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Social Networks and Social Contagion

Optimized Influence Targeting for Adoption in Social Networks

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Abstract

We present work that uses agent-based modeling to represent both intra- and inter-personal interactions to evaluate strategies for message targeting aimed at optimizing technology adoption within a social network. Our work demonstrates the advantage afforded by considering both network (structural) and agent (cognitive) properties of participants in the network when creating and targeting messages for propagation within a network to influence adoption behavior. Using previous empirical work in technology adoption, we discuss an approach that demonstrates the interaction effects of structural and cognitive measurements when used for targeted messaging.

Background

Although decision processes are often described at the individual level of cognition (*e.g.* Tversky and Kahnemann (1981)), they are subject to social and cultural influences at both the interpersonal and societal levels. The adoption of new technology depends on various factors, such as the type of technology, the context or culture in which the technology is introduced, and the individual decisions by people within that culture, as most individuals evaluate an innovation from the subjective evaluations of peers who have adopted an innovation (see Watts and Dodds (2007) for a discussion of network-diffused influence). These influences propagate through the social network as a function of agent interactions. Diffusion, in this sense, is a special type of communication concerned with the spread of messages that are perceived as new ideas. Diffusion of Innovations theory (Rogers 1995), in which an innovation is an idea or technology perceived as new by the individual, proposes that diffusion creates a distinct pattern of innovation adoption. Our work provides an evaluation of the optimization of technology adoption by an exogenous entity, through the targeting of nodes for influence. These targeted nodes may by chosen by determining their structural qualities, as determined by their social network (*i.e.* as measured by node centrality metrics) as well as cognitive properties of the nodes (representing individuals) to evaluate the optimization of the diffusion of adoption behavior in a social network.

Cognitive Network Model

From a cognitive perspective, an individual's adoption of technology requires the integration of multiple attitudes (*e.g.* attitudes regarding expectations of performance of the technology or the effort needed to use the technology). These beliefs are modulated through social interaction. The model we use to represent decision-making for adoption captures both beliefs and how beliefs change as a result of interactions. These beliefs are represented within each agent as propositions that are vertices within a network. Network edges represent relationships between beliefs. As with other network-oriented perspectives of cognition (*e.g.* (Carley 1989)), beliefs are represented as a pairing of cognitive concepts. The resulting *belief network* created for each agent is a framework for studying the social transmission and subsequent use of knowledge resulting from agents' processing of information.

The particular beliefs instantiated within the model are based on a combination of results from empirical studies of technology adoption by Venkatesh et al. (2003). The UTAUT model combines eight of the most prominent technology-acceptance models observed in the literature and provides a definitive list of variables that are critically relevant to an individual's Behavioral Intention (BI) and Use Behavior (UB) for adopting a new technology, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Voluntariness of Use (VoU).

The Socio-Cognitive Network Model

To represent the diffusion of influence, we utilize a socio-cognitive network model that allows for the representation of social influences that interact with agents to affect the agent's beliefs. In this network model, vertices are individual agents, and network edges are the cognitive ties (commonly shared beliefs), communication links, and social relationships between them (see Easley and Klienberg (2010) for an introduction to graph theory and its relationship to social networks). Within the current context, cognitive ties generally refer to the extent of agreement between the individual beliefs of multiple agents. The strength of the cognitive ties (degree of agreement between agents' beliefs) affect the degree to which agents influence-and are influenced by-one another's beliefs during social interactions. The details regarding specific cognitive mechanisms and social factors utilized in the socio-cognitive network model are described further in (Briscoe, Trewhitt, and Hutto 2011).

Analysis and Conclusion

Our aim is to understand how to minimize costs associated with exogenous inputs (*e.g.* marketing) to maximize adoption diffusion within a networked population. To evaluate the advantage afforded by utilizing both structural and cognitive characteristics, we create an agent-based model (see Bonabeau (2002) for a description of agent models) implemented in the Repast framework (North et al. 2007). We simulate the social interaction for an agent population over a discrete time period (600 timesteps), where communication networks are created using a 'small world' approach (Watts and Strogatz 1998).

By comparing overall adoption rates (dependent variable) across our simulated population (200 agents), we determine that the rate from targeting nodes based purely on structural properties (as done, for example, by Kiss and Bichler (2008)) is significantly less than the rate obtained when targeting using the combined heuristic. Our analysis uses node *degree* as the unit structural property (see Borgatti (2005) for determining appropriate centrality measures for attitude propagation) and the similarity of beliefs between a node and its neighbors as the cognitive property. Figure 1 shows the results of a simple experiment aimed at demonstrating the improvement. In this experiment, nodes were ranked by their centrality (structural), then by their belief overlap with their neighbors (cognitive). Highest ranked nodes were selected by centrality in the centrality-alone case and by centrality and belief overlap in the combined case. A t-test shows the statistical significance of the difference: ($p < 0.006$).

Our results show that utilizing even coarse approximations of the cognitive properties of nodes, such as belief overlap (which we propose as related to *cognitive centrality* - a measurable concept that represents an agent's belief overlap with those in his communication network - see Kameda, Ohtsubo, and Takezawa (1997) for more detail) can change

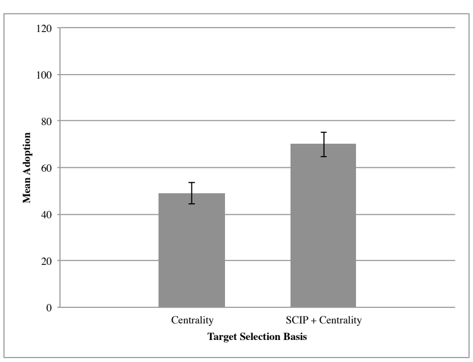

Figure 1: Mean adoption for centrality alone heuristic (left) and combined cognitive/centrality heuristic (right) over 20 simulations. Error bars show the standard error of the mean.

optimal diffusion strategies. Our immediate objectives involve proving that under novel interaction models, influence diffusion is approximately optimal (Kempe, Klienberg, and Tardos 2003). Our future work investigates determining these cognitive properties of nodes from open sources (*e.g.* Twitter) and using it along with structural information found in social networks to provide better prediction of information dissemination in social media.

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