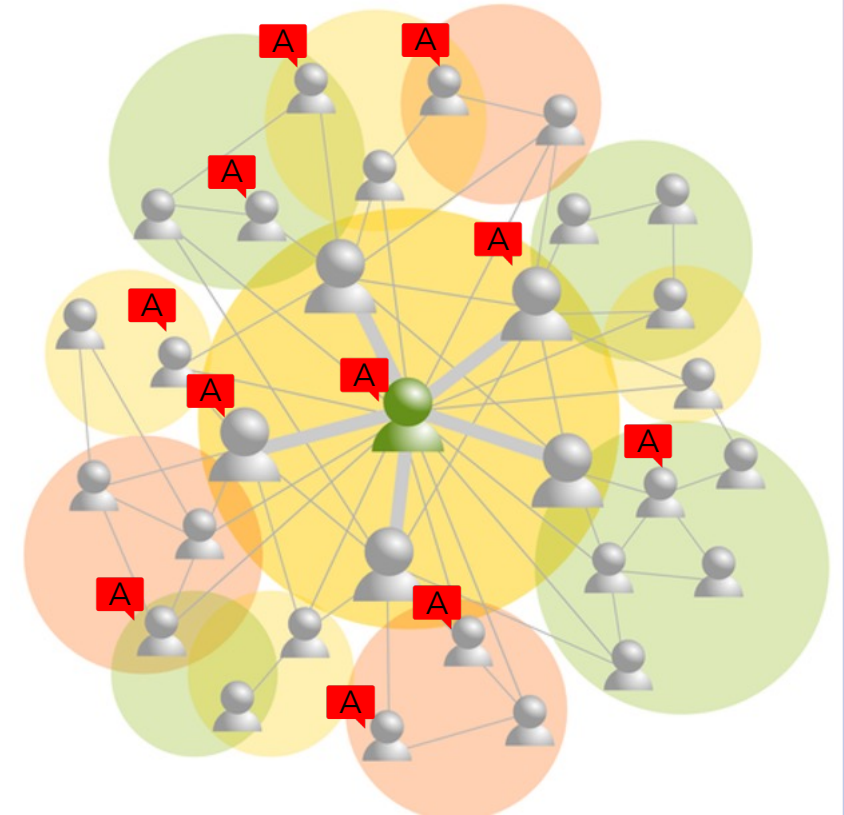
Influence Maximization Problem

- Influence spread of node set S : $\sigma(S)$
 - expected number of active nodes at the end of diffusion process, if set S is the initial active set.
- Problem Definition (by Kempe et al., 2003):

(Influence Maximization). Given a directed and edge-weighted social graph $G = (V, E, p)$, a diffusion model m , and an integer $k \leq |V|$, find a set $S \subseteq V$, $|S| = k$, such that the expected influence spread $\sigma(S)$ is maximum.

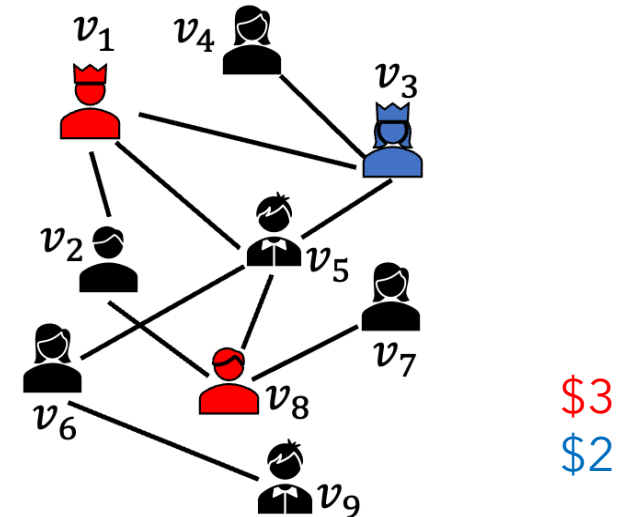
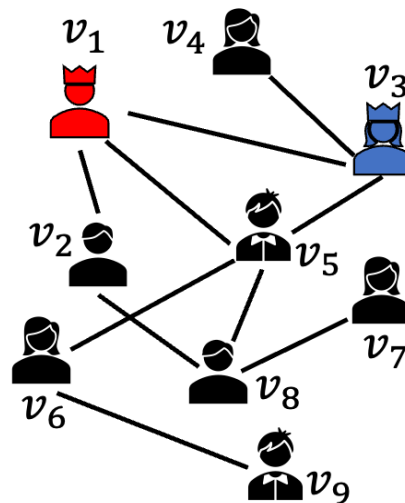
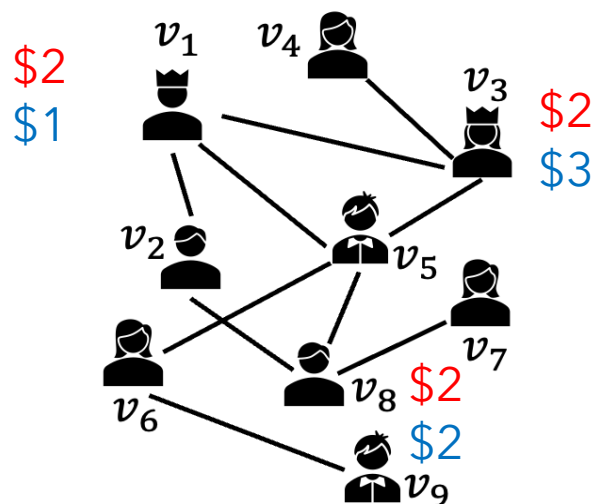
Influence Maximization Problem

- Diffusion Model
 - Linear Threshold (LT)
 - A node has random threshold θ
 - A node becomes active when at least θ fraction of its neighbors are active
 - Independent Cascade (IC)
 - When node v becomes active, it has a single chance of activating each currently inactive neighbor w .
 - The activation attempt succeeds with probability p_{vw}



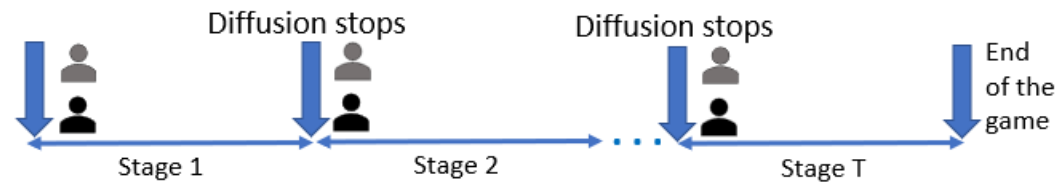
Competitive Influence Maximization

- First, parties identify the most influential nodes of the network.
- Then they compete over only these influential nodes by the amount of budget they allocate to each node.



Multi-round Diffusion

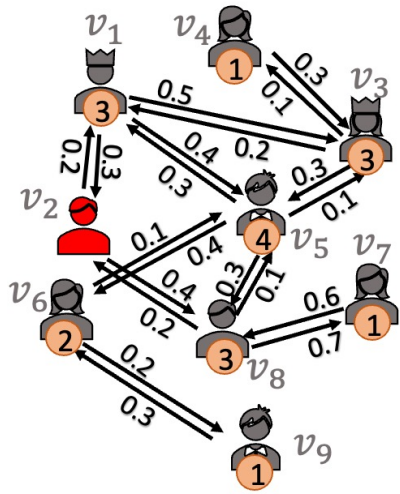
- In a multi-stage CIM problem, competitors need to select seed nodes simultaneously in each of the sequence stages.
- 1) Nod-Node influence competition
- 2) Link-Link influence competition
- 3) Node-Link influence competition



A Budgeted Framework to Model a Multi-round Competitive Influence Maximization Problem

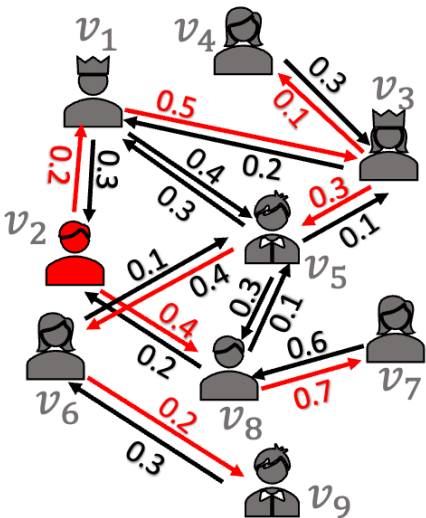
- We integrate seed selection and budget allocation into the RL model.
- Selecting Seed Nodes and Propagation Model
- Most Reliable Influence Path (MRIP)
 - Fixed weight
 - Dynamic weight
- Reinforcement Learning

MRIP



$$w'(u) = \sum_{v \in V} R(v) \times w(u),$$

$$\begin{aligned} w'(v_1) &= 3 * R(v_3) = 3 \\ w'(v_2) &= 2 * (R(v_1) + R(v_8)) = 1.2 \\ w'(v_3) &= 3 * (R(v_4) + R(v_5)) = 1.2 \\ w'(v_4) &= 0 \\ w'(v_5) &= 4 * R(v_6) = 0.48 \\ w'(v_6) &= 2 * R(v_9) = 0.048 \\ w'(v_7) &= 0 \\ w'(v_8) &= 3 * R(v_7) = 0.56 \\ w'(v_9) &= 0 \end{aligned}$$



Algorithm 2 Finding seed set by MRIP

- 1: $S \leftarrow \emptyset$
- 2: **for all** $u \in V$ **do**
- 3: $w'(u) \leftarrow 0$
- 4: **for** $u \in V$ **do**
- 5: Construct \mathcal{T}_u via Alg. 3
- 6: **for** each leaf v in reverse \mathcal{T}_u **do**
- 7: $z \leftarrow \text{parent}(v)$
- 8: **while** $v \neq u$ **do**
- 9: Compute $w'(z) = w'(z) + R(v) \times w(z)$
- 10: $v \leftarrow z$
- 11: $z \leftarrow \text{parent}(v)$
- 12: $\text{new seed} \leftarrow \arg \max_{u \in V/S} w'(u)$
- 13: $S \leftarrow S \cup \{\text{new seed}\}$
- 14: $V_A \leftarrow$ Activated nodes by new seed node
- 15: Constructing \mathcal{G}' with vertex set $V - V_A$
- 16: Recalculate \mathcal{T} and w' in \mathcal{G}'

Algorithm 3 Computing \mathcal{T}_u

Require: $\mathcal{G}(V, E, P)$, source node u

- 1: $A = \{u\}$, $R(u) = 1$
- 2: **while** $A \neq V$ **do**
- 3: Find node $v \in N(A)$ and $v \in V - A$ such that
- 4: $R'(v) = \max_{(s,v): s \in A, v \in V - A} R(s) \times p(s, v)$
- 5: $R(v) = R'(v)$
- 6: $A = A \cup \{v\}$
- 7: Set s as the parent of v in spanning tree \mathcal{T}_u
- 8: **return** \mathcal{T}_u

Most Reliable Influence Path (MRIP)

v_2

v_2, v_8

v_2, v_8, v_7

v_2, v_8, v_7, v_1

v_2, v_8, v_7, v_1, v_3

$v_2, v_8, v_7, v_1, v_3, v_5$

$v_2, v_8, v_7, v_1, v_3, v_5, v_6$

$v_2, v_8, v_7, v_1, v_3, v_5, v_6, v_4$

$v_2, v_8, v_7, v_1, v_3, v_5, v_6, v_4, v_9$

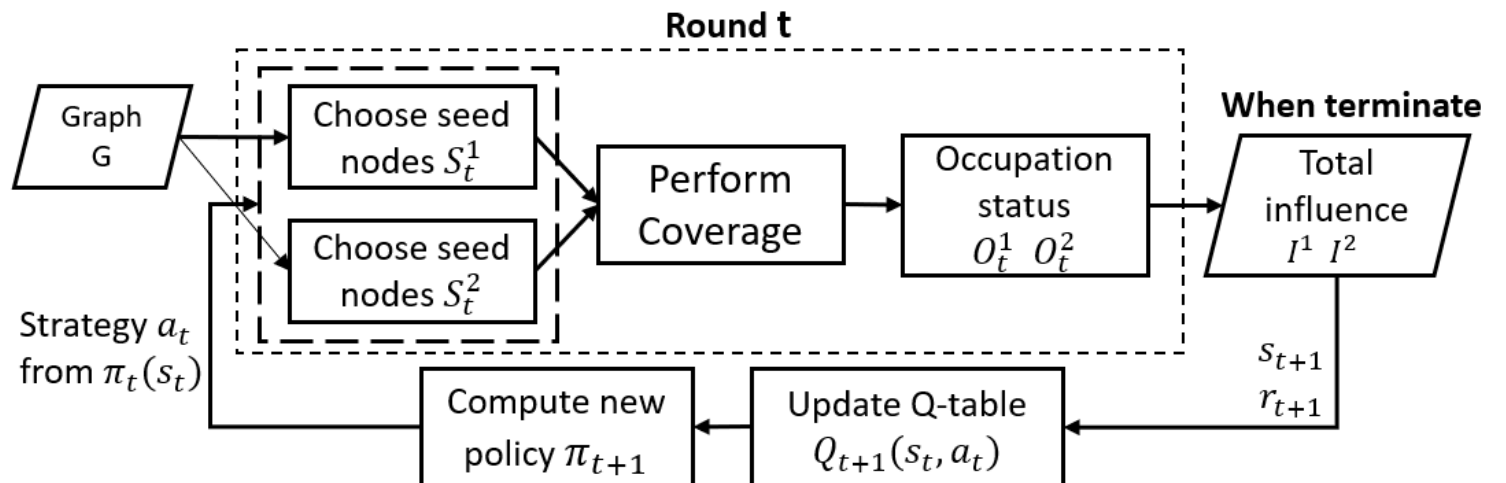
A	N(A)	R(s)* p(s,v)	R(v)
{ v_2 }	v_1	$1 * 0.2 = 0.2$ $1*0.4=0.4$	$R(v_8)$
{ v_2, v_8 }	v_1 v_5 v_7	$1 * 0.2 = 0.2$ $0.4 * 0.1 = 0.04$ $0.4*0.7=0.28$	$R(v_7)$
{ v_2, v_8, v_7 }	v_1 v_5	$1*0.2=0.2$ $0.4 * 0.1 = 0.04$	$R(v_1)$
{ v_2, v_8, v_7, v_1 }	v_1 v_5	$0.4 * 0.1 = 0.04$ $0.2*0.5=1$ $0.2 * 0.4 = 0.08$	$R(v_3)$
{ v_2, v_8, v_7, v_1, v_3 }	v_1 v_5	$0.4 * 0.1 = 0.04$ $0.2 * 0.4 = 0.08$ $1 * 0.1 = 0.1$ $1*0.3=0.3$	$R(v_5)$
{ $v_2, v_8, v_7, v_1, v_3, v_5$ }	v_4 v_6	$1 * 0.1 = 0.1$ $0.3*0.4=0.12$	$R(v_6)$
{ $v_2, v_8, v_7, v_1, v_3, v_5, v_6$ }	v_4 v_9	$1*0.1=0.1$ $0.12 * 0.2 = 0.024$	$R(v_4)$
{ $v_2, v_8, v_7, v_1, v_3, v_5, v_6, v_4$ }	v_9	$0.12*0.2=0.024$	$R(v_9)$

Reinforcement Learning

- In RL, the agent keeps interacting with the environment to find the optimal policy π to maximize his expected accumulated rewards

- State

- Action



Reinforcement Learning

State

- 1) Number of inactive nodes
- 2) Summation of degrees of all inactive nodes
- 3) Maximum degree among all inactive nodes
- 4) Summation of the weight of the edges for which both vertices are inactive
- 5) Summation of the inactive out-edge weight for nodes which are the neighbors of player I
- 6) Maximum sum of the inactive out-edge weight of a node among all nodes
- 7) Ratio of budgets
- 8) Weight of nodes in case of reachability

Action:

- (1) Selecting a new seed node and
- (2) feeding a node in case of tie.

Experiment

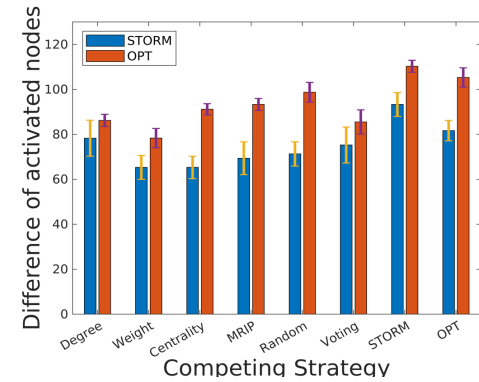
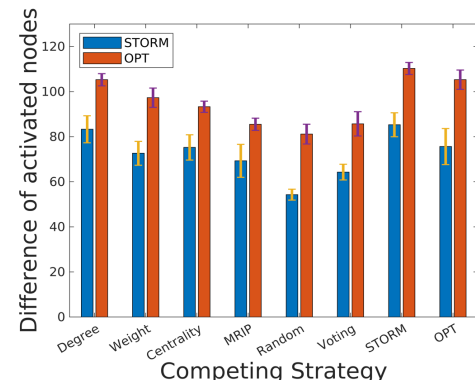
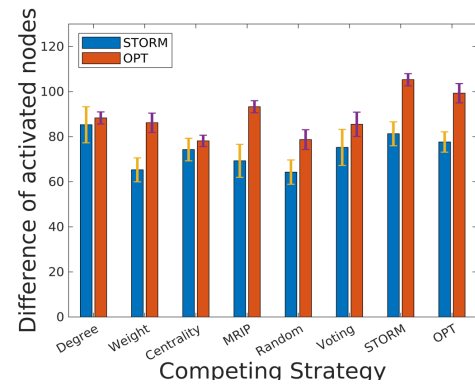
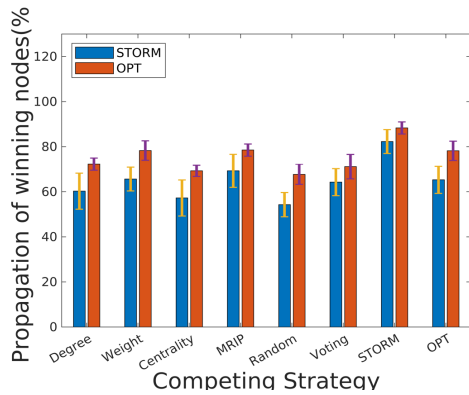
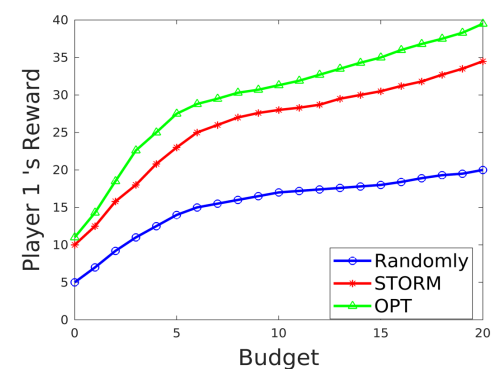
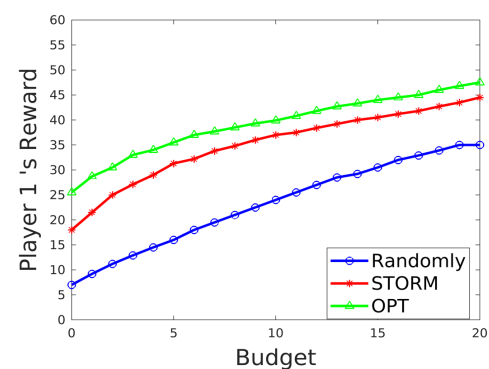
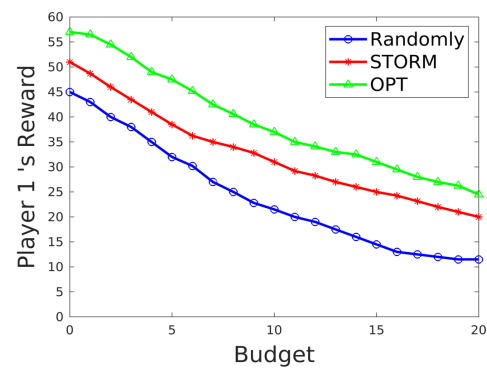
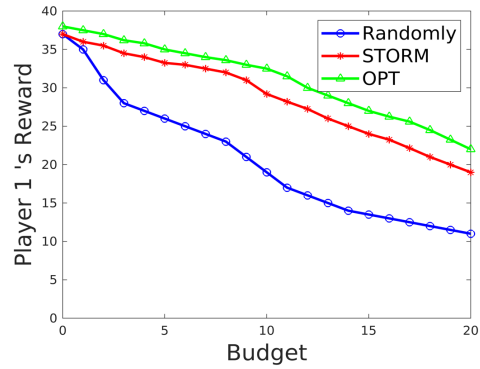
1) Evaluation on Budget Setting

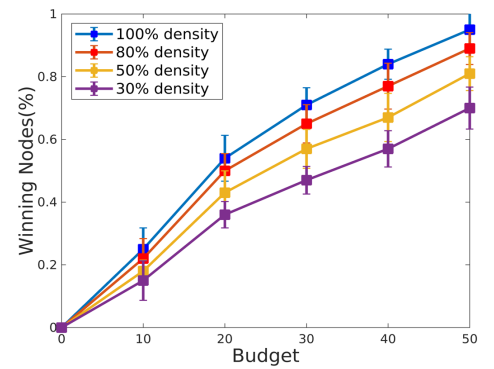
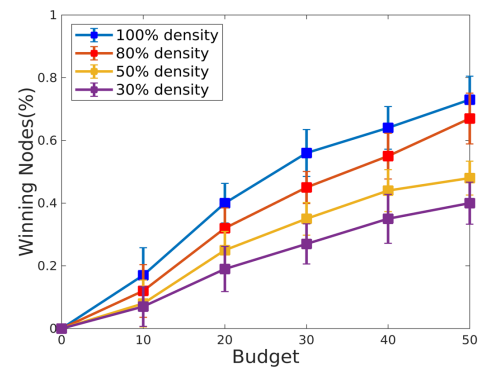
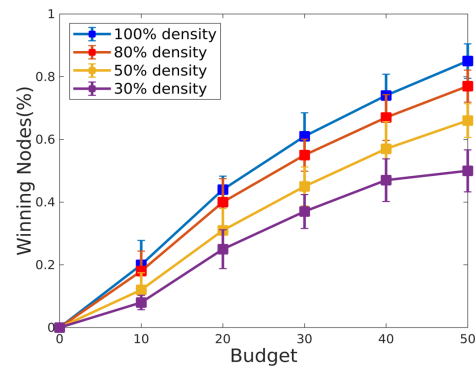
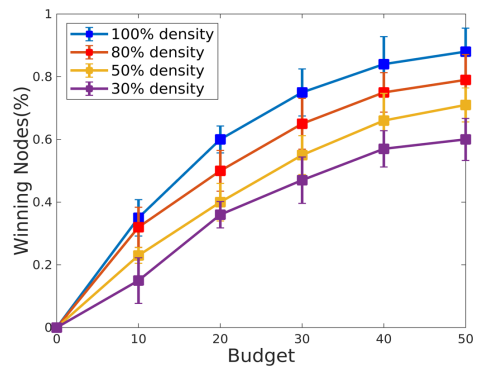
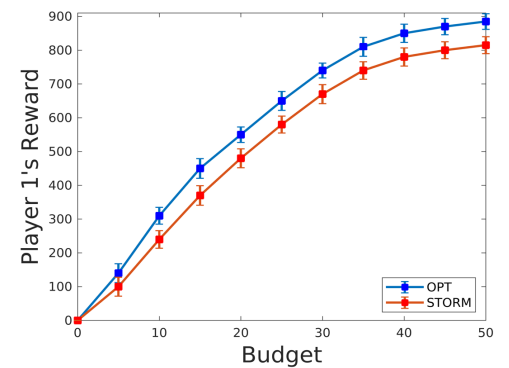
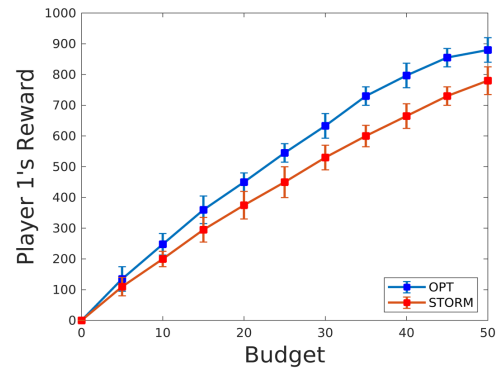
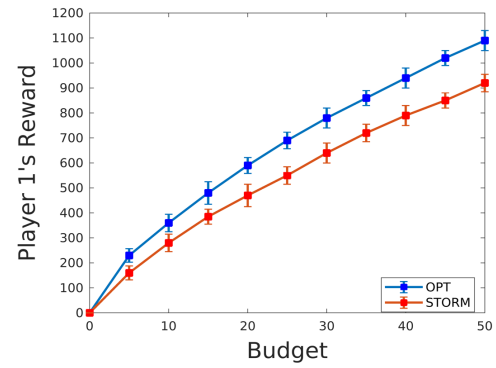
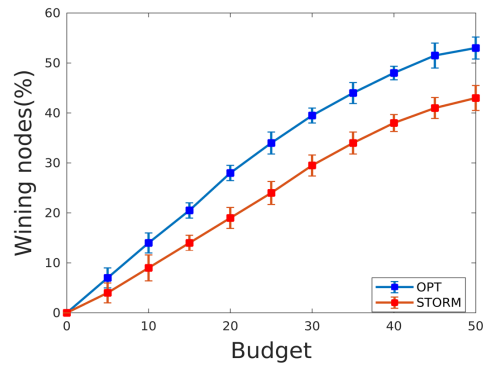
2) Evaluation Based on Different Topologies

3) Evaluation on Edge-weight Setting

- Case 1: uniform probabilities p on each edge
- Case 2: weight of the edges in the range of $[0.1, 0.4]$ and $[0.4, 0.7]$. In addition, the weight for edges are randomly sampled from the normal distribution of $U(0, 0.2)$ and $U(0, 1)$.

4) Evaluation on Different Competing Strategies:





Thank you

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