Proceedings of the 2019 Winter Simulation Conference
N. Mustafee, K.-H.G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y-J. Son, eds.

SOCIAL JUDGEMENT THEORY: A NETWORK BASED IMPLEMENTATION

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ABSTRACT

Agent-based modelling (ABM) can show how interventions influence a society. Social contagion, a subfield of ABM, focuses on the spread of opinions throughout a social network in which the existence of ties dictates how opinions spread. Complexity can be added to social contagion models by utilizing attributes inherent to the agents, such as tolerance for change or exposure to counter-information. Social Judgement Theory is a persuasion theory that utilizes 'latitudes' to determine how an agent will react to another's opinion. The agents' opinion will either not change, move towards, or move away from other agents' opinions depending on how similar their opinions are. Here we explore how the latitudes of social judgement theory can be utilized in a social contagion model to observe the change of opinions in a system.

1 INTRODUCTION

Social Judgement Theory (SJT) claims that the way an agent reacts to a new opinion on a subject is inherent to the agent and not the new opinion. That is, two agents can respond differently to the same information because of their pre-existing opinions on the subject. This theory observes opinions in a Likert scale in which an opinion on a topic can be extremely negative, extremely positive, or somewhere in between. SJT uses the concept of latitudes to explain how these pre-existing opinions interact with new opinions. A latitude is a range of opinions that either is accepted by, neutral to, or rejected by the individual. These latitudes are centered around the agent's own opinion. Opinions within the latitude of acceptance represent opinions similar the agent's – the perception of similarity prevents the agent from changing its own opinion but are deemed reasonable enough to attract the agent's opinion closer to them. Opinions within the latitude of rejection are deemed extremely different from the agent's opinion and repel the agent's opinion away from them. If an agent's opinion changes, then its latitudes change with it.

Social contagion models are another way to explore how opinions spread between agents. These are network-based models and information spreads through connecting links in the network. A traditional example of a simple contagion model is the SI model – one in which the existence of a link between an infectious agent and a non-infected agent (susceptible) means that the information will spread to the non-infected agent. Complex contagion models build on this by adding rules that limit the spread. An example of a rule would be a tolerance in which an agent will not be infected with new information unless a certain number of neighbors are infectious. We can combine the structure of social contagion models with the rules of SJT. This combination allows us to create a unique complex contagion model with which we can examine the nature of opinion spreading.

In complex contagion there are two different ways an agent can interact with others in the network: community observation and individual interaction. Community observation utilizes information from the agent's neighborhood or ego network. Individual interaction just focuses on a link between an agent and a single adjacent node. We will use both interaction types when we create a social contagion model with the SJT rules.

2 METHOD

Our model utilizes an opinion scale with 11 distinct opinions between -5 and 5. When we initialize the model, we randomly assign each agent with an opinion (balanced graph). Alternatives to this initialization method is assigning the top 20% influencers with an opinion of -5 (negative graph), 0 (neutral graph), or 5 (positive graph) with the other agents randomly assigned the other opinions.

For each agent, the latitude of acceptance will be represented in an edge connected to another agent with an opinion that is ±1 of its own. The latitude of non-commitment will be an edge connected to another agent with an opinion that is ±2 of its own opinion. All other edges will represent the latitude of rejection. After we initialize the model, we can then choose one of two algorithms.

The first algorithm is to choose **n** agents from the network, then select an incident edge. To guarantee that each agent participates in only one interaction, we remove any edge that is connected to an agent that was either chosen in the first group or is connected to a previously selected edge. We then examine each to see which latitude it represents. If the edge represents the latitude of non-commitment, then each agent's opinion moves one opinion closer to each other. If the edge represents the latitude of rejection, then each agent's opinion moves one opinion further away from each other. Nothing happens if the edge represents the latitude of acceptance. We repeat this process **T** times.

The second algorithm is to choose **n** agents from the network and then examine its neighborhood or ego network. We then examine the opinions of each agents' neighborhood and determine which opinion has the maximum occurrence. We then determine the latitude by comparing the agent's own opinion to that of the maximum occurring latitude. This algorithm only affects the selected agent and does not affect the neighboring agents. We repeat the process **T** times.

To compare the different implementations of the model, we examine the proportion of each possible opinion to the total number of agents. We also examine the proportion of each possible latitude with the total number of edges. We also run each model multiple times to account for any variation that might occur from random assignment of opinions on initialization and random selection of agents of each time **t**.

3 CONCLUSION

The two algorithms were conducted on the Adamic "Blogosphere" dataset. An interesting result that appeared in both the individual-ties and ego-based algorithms is that a graph that started at one extreme (either a positive or negative graph) was quickly dominated by the opposite extreme. Also, balanced graphs ended up with an equal amount of extreme agents from both sides with nearly no neutral agents. A major difference between the two algorithms can be seen on their implementations on neutral graphs. In the individual-ties algorithm, the neutral graph ended up with an equal amount of extreme agents on both sides with nearly no neutral agents. However, on the ego-based algorithm, the neutral graph ended up with a majority of neutral agents, with both extremes stabilizing at the same lower level. This seems to suggest that if opinion spreading is a passive activity of observing the neighborhood, then a moderate global majority can be obtained. However, if opinion spreading is an active activity of interacting with others, then a moderate global majority cannot be obtained.

REFERENCES

Sherif, C. W., Sherif M., Nebergall, R. E. "Attitude and attitude change: The social judgement-involvement approach" Greenwood Press, Westport, CT (1981)

Granovetter, M: "Threshold Models of Collective Behavior," in American Journal of Sociology 83 (1978)

Adamic, L. A, Glance, N: "The Political Blogosphere and the 2004 US Election," in Proceedings of the WWW-2005 Workshop on the Weblogging Ecosystem chaired by J. Adibi, M. Grobelnik, D. Mladenic, P. Pantel. Chicago, Illinois: LinkKDD.

Lerman, K, Yan, X, Wu, X-Z "The Majority Illusion," in Social Networks PloS ONE 11 (2016)

Watts, D "A Simple Model of Global Cascades on Random Networks," In Proceedings of the National Academy of Sciences of the United States of America (99), 5766-5771 (2002), edited by M. Gell-Mann. Santa Fe, New Mexico: Santa Fe Institute.

Baronchelli, A, Gong, T, Puglisi, A, Loreto, V: "Modeling the Emergence of Universality in Color Naming Patterns" in Proceedings of the National Academy of Sciences of the United States of America (6), 2403-2407 (2010), edited by G. Parisi. Rome, Italy: University of Rome