Effects of exogenous input on adoption rates in social networks

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Abstract. Modeling information diffusion is an often investigated area in social network science. Optimizing propagation through targeting interactions is an intriguing subfocus within this area, where the goal is to identify agents in the network best capable of diffusing information. Our work addresses a pragmatic context where identifying these agents is particularly useful: technology adoption. In this work, we model agent cognitive and social qualities as they are relevant to information communication. We show that a formulation of the social network using cognitively-rich nodes allows for the identification of agents to whom targeting for exogenous input provides for more optimal adoption rates. We then present how the representation falls under the theoretical guarantees of performance, as forwarded by Kempe et al. [12].

1 Introduction

The characterization of social relationships has been attracting interest from researchers in the social and behavioral sciences since Georg Simmel's sociology work in the twentieth century [17]. Today, social network analysis is exploring these characteristics in greater depth using computational models that simulate social interactions among people who are modeled as cognizant agents with complex relationship patterns. While the ability to characterize the *nodal variables* of a social network – those variables that describe the regularities and patterns in relationships between people [21] – is critical, the application of contemporary psychological research to make the agents cognitively realistic allows for a much more rich and realistic understanding.

Social network analytics benefit from relying on the framework of graph theory as a computationally and mathematically convenient means to represent people and their relationships. If we consider the actors (*e.g.* people or organizations) as nodes in a graph, edges are one or more specific types of interdependent connections, such as friendship, kinship, common interest, financial exchange, communications or information transfer. In addition to this convenient representation, the network perspective is more than just a methodological approach, a convenient vocabulary, or intuitive metaphor for discussing social and behavioral relationships. The network perspective presents a theoretical alternative to the assumption of independent social actors: an assumption that is prevalent in much of previous sociological and psychological research. The network perspective offers a common framework for testing theories about structured social relationships and provides a means to precisely characterize important social concepts with explicit formal definitions.

The diffusion of innovations (*i.e.* the spread of information, ideas, attitudes, behaviors, etc., see [16]) within social networks is a phenomenon that has also been given a great deal of attention from a wide variety of fields: economics [10], management [1], marketing [22], and computer science [3]. Usually, however these studies assume relatively simple node characteristics, concentrating more heavily on the relationships between nodes [13], though the effect of node similarity (*i.e.* homophily [14]) has led some to create richer nodal representations (see [18] for a characterization of nodal complexity representation).

We therefore situate the current research within a perspective that considers how nodes of the network interact contributes to dynamic aggregate behavior; however, we also advocate a computational network model that more richly represents the multifaceted nature of humans and their relationships. One of the contributions of this work is to demonstrate just such a computational model that accounts for both the cognitive complexity of individuals who make decisions based on their beliefs (represented as distinct attributes for each of our network nodes) as well as the social complexities that exists when those beliefs moderate the nature of the relationships to other individuals (represented as adjustments to the properties of the edges between our network nodes). Thus, our work here extends the representative power of a social network to a 'socio-cognitive network', in which cognitive properties of nodes are represented to capture beliefs related to the information that is to be diffused via social interactions. A second contribution of this work is to demonstrate how varying the node and edge attributes within this network model allows us to examine how specific network nodes may be targeted by an exogenous entity for optimal network-wide influence (*e.g.* a diffused decision or behavior). These targeted nodes may be chosen based on structural qualities as determined by their social network (*i.e.* using centrality metrics), or by considering the cognitive properties of the nodes (or both) in order to evaluate the optimization of diffused behavior in a social network.

By representing our interacting agents within a socio-cognitive network, we use cognitive models of interaction to understand how beliefs and subsequent behavioral influences spread through the social network. Specifically, in this work, we are interested problems of optimality posed by Domingos and Richardson [4] as well as Kempe et al. [12], who have shown that under certain conditions, marginal gain may be used to identify nodes that, when influenced, can optimize influence diffusion. By incorporating a cognitive model of interaction, we hope to enhance the current level of realism captured in the typical social network model and allow for the relaxation of constraints involved in independent cascade propagation models. By relaxing the constraints on independent cascade, we introduce additional complexity into the interaction model while preserving the analytic result shown in [12].

2 Cognitive Network Model

Our agent model is based on the Beliefs, Intentions, and Desires (BDI) model used in many multi-agent models. In the case of technology adoption, we consider agent beliefs as the dominant feature in making adoption decisions, based on empirical work measuring the major qualities involved in making technology adoption decisions. Previous results show individuals use a set of propositional qualities of technology in adoption decisions (*e.g.* attitudes regarding expectations of performance of the technology or the effort needed to use the technology). Empirical evidence supports a finite set of propositions involved with technology adoption decision making; the particular beliefs instantiated within the model presented herein are based on the work by Venkatesh et al. [20].

We represent the beliefs of agents in the social network as a collection of propositions Π, whose parameterization and interactions characterize human information processing resulting from the social diffusion of information (similar to Carley's notion of *constructuralism* [2]). To ground the demonstration in a relevant domain, the proposition set used in the computational model that is described in this paper contains all of the propositional qualities used in a decision-making task related to technology adoption. Also, for the sake of bounding scope, all agents in the network possess the same proposition set (described below). Propositions π are represented as one-dimensional fuzzy values indicating the strength an individuals belief in the proposition. The set of propositions Π represents the complete beliefs of the agent: $\pi \in \Pi$ where $\pi \in \{0 \ldots 1\}$. This quantitative characterization of the strength of the belief overlaps quite well with existing characterizations of beliefs represented as propositions with a subjective probability of being correct [6; 9; 7; 19].

We assume a linear relationship between the propositions to yield the decision function for technology adoption. The adoption decision value for an agent at time t ($\delta_{a,t}$) is then based on the weighted sum of veracity for propositional beliefs:

$$\delta_{p,t} = \begin{cases} \sum_{p \in \Pi} w_p \pi_{p,1} > \alpha & 1 \\ \text{otherwise} & 0 \end{cases} \tag{1}$$

where α is the decision threshold and is the same for all agents. See figure 1 for a depiction of the belief characterization. The social interactions between individual agents within the network will affect the belief parameters veracity (π_1). If beliefs are between two agents are similar, only small updates will occur; if beliefs are

While BDI-based models are popular in network research, still other models closely parallel the discrete definition of belief modification based on agent interaction. Social Judgment Theory (SJT) models how agent beliefs change as a result of interacting with other agents with differing beliefs [11]. Our agent model is comparable to SJT, where we have replaced discrete ranges of belief acceptance and denial with continuous functions. In our model, a single value measures the belief similarity between agents, and that measure weights the amount of change from interaction.

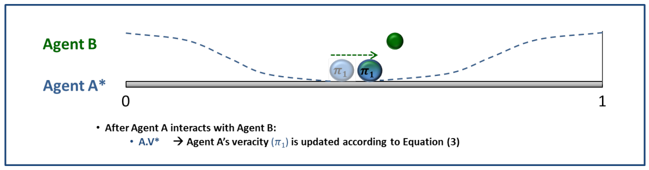

Fig. 1. Notional illustration of belief characterizations, with depiction of change in veracity for a proposition (π) during agent interactions. The dashed line indicates the relative "difficulty" to change veracity as it reaches the extrema points.

2.1 The socio-cognitive network model

To represent the diffusion of adoption we utilize a socio-cognitive network model that allows for the representation neighbors that interact with agent to affect the agent's beliefs. In this network model, any pair of neighboring nodes in the network interact within their friendship network.

Edges are the cognitive ties (commonly shared beliefs), communication links, and social relationships between the nodes. 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 agent beliefs) affect the degree to which agents influence and are influenced by one another's beliefs during social interactions. We use this tie-strength concept to regulate influence propagation in the network model according to Equations 2 and 3 which we discuss next.

The social cognitive influence potential (SCIP) represents the degree to which one agent can successfully influence another agent (i.e. get them to change their propositional belief state). For our demonstration model, SCIP is based on the concept of cognitive homophily [14], and is a computed value representing the similarity of beliefs between two agents a and b:

$$S_{a,b} = \sum_{p=1}^{\Pi} w_p (\pi_{pa} - \pi_{pb})^2 \tag{2}$$

The SCIP is then the weighted sum of the differences squared. Where the weight is uniformly distributed over propositions, SCIP is the mean squared difference in propositional beliefs. See Figure 2 for a graphical depiction of our simulation network with the strength of ties indicated by color.

Interaction with others agents in the social network changes an agent's propositional belief state; thus, veracity (π) for each proposition is updated. Agent a beliefs are updated as a result of interaction with agent b if their beliefs differ sufficiently:

$$\pi_{p,a} = \begin{cases} S_{a,b} > 1/3 & \phi[1 + \exp(\pi_{p,b} - 2\pi_{p,a})]^{-1} \\ \text{otherwise} & \pi_{p,a} \end{cases} \tag{3}$$

where ϕ is a scalar constant: $\phi = 1.03$. This update function is derived from empirical studies conducted by the authors in separate, but related research efforts not reported here. The update bounds $\pi_{p,a}$ in the range: $\{0..1\}$. Further, as $\pi_{p,a}$ reaches the extrema of the function, it becomes increasing difficult to change the value of $\pi_{p,a}$.

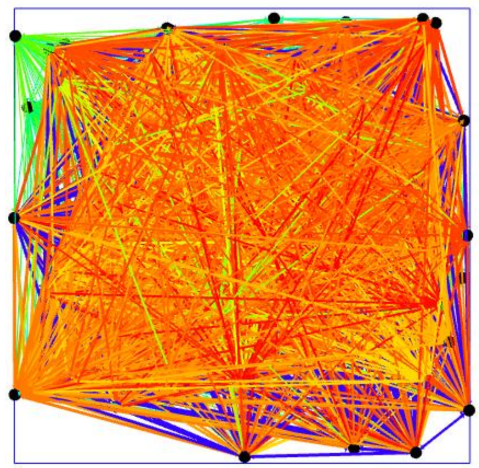

Fig. 2. Social network depicting weighted social ties (SCIP values) in Repast. Nodes represent agents in the social network (100). The fully connected network shown here depicts the cognitive similarity between nodes. Edge color shows the strength of similarity: red=1, blue=0.

3 Adoption diffusion in socio-cognitive network

Given the socio-cognitive network, we can now ask questions of adoption diffusion over time. Using the Repast framework for agent-based modeling [15], we conducted several simulation experiments aimed at testing our predictions of adoption diffusion using different marketing selection heuristics. Within Repast, we initialize a set of agents, each maintaining a set of propositional beliefs derived from Venkatesh et al. [20] and simulate agent interactions over time. The Unified Theory of Acceptance UTAUT holds that there are four key constructs that are direct determinants of usage intention and behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions (see table 1). We measure the total number of adoptions after a discrete time period. The optimality questions first posed by Domingos and Richardson [4] are the same questions we want to ask in this context, namely can we identify a set of nodes whose adoption maximizes the adoption diffusion in the social network?

Proposition	Interpretation
Performance expectancy (PE)	The degree to which an individual believes that using the system will help them attain gains in job performance.
Effort expectancy (EE)	The degree of ease associated with the use of the system.
Social influence (SI)	The degree to which an individual perceives that important others believe they should use the new system.
Facilitating conditions (FC)	The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system.

Table 1. UTAUT model key constructs [20].

To show that targeting nodes on the basis of both cognitive and structural properties results in an increase in adoption over targeting nodes based on random selection, we simulation with one hundred agents over six hundred timesteps. Each agent is situated within a static 'friendship network' which determines which nodes each communicates with at every time step. This network was created as a small-world [23], with a link count of 10 and a rewiring probability of 0.1. During the simulation, a selection of nodes are exogenously 'marketed to' or targeted, based on three selection criteria: random, degree centrality, or through a combination of a nodes' mean SCIP and centrality. The mean SCIP is the sample mean of a node's SCIP values with all of its neighbors.

4 Analysis

By comparing overall adoption rates (dependent variable) across our simulated population (100 agents) in the Repast model, we are able to compare the relative adoption performance (number of adoptions per simulation) of centrality based selection heuristics [1] with random selection (see Figure 3). In addition, we also compare adoption performance between centrality based heuristics and a combination of cognitive and centrality based heuristics.

We also compare centrality heuristics to heuristics based on a combination of centrality and cognitive properties of the units. In the latter case, the selection criteria ranked units by their centrality, then by their mean SCIP value. The mean SCIP value indicates the degree to which a unit may influence its neighbor units. Units with highest centrality and mean SCIP were selected. Figure 4 shows the comparative mean adoption performance between centrality heuristics and the combined centrality and cognitive selection heuristic for 30 simulations. In this case, the mean adoptions resulting from the combined heuristic is higher than the mean adoptions using the centrality heuristic. A t-test between the two sets of measures shows statistical significance for their difference: $p < 0.0002$.

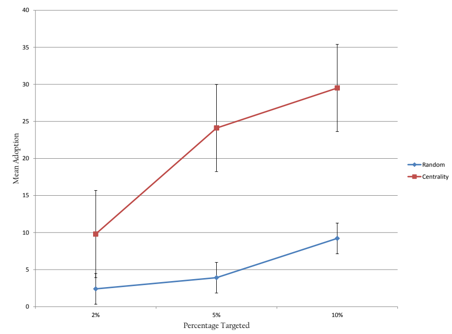

Fig. 3. Mean adoption for random (blue) and centrality (red) heuristics as a function of selection size. Error bars show the standard error of the mean.

5 Submodularity of the socio-cognitive network

Kempe et al. [12] show that for two models of interaction the problem of selecting nodes for optimal influence spread is NP complete, but it is possible to guarantee approximately optimal (*i.e.* within a constant) influence spread. This bound is based on a previous result showing that a hill climbing strategy can be used for optimization with submodular functions [4]. Briefly, a submodular function is a set function that has a diminishing returns property. In the context of influence diffusion, in finding the subset of nodes A that have been influenced, for every $A \subseteq \Omega$ and $a_1, a_2 \in \Omega \backslash A$ then $f(A \cup \{a_1\}) + f(A \cup \{a_2\}) \geq f(A \cup \{a_1, a_2\}) \geq f(A \cup \{a_1, a_2\}) + f(A)$. One interpretation of this is that the marginal gain from adding a node to a set A is at least as large as the marginal gain from adding the node to a superset of A.

The Kempe et al. [12] proof strategy is to show that both interaction models represent submodular functions: independent cascade and linear threshold. Under the *progressive* independent cascade interaction model, only agents who have adopted can attempt to influence agents who haven't adopted, and agents once adopted do not change. They may only attempt to influence another agent once. The progressive case fits our adoption model, where we are interested in agents' decisions to adopt a technology rather than a duration of adoption. Progressive independent cascade interaction is represented as a graph: nodes represent agents, and edges represent possible interactions. A weight on each edge represents the probability that the interaction will result in the receiver node's adoption. The proof unrolls the interactions by showing that the edge weights once generated are checked if they are active by sampling a random uniform distribution. These samples can be generated at once, not requiring a simulation loop. The active node set consists of the nodes having active edge paths to the sender node set: those nodes initially selected as active (see Figure 5). The active node set (*i.e.* the set of adopted nodes) has the property needed for

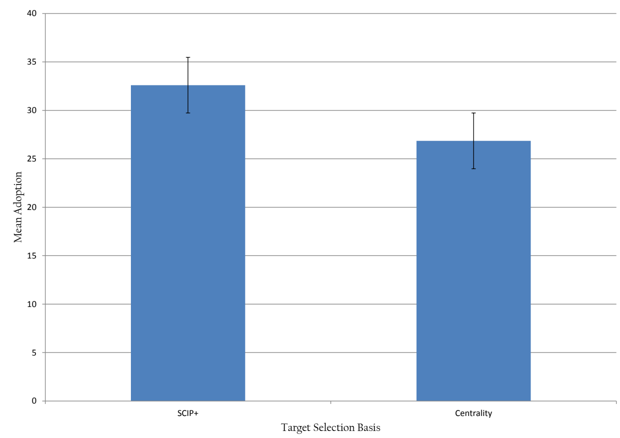

Fig. 4. Mean adoption for combined cognitive/centrality heuristic (left) and centrality alone heuristic (right). Error bars show the standard error of the mean.

submodularity; the probability function of the expected cardinality of the active node set is a submodular function (see [12]).

We want to show our model of interaction is also submodular, and therefore has the same approximately optimal guarantees. We decompose this into two problems. First, we show that the independent cascade model with more than one interaction between agents is also submodular. Using this result, we show that interactions involving our cognitive model are also submodular.

Lemma 1. *Independent cascade where any agent may influence another with finite k interactions is a submodular function of interaction.*

Proof. In this model of interaction, a sender node has k attempts to influence a receiver node. Using the same approach as [12] we represent the interaction graph where nodes represent agents, and there are k edges between nodes, representing the k possible interactions between two agents. Where adopted or unadopted nodes can influence other nodes and the interaction probability is the same for all edges (p_e), we can model the likelihood of interaction between pairs of nodes, each with k interactions and j successful interactions ($j = 1$) as a set of Bernoulli trials where:

$$1 - [p_e^j(1 - p_e)^{(k-j)}] \tag{4}$$

represents the probability that two nodes will communicate in k attempts ($1 - (1 - p_e)^k$ where $p = 0.5$). We can reduce the k edges between nodes to a singular edge whose weight represents the probability that at least one communication attempt is successful. We sample a random uniform distribution to test each edge

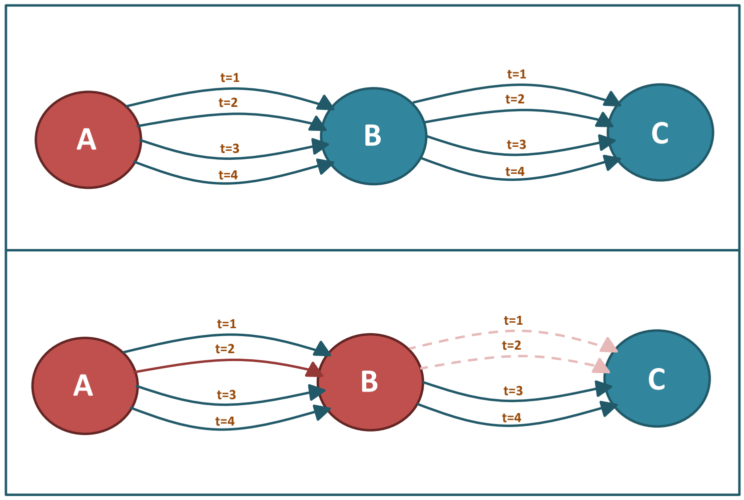

Fig. 5. Interaction example. Active node A interacts k times with inactive node B (top, active nodes colored red, inactive nodes colored blue). When an interaction is successful at $t = 2$ (noted red), node B becomes active, and any interactions B has with C with indexes less than or equal to the minimum successful interactions B receives are not active (noted dashed) (bottom).

as active. The active edge set contains all edges passing the test. Active paths are paths in the graph connecting nodes through active edges. Here, we have the same conditions of the active node set for submodularity as shown in [12].

This proof is not sufficient for the case where sender nodes must adopt before they attempt to convert a receiver node, because sender nodes must adopt before they attempt to convert another node.

Theorem 1. *Independent cascade with finite k interactions between agents is a submodular function of interaction.*

Proof. Again, a node has k attempts to influence a receiver node, and again we represent the interaction graph where nodes represent agents, and there are k edges between nodes, representing the k possible interactions between two agents. We index each edge by its sender and receiver nodes and an index $1..k$ and assign a weight to each edge. Each edge weight again represents the probability that an interaction occurs between sender and receiver nodes. We sample a random uniform distribution to test each edge as active. The active edge set contains all edges passing the test. Active paths are paths in the graph connecting active nodes through active edges, with the added constraint that active edges into an active node have indexes less than indexes from nodes. Here, we have the same conditions of the active node set for submodularity as shown in [12].

We can now show that our interaction model is submodular.

Theorem 2. *Finite interaction, independent cascade with random interaction success is submodular.*

Proof. In our communication model, at each timestep, each node evaluates whether it communicates with its neighbors in the network (one of the k edges between two nodes). Initially, agents are randomly assigned belief values uniformly. Given the active edge graph generated as in theorem 1, we assign updated beliefs to each active node as a result of agent interaction (inactive edges do not affect agent beliefs). Once belief updates are complete, adoption is computed over the active nodes. The adopting active nodes is the set of active nodes passing the adoption test and satisfying the temporal constraints of adoption. Adopting active nodes are nodes that have adopted as a result of interaction with nodes that previously adopted and that have an active path. Again, this can be computed without the need of simulation runs, in one step. The adopted node set is a subset of the active node set.

6 Discussion

We have constructed a novel socio-cognitive network aimed at testing predictions of adoption diffusion in social networks. We have shown empirical evidence of the cognitive aspects of agents impacting adoption diffusion within the social networks. We have also extended theoretical results to include more robust models of interaction. These theoretical results suggest that near optimal selection criteria in these networks exist. Our hypothesis is that the optimal selection criteria should account for the cognitive aspects of agents situated in social networks to improve adoption diffusion..

The results of our empirical experiments tie in well with results shown in earlier work tracing influence [12]. First, random selection heuristics serve as a functional baseline for performance. Centrality based heuristics perform better than random, but are not optimal given influence arising from cognitive factors. In our empirical experiments, a representation of the cognitive state of agents plays a role, and our results show that even with a modest cognitive representation, adoption diffusion is affected by cognitive states of connected agents. In the context of marketing strategies, we can begin to characterize the types of cognitive agents for the purposes of marketing. The combination an agent's cognitive state and their network centrality makes a significant difference in adoption rates.

7 Future Work and Conclusion

Our results both support and extend the work by Kempe et al. [12]. In accordance with the authors, we find a theoretical result where adoption has a lower bound of optimal diffusion, which also holds under the socio-cognitive representation that we discuss. Secondly, we show that targeting nodes based on socio-cognitive qualities is a potentially optimal strategy for choosing nodes to be exposed to exogenous input as compared to selection based on purely structural qualities.

An important quality of our selection criteria that we plan to investigate is the relative stability of influence spread. A method that is able to achieve near-optimal diffusion performance with a high degree of confidence could provide a better outcome. Characterizing the potential trade-off between optimal and stable results represents an important contribution to studying influence spread in social networks. A more pragmatic direction for future work ties the work to marketing strategies. In future studies, we will investigate how to minimize costs associated with exogenous inputs (*e.g.* marketing) to maximize adoption diffusion within a networked population. We also are investigating how behavioral traces derived from open sources (*i.e.* social media) may be utilized as indicators of the tie strength between nodes [8].

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