The Spread of Rumors on Networks

Huanren Zhang and Oana Vuculescu

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1 Introduction

Information usually spread through social networks. Consider the following situation: A rumor has broken out. Some folks want to keep it alive, others want to quash it. In the project, we will define a simple rule of interactions between agents and investigate how the structure of the network can influence the spread of rumors. We find that randomness of the network can promote the spread of the rumor. Higher clustering coefficient and shorter average path length of the network also increase the faction of people who are affected by the rumor, even holding the degree of randomness constant. However, regression analysis shows that only about half of the variation in the final spread of the rumor can be explained by the three variables (average path length, clustering coefficient and degree of randomness of the network), indicating that the spread of the rumor is path dependent and the starting point is vital for the final spread of the rumor.

The model of rumor spreading used in this project can be easily extended to the spread of new ideas, and adoption of new technology. Although rumors are mostly often useless or neutral, the spread of new ideas and adoption of new technology is mostly beneficial to the society. The conclusion of the project provides some preliminary understanding as to how to limit the harm caused by a rumor and how to promote the adoption of new technology.

We will first describe the assumptions made in our model and the rule of interaction between agents. We then run simulations on a range of networks that can be generated by rewiring a regular network and compare the results with the simulation results obtained from scale-free networks.

2 The Model

We have the following assumptions about the agents and their interactions:

1. N agents that form a network, and the rumor spreads through the social connections represented by the links in the network.

2. All agents derive positive utility from spreading the rumor when they believe it is useful, but they are not sure about the "usefulness" of the rumor. Agents are distinguished by their beliefs on whether the rumor is truthful (or useful and valuable) and worth spreading. The initial beliefs of the agents are uniformly distributed on [0,1]. [1]

3. An agent with belief greater than 0.5 will try to spread the rumor, and we call that agent a spreader. Similarly, an agent with belief less that or equal to 0.5 is a quasher. Hence, the spreaders and quashers may vary in their degrees of how actively they want to spread or quash the rumor.

4. Agents update their beliefs in the process of interacting with other agents in a fashion similar to Bayes update. The intuition: when a quasher is exposed to avid spreaders

[1] We also considered the case where the initial beliefs are binary, meaning the agents are "hardcore" spreaders or quashers. It is natural to conjecture that when the initial beliefs are binary, it is harder for the rumor to spread.

frequent enough, she may increase her belief and become a spreader. An agent with belief greater than 0.5 will try to spread the rumor, and we call that agent a spreader.

The rumor spreads in the following pattern:

1. A rumor starts from a randomly selected spreader, and the spreader has belief 1.

2. The spreader tries to spread the rumor to his neighbors, and the neighbors update their belief as the average of initial belief and the belief of the spreader
This updating rule captures the social influence. Here we also assume implicitly that a more hardcore spreader (a spreader with high belief) will try harder to influence others to believe and spread the message

3. The neighbors who are reached by the spreader and who have a updated belief greater than 0.5 will try to spread the rumor to their neighbors who are not a spreader. The new neighbors who are reached by the rumor update their beliefs

4. Repeat Step 3 until no-one's belief changes

Note that during the interaction, only the newly converted agents will try to convince their non-converted neighbors. A non-converted agent can be reached by its converted neighbor multiple times.

To understand this process intuitively, let's use a simple example show in Fig 1. A rumor starts at the red node representing an agent with belief 1. He will try to convince his two neighbors to believe and spread the rumor. The two neighbors then update their beliefs as the average of their prior beliefs and the belief of the spreader. Because the two neighbors both have high prior beliefs, they become spreaders as shown in (b), ans start to spread the rumor. The spreader with belief 0.93 has no neighbors who are not spreader, so he cannot spread the rumor to anyone. The spreader with belief 0.9 instead can try to convince her two neighbors. Because her belief is high, she can successfully convert her two neighbors (because spreaders with high beliefs are more hardcore spreaders, and they are likely to spend more time and energy to convince others, as mentioned in the assumption). We see in (d) that the agent with belief 0.55 fails to convert his neighbor, although he managed to bring up her belief. Later in (f), however, she was converted by her other neighbor. In our example, the rumor was successfully spread to the entire network. If we consider the case of the adoption of new technology, the belief can be considered as how open each agent is to the new technology, or on the other hand, can be considered as how entrenched the agent is into the old technology. The beliefs now can represent how deeply the agents are into iPhone: a 0.5 belief means indifference, a belief of 0 means being really into iPhones, and a belief of 1 indicates distaste. Suppose at first everyone is using iPhone, then someone starts to use an Android and start to convince his neighbors into using Android also. Agents with high beliefs are easier to be converted to use an Android. The more an agent is exposed to Android used by her friend, the more likely for her to start using Android. This is especially the case when there is positive externality such as it is easier for Android phone to share files or there is a specific app on Anroid phone that allows easier communication between Android users but not between an Android and an iPhone.

In the next section we will run simulations on networks with different structures and characteristics and investigate how the network structure can influence the spread of rumors.

3 Simulations and Results

We first investigate a range of networks that can generated by rewiring of the links of a regular network, represented in Fig 2. If with probability 1, the links in a regular network are rewired, we have a random network. When the probability is at the intermediate level, we obtain a small-world network. Denote the average path length between nodes as L, the clustering coefficient as C. A regular network has a high L and a high C, a random network has a low L and a low C, while a small world network has a low L and a high C.

To see how the rewiring probability (which is a measure of randomness) affects the spread of the rumor, we had 60 runs of simulation for each of the rewiring probabilities p in $\{0, 0.1, \ldots, 0.9, 1\}$ with $N = 50$ and the average degree $d = 4$. The result is shown in Fig 3. We see that although there is a large variation on each p, on average random connection between the agents helps spread the rumor. We did the same thing for the case of the average degree $d = 6$, and obtained similar result shown in Fig 3. Comparing these two figures we see that a higher average degree of the network increase the fraction of people influenced by the rumor.

An interesting observation shown in the graph is that when p is at intermediate levels(which means that the network exhibit small-world properties), the confidence intervals are narrows, indicating there are less variations for small world networks compared to networks that are more regular or more random. This result merits further investigation.

The large variation for each level of p implies that p alone is not effective in predicting the spread of rumors. To understand how other characteristics of the network influence the spread of the rumor, and whether these characteristics can provide better prediction, we run simulations for the following parameter sets $N = \{20, 50, 100\}$, the average degree of the network $\{2, 4, 6\}$, rewiring probability $p = \{0, 0.5, 1\}$, and compare the results. For each set of parameters, we had 5 runs.

As the large number of sets of possible parameters prevents effective graphical illustration, we resort to regression analysis. Model (1) in Table 1 provides the results. We find that the size of the network does not have a significant effect on the spread of the rumor (although it is statistically significant). A shorter path length, a higher clustering coefficient both lead higher fraction of population affected by the rumor, even after controlling the effect of the randomness presented in the network (p). We also tried to investigate what if initially the agents are either avid spreaders or hardcore quashers, meaning the initial beliefs are either

0 or 1. The result is intuitive: if agents initially have poler belief, the rumor spread less effectively.

To compare the result with a different type of network, we also run similar simulations on scale-free networks. The scale-free networks we used for analysis are generated using preferential attachment process. An example of scale free network is shown in Fig 3.

Because the clustering coefficient is 0 for such network and there is no rewiring probability, we can only study the effect of average path length. Same as the networks generated from rewiring regular networks, shorter average path length leads to more spread of the rumor.

Intuitively, scale-free networks should be less conducive for the spread of rumors compared to the "rewiring networks", because unless the rumor starts from a hub, it is very unlikely for the rumor to spread out in the network. Model (3) confirms this reasoning. The coefficient of the dummy variable SW indicates that, controlling the effect of clustering coefficient and rewiring probability, the rumor is on average less spread out in scale-free networks.[2]

The R^2 in the regressions show that only about half of the variation in the final spread of the rumor can be explained by the three variables (average path length, clustering coefficient and degree of randomness of the network), indicating that the spread of the rumor is path dependent and the starting point is vital for the final spread of the rumor.

4 Discussion

The diffusion process modeled here has been and can be applied in other contexts other than opinion formation, more significantly in innovation adoption. So far product adoption models have largely assumed users to be indifferent towards the product, but by introducing payoffs (linked with for instance network effects) and an adoption threshold this model could

[2] The result might be biased because most of the rewiring networks are with clustering coefficients greater than 0. Further investigation is needed to confirm the validity of the result by carefully generating rewiring networks with 0 clustering coefficient.

account for more complex, endogenous adoption dynamics.

Further utility distributions can be tested to explore for instance the diffusion of unlikely rumors, as well as other network topologies. Further extensions could look at dynamic networks — i.e. our model does not account for the effect of homophily on interactions. However, social networks literature acknowledges the importance of similarity in social interactions and likely allowing our agents to form new ties with similar agents and ignore dissimilar agents would impact the dynamics of the model.

An easy extension of the implications of our model is a scenario where the seed is a focal agent which is a well-connected node. The influence such an agent might have is likely mitigated by his payoffs as well as the payoffs of his immediate neighbors, which will likely lead to a containment of the rumor.

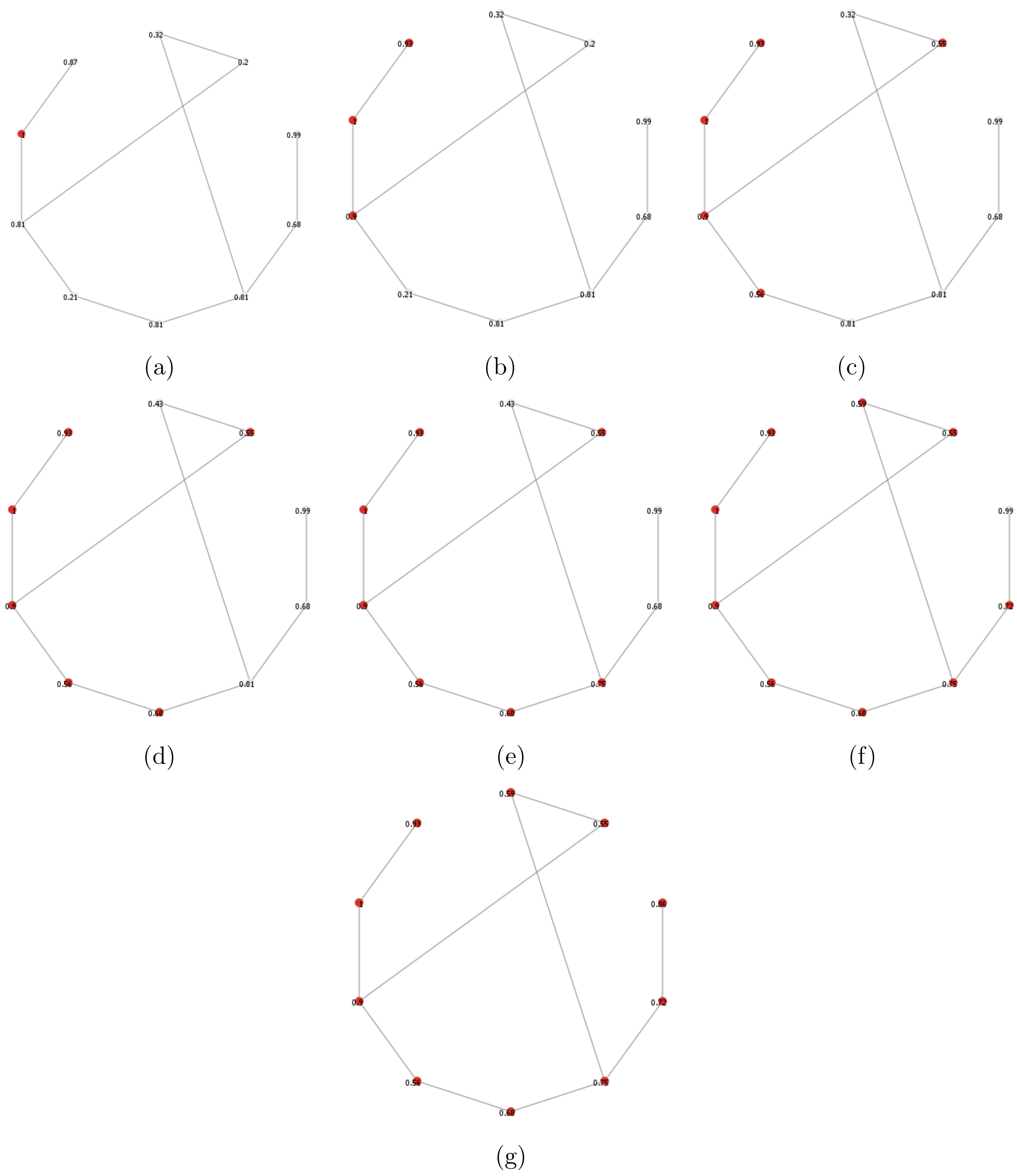


Figure 1: The spread of rumor on a simple network

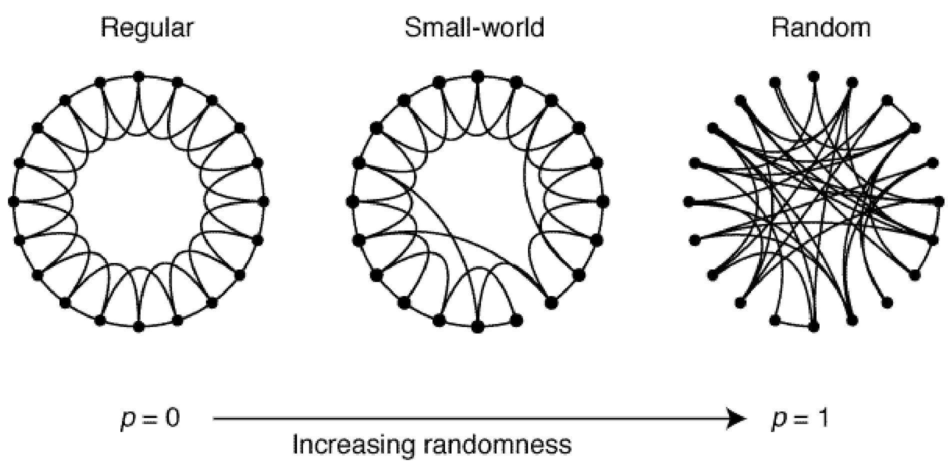
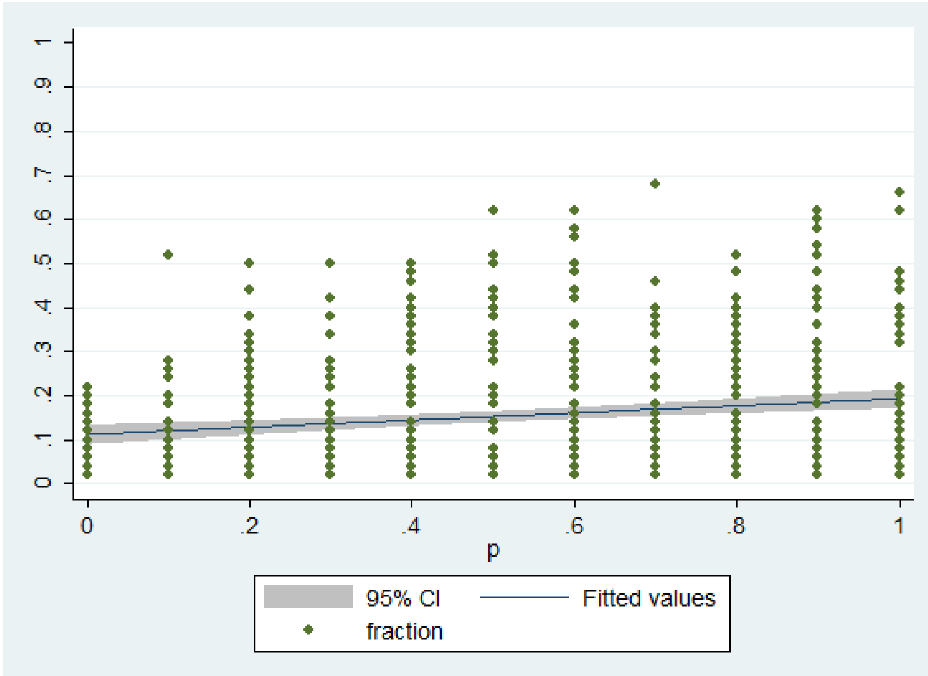
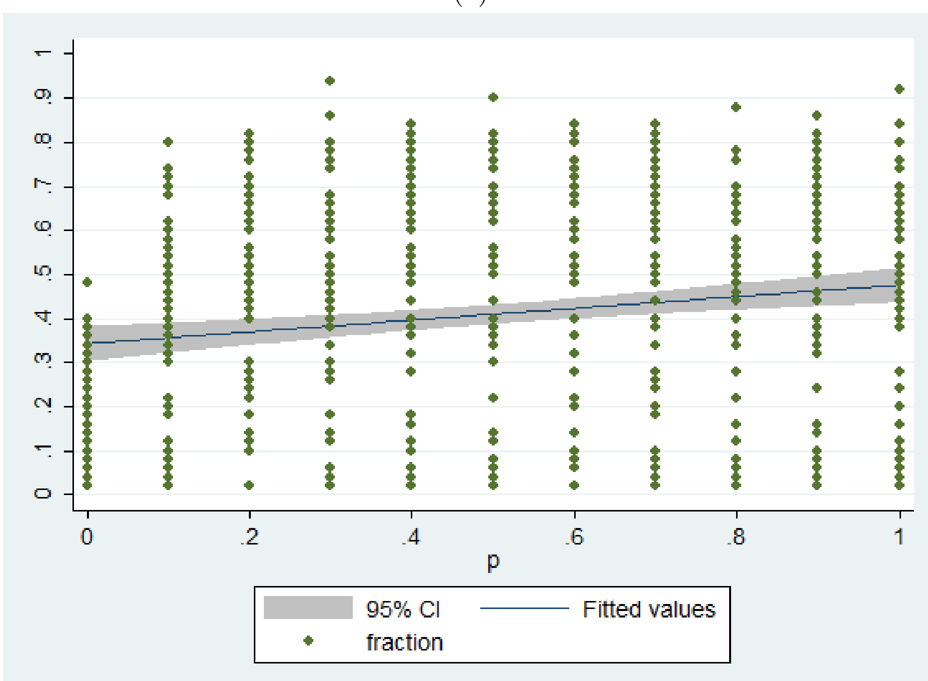


Figure 2: By varying the rewiring probability of a regular network, we obtain a category of networks from regular networks to random network.



(a)



(b)

Figure 3: Fraction of population affected by the rumor vs. the rewiring probability. $N = 50$ and the average degree of the network is (a) 4 and (b) 6

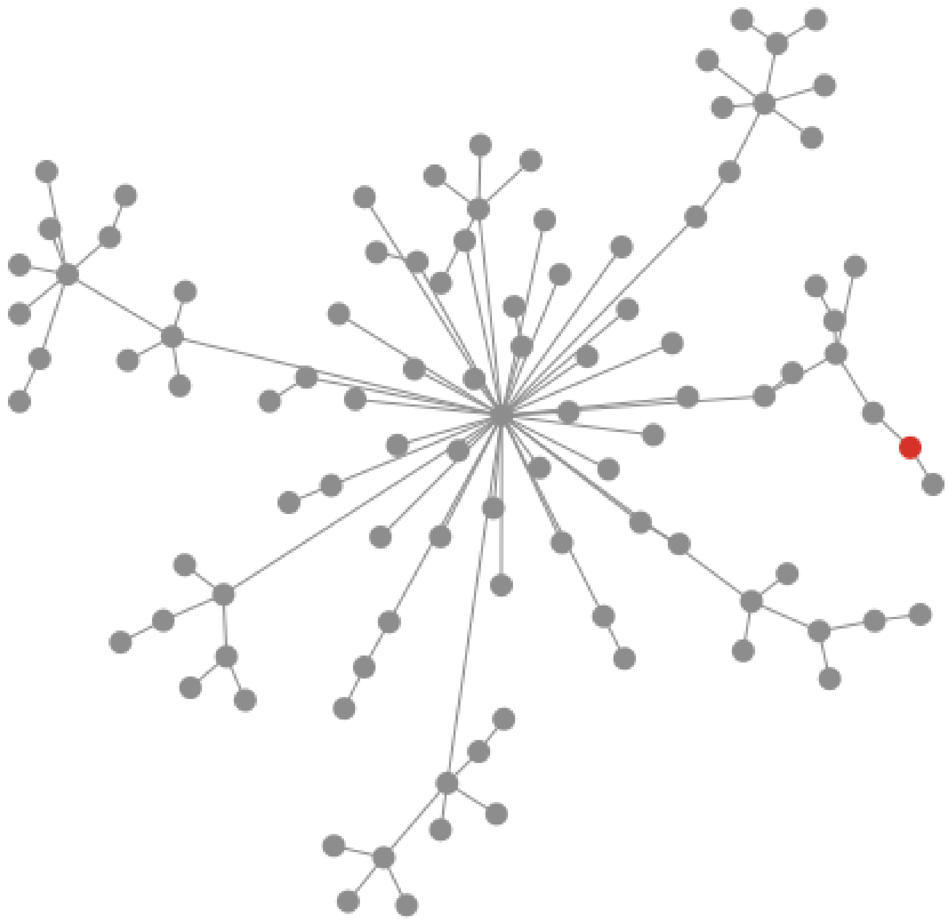


Figure 4: A scale free network with 100 nodes, generated by preferential attachment. Note that the clustering coefficient for a network generated by preferential attachment is 0. A random node (the red node) is chosen as the start of the rumor. The low clustering coefficient makes rumors less likely to spread.

Table 1: Regression analysis.

	Dependent variable: fraction of population influenced by the rumor		
Model	(1)	(2)	(3)
Date used	Rewiring networks	Scale free networks	Both types of networks
N	0.001***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
L	-0.022***	-0.061***	-0.017***
	(0.002)	(0.019)	(0.002)
C	0.311***		
	(0.101)		
p	0.193***		
	(0.062)		
Binary Belief	-0.112***	-0.291***	-0.218***
	(0.035)	(0.019)	(0.019)
SW$\times C$			0.250***
			(0.088)
SW$\times p$			0.205***
			(0.053)
SW			0.338***
			(0.047)
Constant	0.655***	0.693***	0.456***
	(0.061)	(0.063)	(0.021)
Observations	238	360	598
R^2	0.483	0.445	0.595

Note: Standard errors for the mean shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1. N is the number of nodes. L represents the average path length. C is the clustering coefficient. p is the rewiring probability for the networks generated from a regular network. SW is a dummy variable which takes 1 if the network is generated by rewiring regular networks. Binary Belief is a dummy variable indicates whether the agents have binary belief on the usefulness of the rumor. Networks that are not fully connected are excluded from the regression as their average path length is infinity.