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Reaching consensus in a temporal epistemic network

social networks, temporal networks, opinion dynamics, agent based modeling, social learning

Extended Abstract

1. Introduction

Social learning and social choice theory assume that animals including people learn the rules of the world and the surrounding environment by observation and interaction with members of their community. The abundance of information present in today's world seem to make social learning necessary as well for filtering vast information to establish a consensus and communicate it to the masses. Different methods and approaches have been proposed to explain this phenomena and capture the nature of this complex social process.

It is certain, that the human learning process would not be possible without social relationships allowing communities to exchange views and to learn through social interactions. The analysis of how this process works led to the development of a network epistemology field that studies how people exchange information and make decisions based on the acquired knowledge. Previous research in this area has focused on static networks which do not capture the dynamics of connectivity changes that are present in real social networks. In our work, we proposed a new model closer to the real-world scenario, capturing complex dynamics of social relationships and analyzed the impact of network dynamics on social learning process.

The work covers the concept of the temporal network epistemology model enabling simulation of the social learning process in dynamic networks. In our study, we use the epistemological framework proposed by Zollman [1], which utilizes agent-based modeling approach based on a static network. In this model, agents are faced with a multi-armed bandit problem. They try to solve it by iteratively collecting evidence and updating beliefs based on both this evidence and the knowledge of their neighbors. In our work, we proposed an extension that allows working with temporal networks. As a temporal network model, we used the continuous CogSNet method [2], which is based on event streams and also based on the human brain's cognitive abilities.

2. Data and methods

We run the simulations on both real social temporal networks built by applying the CogSNet model to the NetSense dataset and static synthetic networks. Some of these static topologies have already been studied in previous work on learning in social networks,10 while the others have been included due to their distinctive features. These synthetic networks are intended to serve as a reference for our temporal model.

NetSense is an empirical dataset generated by human interactions [3]. The data were collected among a group of about 180 students using a special application installed on their smartphones that recorded metadata on phone calls and text messages. This research uses data from a NetSense study that contained student interactions (calls and messages) over one semester. We used the following static networks to compare the effect of dynamic graph structure on consensus reaching: complete, cycle, circle, Erdős-Rényi, Watts-Strogatz, Barabási-Albert, real social network.

We performed two different experiments. First one was dedicated to compare results of different settings, including newly developed temporal one, with regard to convergence to correct consensus. Following study was performed to examine the course of the temporal setting in relation to simulations run with for topologies. The simulations in each experiment were run 1000 times and their results averaged to provide reliable data for further analysis.

3. Results and conclusions

The results of the research, conducted on both the temporal social network generated using the CogSNet model and static topologies as a reference, indicate a significant influence of the network temporal dynamics on the outcome and flow of the learning process. It has been shown that not only the dynamics of reaching consensus is different compared to baseline models, but also that previously unobserved phenomena appear, such as uninformed agents or different consensus states for disconnected components. It has also been observed that sometimes only the change of the network structure can contribute to reaching consensus. The introduced approach and the experimental results can be used to better understand the way how human communities collectively solve both complex problems at the scientific level and to inquire into the correctness of less complex but common and equally important beliefs' spreading across entire societies. The proposed approach is also valuable because, due to the proposed design of the social learning process, it allows to consider this social phenomenon from a game theory perspective and fits into the reinforcement learning approach.

References

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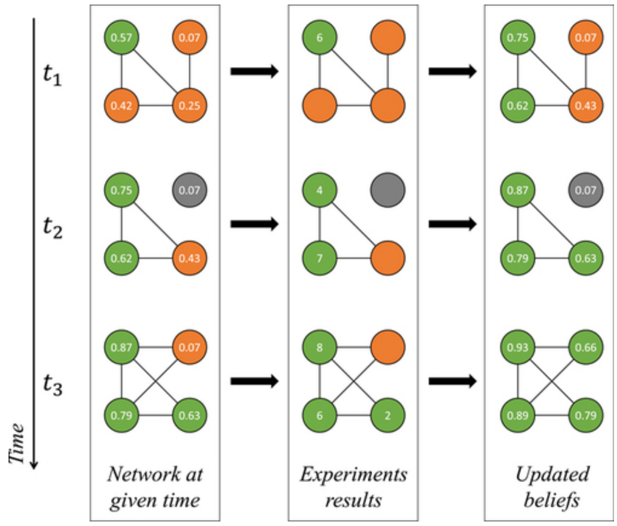

Figure 1: An example of a learning process performed for a temporal network. Rows represent times points at which the network is inspected. Columns depict different phases of the learning process. The values in the circles acting as nodes stand for agents' beliefs, in first column - before an interaction, and in the third column after iteration of social leraning process; for the second column — the number in the centre presents reward returned from environment based on agents' chosen action. Green nodes correspond to agents choosing supreme action over the other presented as orange ones, and gray ones are disabled agents.

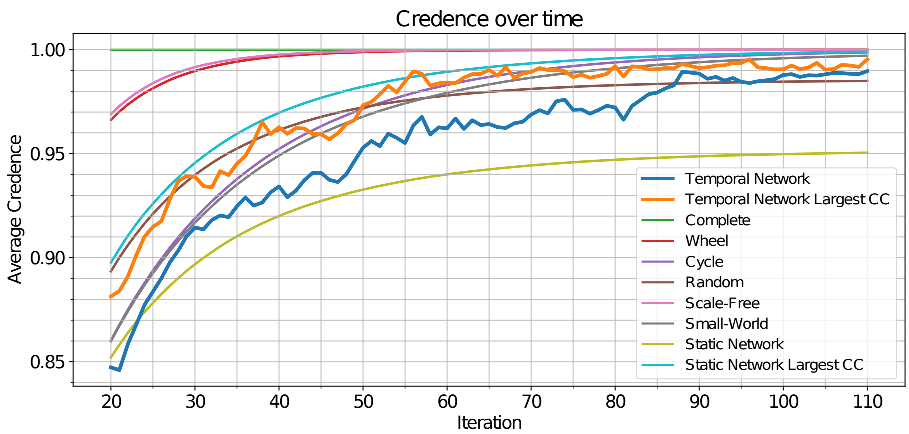

Figure 2: The course of the community learning process for different network settings including real-world temporal network.