Information and Attitude Diffusion in Networks

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Abstract. The availability of diverse information does not guarantee that a person's views will be equally diverse. Research has consistently shown that attitudinal positions on an issue will lead to selective reception and dissemination of information, which in turn have reciprocal effects on those attitudes. The current paper aims at understanding how the diffusion of information and attitudes in networks are dynamically related to each other from a computational perspective. Simulations from an agent-based model show that selective exposure of information and social reinforcement in active dissemination of information can lead to polarization of attitudes in the network. Network structures are shown to have significant effects on information and attitude diffusion. While simple contagion models of information diffusion predicts that hub nodes in a small-world network can facilitate propagation of information, our model shows that hub nodes can induce stronger polarization of attitudes when information and attitude diffusion can mutually influence each other. Results highlight the importance of incorporating social science research in network models to better establish the micro-to-macro links.

Keywords: Attitude diffusion, selective exposure of information, active dissemination of information, information cascades.

1 Introduction

Research on information diffusion shows that a small number of bridge links in a network can lead to wide spread propagation of information [4, 12]. However, to predict the spread of more complex social behavior, such as political, religious, or cultural movements, it is important to understand how information may impact attitudes of individuals, such that one can predict how their behavior will be changed by the information. There is, however, still a lack of research on how information diffusion is related to attitude diffusion, and how their relations are impacted by different network structures. Indeed, observations of most groups seem to suggest that there is almost always some diversity of opinion even after extensive exchanges of information, and our world remains incredibly divided even on basic factual issues[9].

2 Background

Research on information diffusion show that propagation of information can be surprisingly efficient in networks that have few bridging or weak links [4]).

S.J. Yang, A.M. Greenberg, and M. Endsley (Eds.): SBP 2012, LNCS 7227, pp. 205–213, 2012.

Assuming that information from one node can trigger activation (propagation of information) of its neighboring nodes, these weak links act as shortcuts in the network such that information can quickly spread through the network in ways that are similar to the spreading of diseases. However, while a single exposure is enough to propagate information (e.g., a piece of news) from one node to another as assumed in these epidemiological models of information diffusion, the spread of the impact of the information, such as changes in attitudes or beliefs, goes beyond a single exposure to the information and does not occur *tabula rasa.* Decades of research in social psychology have revealed a large number of factors (e.g., informative vs normative influence, compliance, power, involvement, ego and identity expression [10], etc) that impact attitude formation and change. As a first step, the current goal is to abstract away these important details to investigate the effects of structural relations between information and attitude diffusion. Specifically, we will focus on the interactions among the processes of the: (1) impact of information on individual attitude change [8], (2) selective exposure to information [5], and (3) active dissemination of information [1]. The current goal is to quantify these relations and computationally examine how they impact information and attitude diffusion in different networks.

2.1 Individual Attitude Change

Attitude can be defined generally as an evaluation of an object that ranges from people, groups, and ideas. Changes in attitude towards an object may spread through a network. While propagations of information between pairs of individuals are assumed to be independent in simple contagion models, attitude diffusion has local dependencies - that is, the state of a single node depends critically on the states of the node's neighbors. This is consistent with the large number of studies in social psychology that show that evaluation of information is subject to social influence (e.g., [1]) such that the more people who oppose one's position (relative to those who share it), the more likely one will change their attitudes. The impact of consensus information on attitudes implies that the level of heterogeneity of the network in terms of different number of neighbors and diversity of attitudes – is important for attitude change. In the current model, we assume that as an agent receives a piece of information that argues for or against an idea i, the attitude towards the idea A_i will be changed according to a threshold model [4]:

$$A_i = \frac{A_m}{1 + exp[-c(S_i - \tau_A)]} \tag{1}$$

A_m is the maximum attitude value, S_i represents the strength of social influence, c is a slope parameter, and τ_A is a threshold parameter. The sigmoid function is traditionally used in threshold model. We set $S_i = P_i/(P_i + N_i)$, in which P_i and N_i are the frequencies of information supporting and opposing idea i respectively. S_i represents the amount of information the agent receives that may change her attitude, and it is expressed as a fraction of relative information that supports the attitude. The frequencies are calculated by summing up the information sent by its neighbors (local persuasion) as well as information broadcasted throughout the network (global information, e.g., from a mass media such as TV). In the current model, local persuasion will always be received (e.g., conversation with a friend), but global information may or may not be received (see the next subsection on selective exposure of information).

It is important to note that, unlike simple contagion models (e.g., [8]), we assume that attitude change is mediated by information exchanges. This is important because we will model how likely people with different attitudes may decide to spread information in the network, and we assume that even when two neighbors are connected, their attitude changes depend on how frequently they exchange information. We justify this assumption by considering the fact that people connect for many reasons (sharing an office, cooperating on a task, etc) but unless they start to talk and exchange information about an issue, their attitudes may not influence each other.

Similar to previous threshold models, τ can be interpreted as the resistance to persuasion, and c can be interpreted as the sensitivity to impact of new information on attitudinal positions. Due to space limitation, we will not show their effects in this paper and will fix the values at c=1 and τ=0.1 throughout the simulations.

2.2 Selective Exposure of Information

The availability of diverse information does not guarantee that opinions will be equally diverse. For example, individuals strongly committed to certain religions often avoid contact with information or people that can tempt them away from their doctrine. Research shows that, unless people are guided by rather rare accuracy motives, they actively choose information that confirms their prior attitudes. This congeniality bias is found to be robust across a diverse range of situations [5]. One general explanation for this bias is based on the need to defend ego-relevant beliefs and reduce the discomfort of disconfirmation. In fact, research has consistently shown that the greater the ego threat (e.g., the stronger the attitude one has), the stronger the motivation to defend prior attitudes by shunning inconsistent information [5]. In the model, we assume that attitude and the propensity to select information has a reciprocal relationship. Specifically, the log odds O_i of selecting a supporting information to idea i is represented as

$$O_i = k * log(\frac{A_i}{A_m - A_i}) \tag{2}$$

In eqn 2, k stands for the strength of the congeniality bias - the larger the value of k, the more likely the agent will select information that is consistent with their attitude. For example, people who have high involvement in a particular idea (e.g., religion) tend to have stronger ego threat when exposed to opposing views, and thus have a stronger tendency to avoid (or not pay attention to) inconsistent information.

2.3 Active Dissemination of Information

Forming an attitude also alters the course of information dissemination. In the beginning, people who strengthen their attitudes may be mere receptors and seekers of information, but as their attitudes are integrated with their identity, many adopt an activist role. Strengthening confidence in an initial attitude can over time trigger feelings of invincibility, which result in communicating one's attitudes to others and actively debating individuals with opposite points of view. For example, many argue that people who seek to express their views on social media are often those who want to argue with others and to influence people to agree with their views[9].

We assume that the change from a passive to active role depends on the strength of the attitude. However, maintaining an activist's role in disseminating information is subject to social reinforcement i.e., when an agent perceives that the information is received by others, the act of dissemination is reinforced. This reinforcement accumulates as more people show positive reception to the information [6]. Specifically, we assume that there is an attitude threshold λ for information dissemination, and unless the magnitude of the agents attitude is above λ, the agent will not disseminate information. Once the threshold is reached, the probability P_D that an agent will disseminate information again after n attempts is determined by its utility $U_D(n+1)$, which are calculated by

$$U_D(n+1) = U_D(n) + \alpha * [R(n) - U_D(n)] \tag{3}$$

$$P_D = \frac{1}{1 + exp(\beta - U_D)} \tag{4}$$

In the above equations, *R(n)* is the social reinforcement received, which is operationalized here as the number of times the information is received [6], and β represents the utility of not disseminating information, and is set to 1. For the current purpose, it is assumed that the agent knows how many of the agents received the information (e.g., the number of times a video is watched on YouTube). We set λ=0.1 and α=0.5. Due to space limitation we cannot demonstrate the effects of these parameters, but these values are chosen to demonstrate the typical effect of active dissemination of information on information and attitude diffusion (i.e., they are in a range that does not radically change the behavior of the model).

3 The Model Simulation

We aim at simulating how information and attitude diffuse in networks to explore how network structures moderate the impact of information that supports or opposes a particular idea on the distribution of attitudinal positions among the agents. Agents are characterized by a continuous function of attitudinal positions with mechanisms of attitude change, selective information exposure, and information dissemination as discussed above. We assume that the processes of selective information exposure and dissemination are functions of the strength of agents attitudinal positions, and thus can explain how information and attitude diffusion interacts in different networks.

3.1 The Network

We created networks with 1000 agents (N), with each agent initially having n neighbors (n=5, 10, and 20). Following Watts and Strogatz [11], we use a perturbation algorithm to study the effects of changing connections on information and attitude diffusion. For each agent, with probability p, one of its neighbors is removed and a randomly selected agent is added as its neighbor. As p increases from 0 to 1, the network transition from a regular to a small-world to a random network. We then use a uniform random distribution [-1, 1] to assign prior attitude strength to each agent ($A_m = 1$).

3.2 Spread of Information and Attitude

Global information is broadcasted to all agents in each simulation cycle, and the information is randomly chosen to be supporting or opposing the idea. However, the probability that each agent will pay attention to (i.e., receive) the global information is determined by eqn 2. At the end of each cycle, attitude strength is updated according to eqn 1. When the magnitude of the attitude strength exceeds the dissemination threshold λ, the agent will attempt to disseminate the last received information to its neighbors in the next cycle. Spread of information will be measured by the percentage of agents who received the information over 10,000 simulation cycles (all networks stabilized at that point).

We measure attitude distribution by calculating the relative mean difference in the attitude strengths $|A_i - A_j|$ between any two agents i and j at the end of the simulation cycles. This is mathematically equivalent to the *Gini coefficient G*. A higher G value indicates that the network has more polarized attitudes. For N agents, G can be calculated as:

$$G = \frac{\sum_i^N \sum_j^N |A_i - A_j|}{2N \sum_i^N A_i} \tag{5}$$

4 Results

The top panel of figure 1 shows the Gini coefficients (G) in networks with different values of k (which represents the strength of congeniality bias in selecting information) as a function of p. A higher value of G indicates stronger polarization of attitudes. One can clearly see that network structures have significant effects on attitude diffusion. In general, polarization increases as p increases from 0.001 to 0.1, which reflects a transition from a regular to a small-world network; but as p is larger than 0.1, polarization quickly drops. Polarization also becomes stronger as k increases. In addition, as the initial number of connections (n) increases, the effects of network structures on attitude diffusion are strengthened.

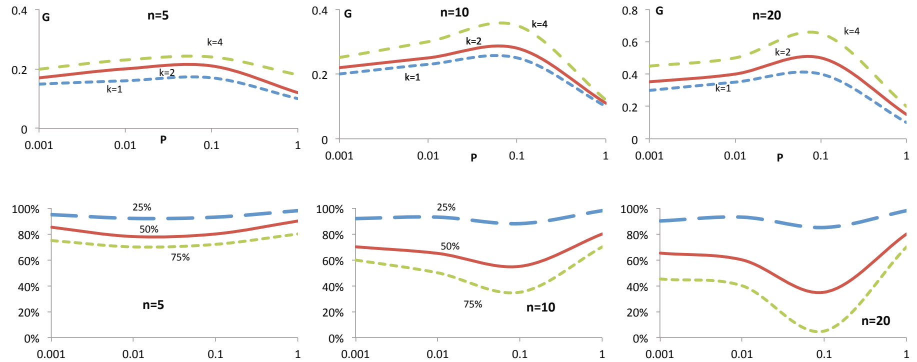

Fig. 1. [Top]:Gini coefficient calculated based on distributions of attitude strengths in the network (note that scales of y-axis have changed).[Bottom]:Percentage of agents who received 25%, 50%, and 75% of the global information.

To understand these counterintuitive results, one needs to note that as p increases, there are a number of changes in the network that impact information and attitude diffusion. When p increases from 0 to 0.1, the average path length dramatically decreases as links are re-created, which changes the network from a regular to a small-world network [11]. In other words, as p increases there are more hub nodes that reduce the average path length in the network.

While hub nodes are typically associated with more efficient information diffusion, they are more likely exposed to heterogeneous information in our simulation. In contrast, nodes that are connected locally tend to be less connected to the rest of the network (except through the hub nodes). Initially, these local neighboring nodes are exposed to only global information, which drives their attitudes randomly to either position. However, when any of these neighboring nodes reach the attitude threshold to disseminate information, they will have a large influence on its neighbors. As neighboring nodes are persuaded and shifted their attitude to one side, they become more selective in receiving global information, triggering a form of local information cascades of attitude change [3]. Given that active dissemination of information is subject to social reinforcement, denser local connections tend to lead to more local coherence (i.e., similar attitudes) among its nodes. This kind of local subnetwork is commonly observed even in large social networks [7].

So why do small-world networks lead to more polarized attitudes than regular networks? The main reason is that, unlike epidemiological models of information diffusion, hub nodes are actually more difficult to be "activated" in our model (see also [2]). Because hub nodes are exposed to heterogeneous information, they will less likely develop extreme attitudes. Thus, they will less likely become activists and disseminate information to their neighboring nodes. Rather than providing bridging links to its neighbors, a hub node in our model is actually shielding the local nodes from receiving opposing information from other local

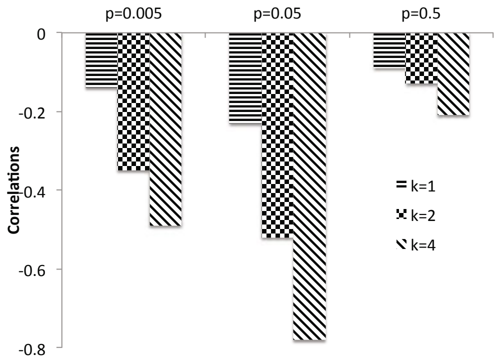

Fig. 2. The correlation between node degrees and magnitudes of attitude strength for representative values of p in the network with n=5

networks. To test this idea, we calculated the correlation between node degrees and their absolute attitude strengths in the networks. If hub nodes are inhibiting attitude diffusion, one will expect a negative correlation between node degree and absolute attitude strength. Figure 2 shows that the negative correlations are strongest when p=0.05 (in the small-world network range) than when p=0.005; and it is weakest when p=0.5. When p is larger than 0.1, the network loses local coherence and thus there is a much smaller chance for information cascades to occur among its neighbors. However, when propensity to selectively receive information is strong (k is high), global influence may still induce smaller scale polarization in the random network. However, in a small-world network, both local and global information cascades may contribute to local subgroups that support each other's attitudinal position while shunning inconsistent information, leading to stronger polarization. Figure 2 also shows that when the number of initial connections increases, the hub becomes larger. However, hub nodes do not promote attitude diffusion. They actually lead to fewer local polarized subgroups.

Finally, we will analyze how attitude diffusion is related to information diffusion. The bottom panel of figure 1 shows the percentages of agents who receive 25%, 50%, and 75% of the information broadcasted to the network. Consistent with the patterns of attitude diffusion, when p increases from 0.001 to 0.1, information diffusion decreases rather than increases. When p further increases from 0.1 to 1, however, there is less polarization of attitudes in the network as local coherence is lost, and increases information diffusion in the network. Similarly, as the number of initial connections increases, the effect of network structures is strengthened because the networks become less polarized. In other words, polarization is limiting the general exposures to information in the network.

5 Conclusions

Using an agent-based model, we have investigated the dynamic relations between information and attitude diffusion, and how the relations are influenced by network structures. We show that as connections are rewired to change from a regular to a small-world network (while keeping density constant), polarization of attitudes tends to intensify. Strong local connections and coherence are critical for the development and maintenance of extreme attitudes among members of a subnetwork, as members receive social reinforcement as they exchange information and begin to shun themselves from information inconsistent with their attitudes. This is similar to recent findings on the effects of hub nodes on complex contagion [2]. Counterintuitively, hub nodes may inhibit information diffusion, as they are difficult to be "activated" by its neighbors because of their exposure to heterogeneous information from different subnetworks. While the model is a general attempt to demonstrate the relations between information and attitude diffusion, it does show clearly that epidemiological models of information diffusion is too simple to capture the spread of social behavior that involves complex interactions among external information and prior beliefs, attitudes, or ideas of individuals. More generally, our results demonstrate the importance to take into account results and theories from cognitive and social behavioral studies to enrich the complex representations and processes of a node in a network, so as to establish a stronger micro-to-macro link between individual and network behavior.

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