Targeting Individuals to Catalyze Collective Action in Social Networks

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Abstract. To increase the level of collective action to solve problems related to sustainability and public health behavioral scientists have shown that the use of social influence and peer pressure can be effective. How to nudge a small set of individuals to generate cascades of cooperation? Using a stylized agent-based model we explore how different assumptions on network structure and attributes of agents, as well as forms of feedback will influence the level of adaptation. Our analysis shows that targeting those who are most socially influenceable is more effective than those who are most or best connected in social networks.

Keywords: Nudging, social influence, networks, collective action, intervention.

1 Introduction

Many of the challenges facing contemporary society are collective action problems, varying from emission reductions to reduce risks of climate change or vaccination for infectious diseases. Social scientists in various disciplines study collective action and there is a good understanding of the ability of small homogenous groups to cooperate in commons dilemmas [11]. Many of contemporary problems such as climate change and pandemics cannot be solved by small scale communities alone. What is needed is a better understanding of collective action in larger heterogeneous groups.

Although governments address collective action problems by implementing rules and legislation through a legal and parliamentarian process, this does not necessarily lead to behavioral change. We are interested in exploring findings from behavioral studies that can contribute to solving collective action problems. Empirical research has shown that individuals have an increased likelihood to participate in collective action due to social influence, such as social pressure and reputation [3], [5], [8]. Examples include the provision of data on energy use and voting turnout of neighbors and towel recycling rates of other hotel guests leading to significant increase of energy savings, voting turnout and towel recycling.

Can we leverage this effect of social influence by nudging the right individuals to contribute to the public good? Targeting influential persons may lead to cascades of cooperative behavior. In fact, cascades of cooperative behavior in social networks have been found in [4] where participants played one-shot social dilemmas. Experiencing cooperative behavior lead to increased likelihood of cooperative behavior in future games with other participants. As a cooperation event had an impact beyond the direct interaction of the participants and spread through the network.

Strategies to spread the influence in social networks have been studied with regard to viral marketing (e.g. [8]). Such studies are mainly focused on information spreading, the nodes are influenced by neighbors not by their own preferences. Centola [1] showed that behavioral change spread faster in a clustered network compared to a random network. This is in contrast to the spread of information. Hence information diffusion is a different process than diffusion of behavioral change. One of the proposed reasons is the importance of peer pressure. Only when enough neighbors have adopted the new behavior, this leads to adoption of others. For the spread of information or pathogens just having one of the neighbors being "infected" is sufficient to propagate the information or pathogens. The short cuts in random networks make that information and pathogens spread quickly.

In this paper we present a stylized model of agents making decisions to contribute to a collective action problem. By contrasting different variations of clustered and random networks we explore when collective action is higher. Furthermore, we explore the attributes of individuals to nudge to increase the level of adoption. Finally, we compare different strategies of increasing collective action.

2 Collective Action and Social Networks

Collective behavior can be triggered by a small number of "seeds". Building on the work of Granovetter [7] presented a threshold model that works as follows. Suppose there are 100 individuals who join a riot when x others a rioting, where x is the threshold of the individual. All individuals have a unique threshold varying from 0 to 99. The individual with threshold 0 starts rioting, and the individual with threshold 1 will join, etc. until all 100 individuals join. The distribution of the thresholds affects the size of the riot. Schelling [14] presented a similar model. He assumes that an individual participate if enough others will do so too. Schelling's model depends on the expected participation, and also here the distribution of expectations leads to different macro-level outcomes.

There has been substantial work on collective action and social network since. For sophisticated reviews of this literature we refer to [2], [9], [16].

3 Model Description

We will now discuss a very stylized model of agents who make decisions about adopting behavior A or B. Each behavior provides a personal reward to the agent.

Furthermore, each agent's utility of the action it is taken is affected by behavior the network neighbors. Initially all agents have behavior A. What are the conditions for which behavior B is adopted?

The utility of a behavior i consists of an individual part and a social influence part. The individual part expresses the degree of fit between the behavior and the preferences of the consumer. In the model this individual utility is expressed as the difference between the personal preference of an agent and the behavior. The personal preference of agent i, p_i, is expressed by a value between 0 and 1. In this model we only vary the preference for behavior B assuming a default preference for behavior A equal to p_A.

The social influence holds that the utility of a behavior increases when more network neighbors have the same behavior. The variable x_A denotes the average fraction of network neighbors with behavior A. The total expected utility of behavior is equal to:

$$E[U_{iA}] = \beta_i \cdot p_A + (1-\beta_i) \cdot x_A \tag{1}$$

$$E[U_{iB}] = \beta_i \cdot p_{i,B} + (1-\beta_i) \cdot (1-x_A) \tag{2}$$

The components of the utility function, the individual part and the social part, are weighted with β_i and 1-β, with $\beta_i \in [0,1]$. A low β_i holds that the personal preference is weighted less, as is usually the case with less innovative people (Rogers, 1995), whereas a high β_i holds that the social needs are weighted less, as is usually the case with more innovative people.

Agents make decisions each time step with probability p_U. When at time step t agents update their decisions they make use of the information of other agents from time step t-1. If the expected utilities are equal one of the options is chosen randomly. If $E[U_{iB}] > E[U_{iA}]$, behavior B is adopted.

Figure 1 shows the minimum level of $p_{i,B}$ that is needed for an agent to chose behavior B. In the beginning of the simulation, when x_A is high, only agents with a high value of β, the innovators, will adopt. Agents who are more affected by social influence (low β) will only adopt if the majority of their neighbors have adopted.

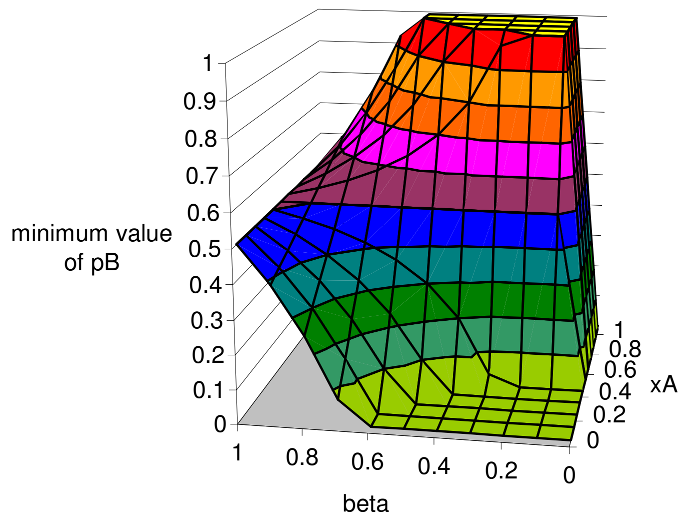

Fig. 1. The minimum level of $p_{i,B}$ for an agent to adopt behavior B.

. The agents are located in a network. This network is generated by first placing N agents randomly in the model space of dimensions 1x1. The agents are connected via links so that a parameterized average network density is achieved. The probability of any two agents being connected to each other is calculated so that the probability of a connection between any two agents decreases as the spatial distance between them increases. The probability that a short-length connection will be made rather than a long-distance connection is determined by a parameter, D, which represents the desired link length in the network.

$$p = \frac{n}{2\pi D^2} e^{-Nd^2/2D^2} \tag{3}$$

where n is the average number of links in the network, d is the average network density, D is the desired length-scale for generating networks, and N the number of agents. When D is small, i.e. D = 2, agents will be preferentially connected to agents within their immediate spatial vicinity. When D is larger, i.e. D = 10, agents are more connected with individuals at greater distances from Ego, that is, they are more 'globally' connected (Figures 2 and 3).

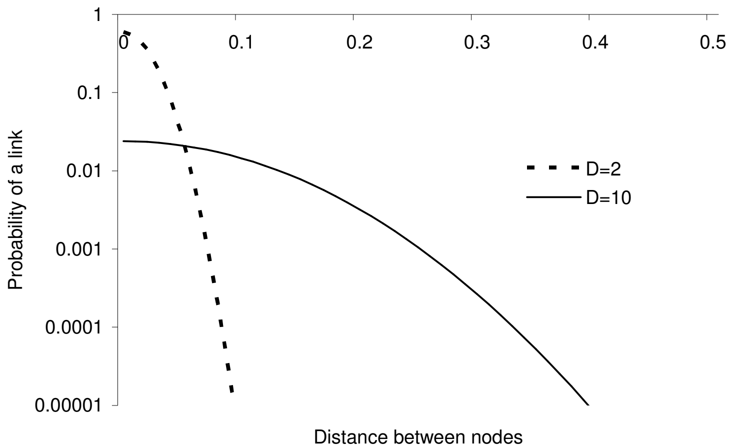

Fig. 2. The effect of D on the network structure. With D=2 the connections are more local compared to D=10.

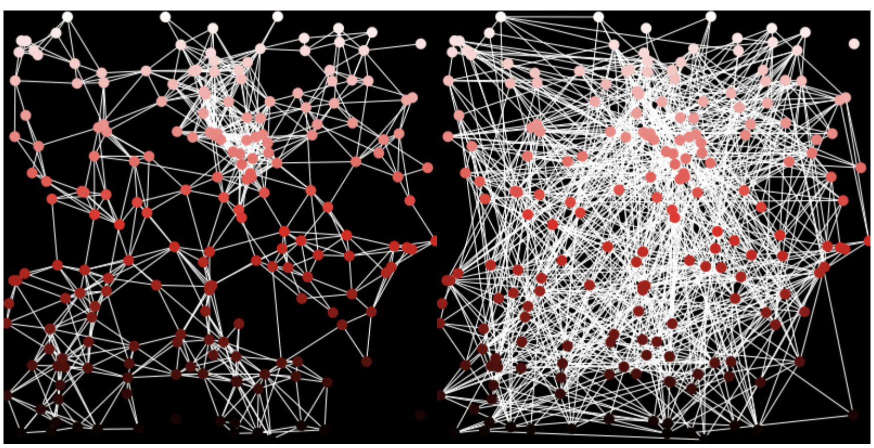

Fig. 3. Examples of network structures. Left is for D equal to 1, and right is for D equal to 10.

In the model analysis we explore the effect of homophily, the similarities of attributes of agents in a network [10]. Homophily is implemented by the way how agents are put randomly on the screen. If there is a high level of homophily, the horizontal position is determined by the values of p_{iB}. If the agent is not allocated based on similarity it is placed randomly on the screen irrespective the values of p_{iB}. As a consequence, we can vary the level of homophily by the frequency fp in which agents are placed on the screen based on their p_{iB} value. In the results reported in this paper fp will be varied from 0 to 1.

In our model analysis we will include interventions. An intervention is assumed to represent an incentive for an agent to make behavior B more attractive. This is implemented to increase the value $p_{i,B}$ by ε. This "nudge" may trigger the agent to switch from behavior A to B. In the next session we explore different ways to target which agents to nudge to have the most effect. Independent of the rule who to target, only agents who have not been nudged and have not adopted behavior B are considered.

4 Model Analysis

In this section we present some initial results of the model. The model is implemented in Netlogo and available at http://www.openabm.org/model/2587/version/1/view. For each parameter combination we explore we run the model 100 times for 100 time steps. We report the average level of adoption of behavior B in the graphs. The default parameter values are listed in Table 1.

Figure 4 depict some illustrative results of the model simulations for a network with D equal to 1. The network where agents allocate based on the homophily assumption show adoption in a cluster of the network. When there is no homophily, the adoption is spread among pockets of the network.

Table 1. Parameter values used in the model analysis.

Parameter	Description	Value
β_i	Sensitivity of agent to social influence	[0,1]
p_A	Default preference for behavior A	0.5
$p_{i,B}$	Preference for behavior B by agent i	[0,1]
D	Desired link length	[1,10]
N	Number of agents	200
d	Average network density	8
p_U	Probability an agent update it's state	0.5
f_p	Level of homophily	[0,1]
ε	Nudge	0.1

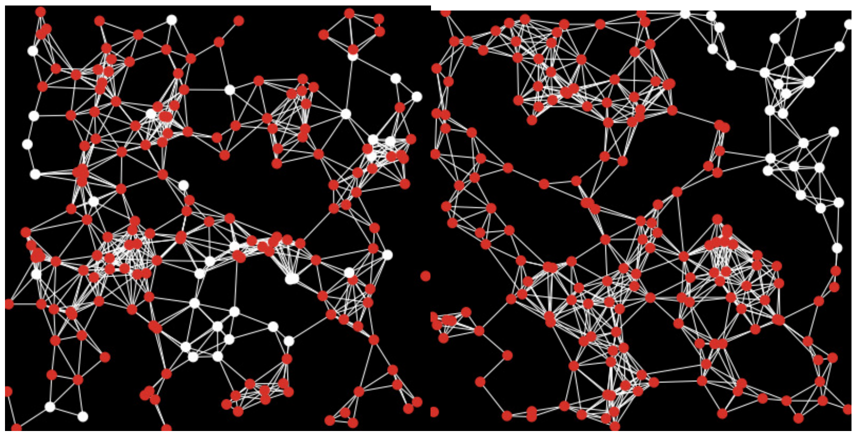

Fig. 4. Examples of spread of adoption of behavior in a network with no homophily (left), and with homophily (right).

In the analysis of the model we will use a default case where agents only receive global feedback. This means that x_A is the same for each agent, namely the share of behavior A in the whole population. Hence network structure and homophily do not impact the outcomes. Without an intervention the average fraction of behavior B after 100 ticks is 11.4%.

The next step is to compare the effect of local information. We show that there is a significant effect of providing information of adoption of behavior B in the direct local network. Figure 5 shows the result of adoption of behavior B for different assumptions of network structure and homophily. In all cases the adoption rate increases. It increases especially if there is a high level of homophily. In such a case agents who have similar preferences are switching to behavior B is a small part of their neighbors adopt. Note that other parts of the network consist of agents who do not prefer behavior A and will be very difficult to change.

When the network structure is more clustered (low values of D) the adoption rate is also higher. Hence, just providing local information instead of a global aggregate will increase the level of collective action. This effect is less profound in random networks (D=10), as found by experimental studies of Centola [1].

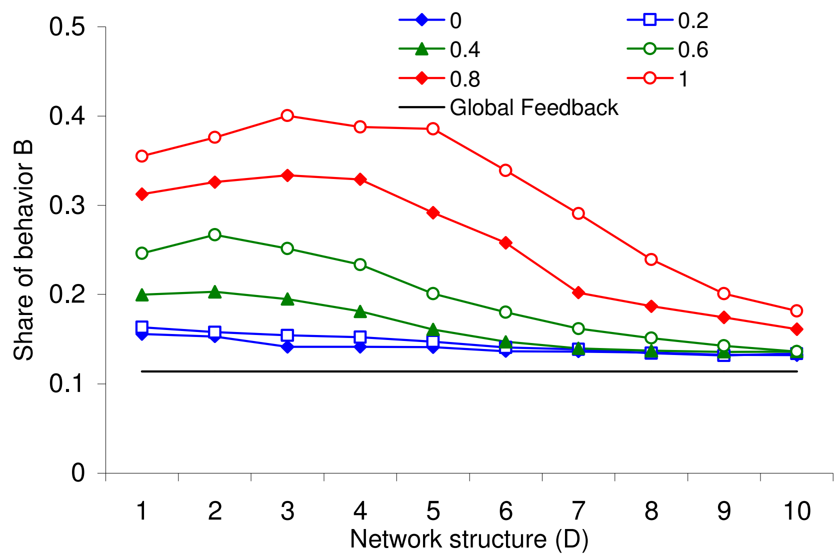

Fig. 5. The level of adoption for different values of D and different levels of homophily.

The next set of experiments compares four different types of interventions. An intervention is a sequence of 25 nudges of different nodes. We start the intervention at time step 25 after the non-intervention adoption of behavior B has spread through the network.

We compare four ways to define which agents who have not adopted B to target. The first option is to target agents the highest preference for behavior B (value of p_B). The second option is to target agents with the lowest level of being affected by social influence (value of β). The third option is to target with the highest degree (number of neighbors), and finally the forth option is to target agents with the highest closeness (meaning the lowest average path length with any other node in the network).

Table 2 shows the average adoption share for different assumptions of homophily and network structures. We find that on average targeting those agents who are least vulnerable to actions of others is the most effective strategy. Agents who are not socially influenced by others and not yet adopted behavior B are more likely to be affected by the nudge. A nudge can get such an agent switch and nudge their neighbors. Targeting agents who have most connections is least effective since peer pressure reduce the effectiveness of the individual nudge.

Table 2. Parameter values used in the model analysis.

Strategy	Percentage of Behavior B
Default	20.3%
Target individual preference p_b	24.4%
Target social influence β	26.0%
Target degree	23.3%
Target closeness	23.5%

When we look at different assumptions of homophily and network structure we find that targeting agents with high values of β is not always the most effective strategy. In networks with high homophily ($f_p \geq 0.8$) and high levels of clustering ($D \leq 6$) targeting agents with high p_B values is more effective. The reason is that in such networks it is most effective to unlock clusters of agents who like individually behavior B but are locked due to reinforcing social influence of agents still following behavior A.

5 Conclusion

This paper provides some initial results to catalyze collective action in social networks. The aim is to understand who to nudge to adopt preferred behavior such that this leads to cascades of adoption of preferred behavior. We acknowledge that the stylized model can be improved by including more specific assumption of human behavior such as how derive information (we assumed full information), a change of the preference for a product (e.g. due to price changes). We also made simplistic assumptions about the underlying distributions of the attributes of the agents. Future sensitivity analysis may reveal the importance of those assumptions.

One of the challenges is to test the model on empirical data. This is one of the reasons we are implementing controlled experiments using websites and mobile devices where we can test collective action in large artificial networks.

Although the paper is a very simplistic model of human behavior, it provides some interesting findings. Just providing feedback to agents on the adoption in their social network instead of global level information increases the adoption of the desired behavior up to 400%. Hence, more targeted information to consumers can increase the adoption rates. The second finding is that in the current version of the model targeting agents who are not likely by influenced by decisions of others is the most effective strategy to increase the adoption rates.

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