Expressive and Flexible Simulation of Information Spread Strategies in Social Networks Using Planning

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Abstract

In the digital age, understanding the dynamics of information spread and opinion formation within networks is paramount. This research introduces an innovative framework that combines the principles of opinion dynamics with the strategic capabilities of Automated Planning. We have developed, to the best of our knowledge, the first-ever numeric PDDL tailored for opinion dynamics. Our tool empowers users to visualize intricate networks, simulate the evolution of opinions, and strategically influence that evolution to achieve specific outcomes. By harnessing Automated Planning techniques, our framework offers a nuanced approach to devise sequences of actions tailored to transition a network from its current opinion landscape to a desired state. This holistic approach provides insights into the intricate interplay of individual nodes within a network and paves the way for targeted interventions. Furthermore, the tool facilitates human-AI collaboration, enabling users to not only understand information spread but also devise practical strategies to mitigate potential harmful outcomes arising from it. Demo Video link - https://tinyurl.com/3k7bp99h

Introduction

The spread of information across social networks profoundly impacts public opinion, collective behaviors, and societal outcomes (Acemoglu and Ozdaglar 2011). Opinion dynamics, a subset of this broader field, delves into the intricate mechanisms by which individual beliefs and attitudes evolve within a network. Recent research has explored the evolution of opinions, influenced by factors like peer interactions, media dynamics (Quattrociocchi, Caldarelli, and Scala 2014), and inherent predispositions (Sîrbu et al. 2017). Historically, several models have been introduced to understand these dynamics. Prominent among them are DeGroot's consensus model (DeGroot 1974), the Voter model (Clifford and Sudbury 1973), and the bounded confidence approach (Krause and Hegselmann 2002).

Understanding the dynamics of opinion formation is essential. Yet, steering these dynamics towards specific outcomes is challenging. Traditional models of opinion dynamics often rely on broad strategies without considering the intricate interplay of individual nodes within a network. In contrast, Automated Planning offers a granular approach, devising specific sequences of actions tailored to transition a system from its current state to a desired state (Ghallab, Nau, and Traverso 2004). In the context of opinion dynamics, this could mean formulating targeted strategies to sway the collective opinion of a network in a more positive or negative direction, taking into account the unique characteristics and dependencies of each network node.

In this research, we bridge the domains of opinion dynamics and Automated planning. We introduce a novel framework that not only models and simulates the evolution of opinions within a network but also employs Automated planning techniques to strategically influence that evolution to achieve user-defined objectives. The system architecture for our project is shown in Figure 1(a). To illustrate the practical applicability and efficacy of our framework, we have developed an online demonstration platform. The platform provides an interactive visualization of an opinion network, allowing users to set parameters, view real-time opinion propagation, and employ AI planning strategies to influence opinion outcomes, making the complex domain of opinion dynamics more accessible and comprehensible.

PDDL Model for Opinion Dynamics

In our research, we have developed a numeric PDDL (Fox and Long 2003) model (provided in the supplementary material) for the opinion dynamics domain, specifically focusing on information spread.

Types and Predicates: The model introduces three types: `agent`, `source`, and `topic`. While both `agent` and `source` represent network nodes, `agents` adjust opinions based on information flow, whereas `sources` remain static but can be modified by users via the interface. The `topic` type denotes the subject of the information. The primary predicate `connected-agent` captures the relationship between two entities (either `agents` or `sources`).

Numeric Fluents: Two numeric fluents are defined: (1) `have-opinion` represents the opinion of an agent or source about a particular topic. The value ranges from -1.0 to 1.0, with negative values indicating disagreement or opposition, positive values indicating agreement or support, and zero indicating neutrality; (2) `have-trust` captures the trust level between two node types. The trust level influences how information flows from one node to another node.

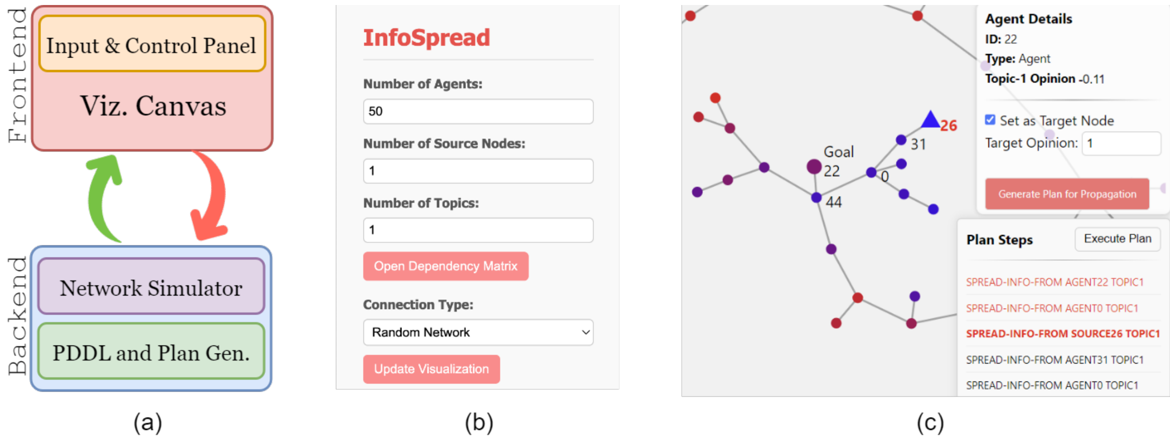

Figure 1: An overview of the project components. (a) System architecture, (b) Side panel interface showcasing network customization options, and (c) Network visualization showcasing the generated plan execution for opinion propagation. We show an example of input and output (b & c) where information flows from Nodes 26 to 22; a partially executed plan is shown in red.

Actions: The primary action, `spread-info-from`, models the process of information spread from an `agent` or `source` to all its connected `agents`. When the action takes place, all connected agents adopt the opinion from the disseminating source/agent following equation 1. The mathematical representation of the updated opinion for a connected agent i, based on this action, when influenced by a disseminating source/agent j, is:

$$a_i(t+1)^T = a_i(t)^T + \mu_{ij} \times (a_j(t)^T - a_i(t)^T) \qquad (1)$$

Where,

- $a_i(t+1)^T$ is the updated opinion of agent i at time $t+1$ for information topic T.
- $a_i(t)^T$ is the current opinion of agent i at time t.
- μ_{ij} represents the trust level between agent i and the disseminating source/agent j.
- $a_j(t)^T$ is the opinion of the disseminating source/agent j at time t.

Details of Online Demonstration Platform

The demonstration platform bridges a formal PDDL model with an interactive visualization of opinion dynamics.

User Interface and Interactivity: Upon accessing the platform, users encounter a side panel, shown in Figure 1(b), that presents customization options for the network, such as defining the number of agents, sources, and topics. The intuitive interface also integrates a Topic Dependency Matrix, granting users the ability to outline inter-topic relationships and model the opinion dynamics based on topic-dependencies, as described by Anderson and Ye (2019). Additionally, an opinion scale ranging from red (negative opinion) to blue (positive opinion) is provided to aid interpretation, enabling users to gauge node opinions at a glance.

Network Visualization and Back-End Integration: At the heart of the online platform is a vibrant network visualization. Each node and connection is vividly displayed, with node color intensities showcasing opinions on a selected topic. The back-end is responsible for generating network data, running opinion simulation models, devising PDDL plans based on user-set goals, and updating the network's state, ensuring users receive immediate feedback.

Plan Generation and Execution: A standout feature is the flexibility for users to set opinion goals for specific nodes and subsequently generate propagation plans, as shown in Figure 1(c). Utilizing the PDDL model and the current state of the network, we use the MeticFF Planner (Hoffmann 2003) to formulate a sequence of actions to attain the desired opinion outcome. Users can then execute this plan incrementally, witnessing the ripple of information across the network to achieve the specified goal.

Discussion and Conclusion

The choice of integrating AI planning into the domain of opinion dynamics stems from the inherent need for a systematic and strategic approach for information spread. While the traditional models of opinion dynamics capture the essence of how beliefs evolve, AI planning offers a blueprint to influence this evolution in a directed manner. The granularity and adaptability of planning techniques enable targeted interventions, ensuring that specific objectives within a network are met efficiently.

Our novel numeric PDDL model, designed for opinion dynamics, serves as the foundation for this research. This model, in tandem with our interactive online platform, enables users to both visualize and strategically influence opinion shifts. The integration of opinion dynamics and AI planning equips stakeholders with a comprehensive toolkit, deepening their understanding of information trajectories and providing avenues to guide these dynamics. Our findings underscore the potential of integrating opinion dynamics with AI planning, offering a novel perspective on information spread and its strategic manipulation in networked systems.

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