Towards Effective Planning Strategies for Dynamic Opinion Networks

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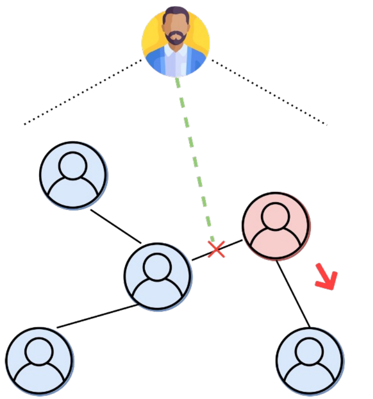
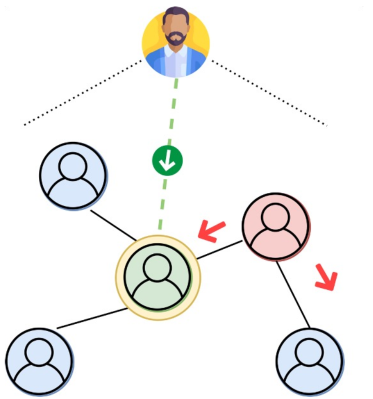
Intervention Planning

Intervention planning involves designing strategies to address problems and influence outcomes within systems. In network analysis, this includes **controlling information spread** by targeting key nodes or altering system behavior.

- Understanding misinformation spread is challenging due to limited access to real-world data.
- Model-based analysis becomes essential, allowing us to simulate and study complex network interactions in controlled environments.



Break communication link



Protect key node

Application: Opinion Networks

- Graph G = (V,E)
  - V = Agents with opinion values → Opinion Value ϵ [-1,1]
  - E = Connections between agents → Trust Value ϵ [0,1]
- Opinion networks model the spread and influence of individual opinions within a social structure, focusing on how connections between nodes shape collective beliefs and behaviors.

Network Dynamicity

Case-1: Binary opinion value and Binary trust value

Case-2: Continuous opinion value and Binary trust value

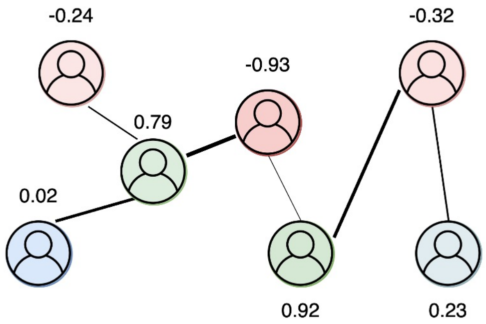
Case-3: Continuous opinion value and Continuous trust value

Topic: A statement e.g., '*NeurIPS submission deadline is on May 22*'

Opinion: Belief of the agent in the truthfulness of the statement

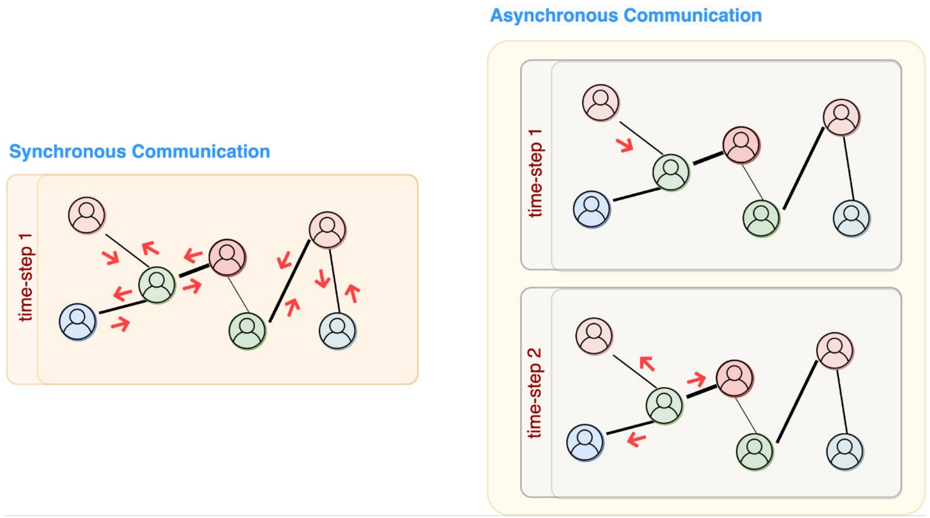
- ➔ Positive/Negative opinion value → agent believes the statement is True/False

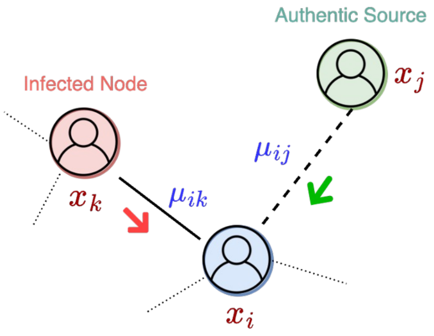
Sample Opinion Network with ***continuous opinion values*** and ***continuous trust relationship***.



Opinion Propagation

- Opinion dynamics - Studies opinion evolution using Dynamical Models.
    - Synchronous Propagation
    - Asynchronous Propagation
- We provide our solution based on **asynchronous propagation model**.

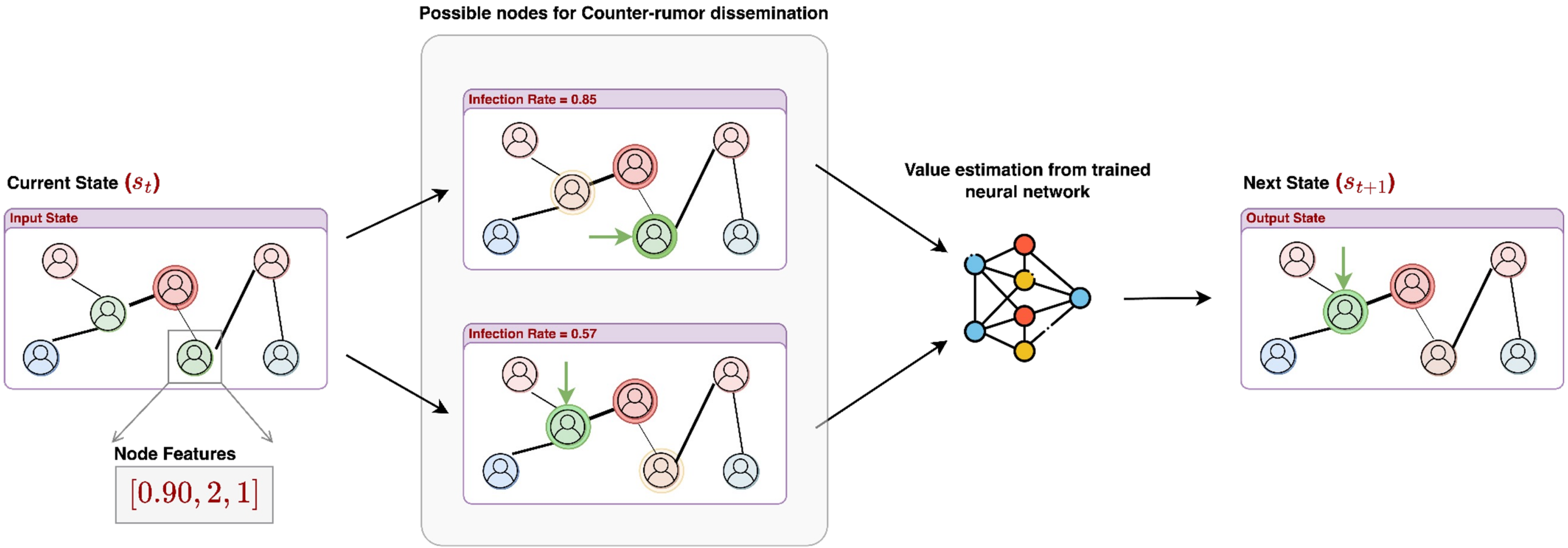




$$x_i(t+1) = x_i(t) + \mu_{ik}\left(x_k(t) - x_i(t)\right) + \mu_{ij}\left(x_j(t) - x_i(t)\right)$$

State Representation

- *Node Features for State Representation* - Three key features:
  - **Opinion Value**: Reflects the agent's belief, ranging from -1 (misinformed) to 1 (accurately informed).
  - **Connectivity Degree**: Indicates how many connections (edges) the node has to other nodes.
  - **Proximity to Misinformation**: Measured as the shortest path to a misinformed node.



Methodology:

Ranking Algorithm based Supervised Learning

Subset generation

- **M:** The number of candidate nodes in **S** that are neither infected nor blocked.
- **C:** Set of all possible combinations of **K** nodes from **M**

$$C = \{c \subset M : |c| = K\}$$

Infection rate

- **r(c):** Infection rate from blocking the **c** nodes can be represented as

$$r(c) = \frac{\text{Number of Infected Nodes}}{\text{Total Number of Nodes}}$$

Find optimal subset

- Subset **c*** with minimal infection rate

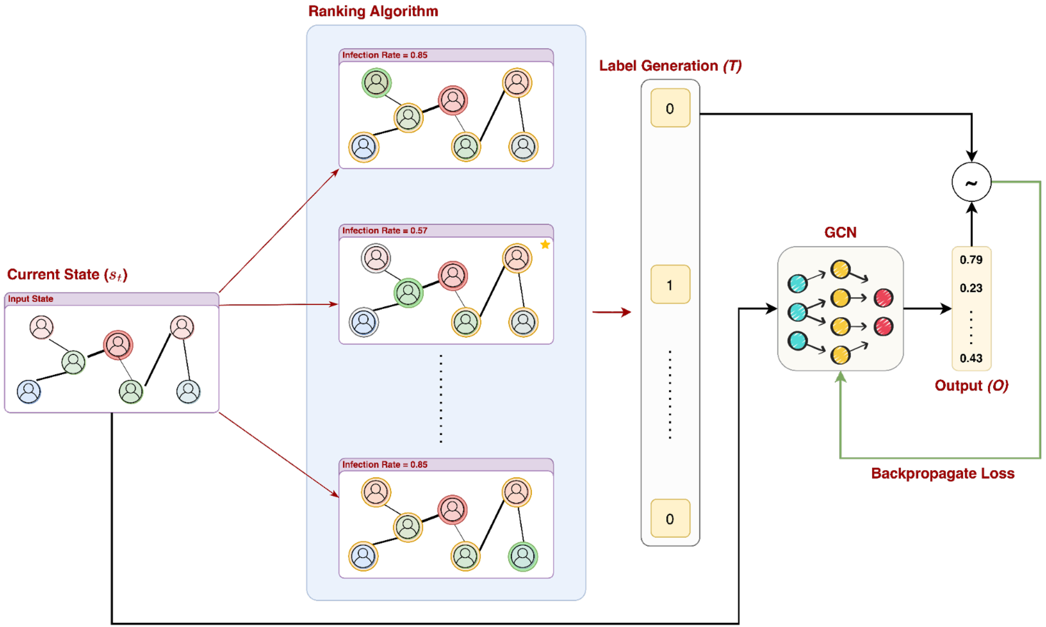
$$c^* = \arg\min_{c \in C} r(c)$$

Construct target matrix:

- **T** is used as the label for training GCN

$$T \in \mathbb{R}^{N \times 1}$$

$$T[i] = \begin{cases} 1 & \text{if } i \in c^* \\ 0 & \text{otherwise} \end{cases}$$



Ranking Algorithm for supervised label generation is **computationally complex** and infeasible especially when considering *continuous opinion and trust values (Case 3)*.

Methodology:

Reinforcement Learning-based Centralized Dynamic Planner

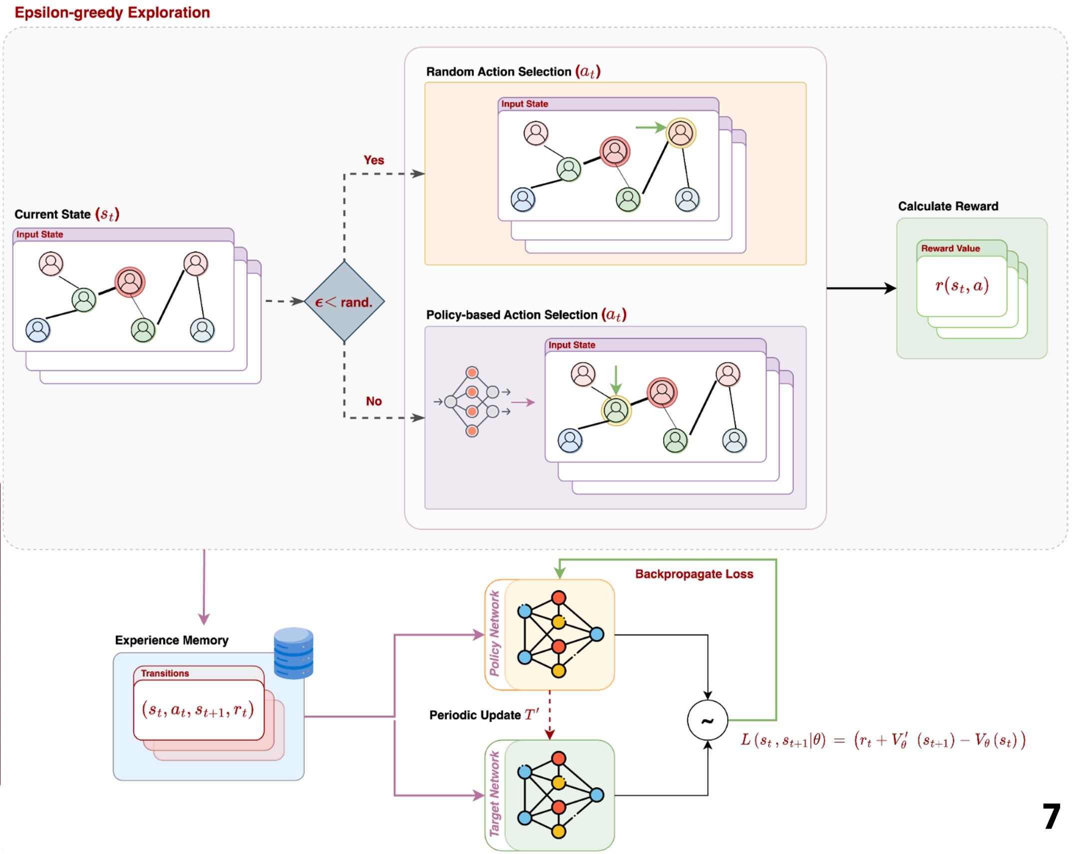
→ No supervised label generation is needed.
→ Works well for both Discrete and Continuous opinion and trust values.
→ Computationally complex.

We use **Deep Value Network (DVN)** instead of Deep Q-Network (DQN). Unlike the classic DQN, the DVN outputs the value of each state without requiring a fixed number of actions, making it adaptable to dynamic network conditions.

Reward Functions

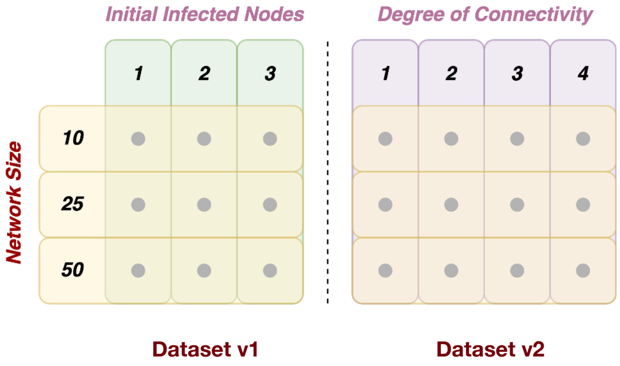
Network Information

Global	Local	
✓	✗	R0: $-\Delta\,\text{infection rate}$
✗	✓	R1: $-(\#\,\text{candidate nodes})$
✓	✓	R2: $-(\#\,\text{candidate nodes})$ - $\Delta\,\text{infection rate}$
✗	✗	R3: $1-\dfrac{(\#\,time\ steps)}{(Total\,time\ steps)}$
✓	✗	R4: $-\,\text{infection rate}$
✗	✓	R5: $-(\#\,\text{candidate nodes})$ - $\dfrac{(\#\,time\ steps)}{(Total\,time\ steps)}$



Dataset Generation

- **Watts-Strogatz** network structure.
- **Dataset v1**: Examines the effect of network size (10, 25, 50 nodes) and number of infected nodes (1-3).
- **Dataset v2**: Focuses on the initial connectivity of infected nodes (degrees 1 to 4).
- **Open-Source Datasets** considered for evaluation -
  - Zachary's Karate Club [*Undirected*]
    - V: 34, E: 78, Avg. Deg.: 4.59
  - Facebook [*Undirected*]
    - V: 250, E: 1352, Avg. Deg.: 10.8
  - Email [*Directed*]
    - V: 300, E: 2358, Avg. Deg.: 7.9
  - Cora [*Undirected*]
    - V: 2000, E: 2911, Avg. Deg.: 2.9

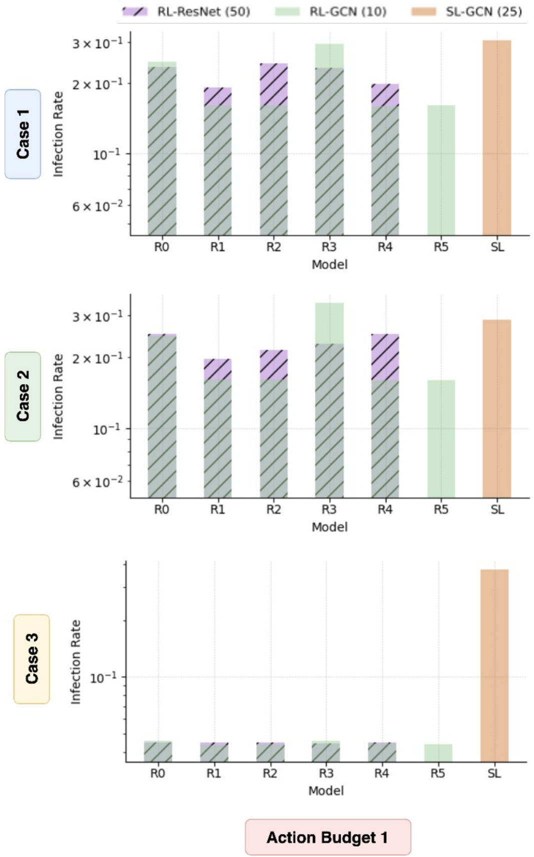


1000 network samples for each combination

Representative results on Dataset v2

Results on dataset v2 with network sizes 50 and degree of connectivity 4.

- **Blocking Time vs. Spread Magnitude:**
    - *Blocking Time (R3):* Prioritizes fast response but may overlook total infection control.
    - *Combined Reward (R5):* Adding neighbors' information to R3 improves control, balancing speed with reduced spread.
- **Local vs global network observability:**
    - *Global (R4):* Best performance but requires full network observability.
    - *Local (R1):* Effective with only neighbors' information, suited for partial views.
- **Model scalability**
    - *GCN model* trained on only 10 node networks consistently exhibits lower average infection rates when compared to ResNet model trained on 50 nodes networks.



Summary

- ***Significance of timely interventions:*** Timely interventions help to minimize the reach and impact of misinformation, protecting public trust and preventing long-term societal and economic damage.
- Existing literature works focus on -
  - Node removal, edge removal, and counter-rumor dissemination.
  - Only **discrete states of opinion and trust** network model.

Implications	Features of Our work	Our Work	Previous Work
Action-Space Invariant	Deep Value Network	✓	✗
Expressive Models	Network Dynamicity	Case 1, Case 2, Case 3	Only Case 1
Realistic Communication Dynamics	Asynchronous Communication	✓	✗
Wider Applications	Reward Models	5 variants studies	Typically 1

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THANK YOU ALL

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