Technology adoption in complex social networks

Petr Svarc
Institute of Economic Studies
Faculty of Social Sciences
Charles University in Prague
petrsvarc@email.cz

Natalie Svarcova
Institute of Economic Studies
Faculty of Social Sciences
Charles University in Prague
natalie.svarcova@email.cz

Using a simple computational model, we study consequences of herding behavior in population of agents connected in networks with different topologies: random networks, small-world networks and scale-free networks. Agents sequentially choose between two technologies using very simple rules based on the previous choice of their immediate neighbors. We show that different seeding of technologies can lead to very different results in the choice of majority of agents. We mainly focus on the situation where one technology is seeded randomly while the other is directed to targeted (highly connected) agents. We show that even if the initial seeding is positively biased toward the first technology (more agents start with the choice of the first technology) the dynamic of the model can result in the majority choosing the second technology under the targeted hub approach. Even if the change to majority choice is highly improbable targeted seeding can lead to more favorable results. The explanation is that targeting hubs enhances the diffusion of the firm's own technology and halts or slows-down the adoption of the concurrent one. Comparison of the results for different network topologies also leads to the conclusion that the overall results are affected by the distribution of number of connections (degree) of individual agents, mainly by its variance.

1 Introduction

In many real life situations our choice is more or less influenced by the choice or opinion of other people, whether it be our friends, parents, colleagues, teachers, mentors or hired specialists. The list of such situations is very diverse: from everyday life choices such as where to dine or what television programs to watch, through voting in elections, having children, changing jobs, or deciding how firms should invest. Very often people simply choose what majority of others has chosen. This kind of behavior is called herding behavior. As posted by [Banerjee 1992], herding behavior is when: "... everyone is doing what everyone else is doing, even when their private information suggests doing something quite different."

In this work we use computational model to study consequences of herding behavior in case of technology diffusion if a population of agents is connected through networks with different topologies. The topologies considered are random networks [Erdös and Rényi 1959], small-world networks [Strogatz and Watts 1998] and scale-free networks [Barabási and Albert 1999]. Agents one after another choose between two technologies using very simple rule based on the previous choice of their immediate neighbors. We show that different initial seeding of technologies can lead to very different results in the final majority choice. We mainly focus on the situation where one technology is seeded randomly while seeding of the other technology is targeted to highly connected agents – hubs. We show that even if there are more agents starting with Technology 2, Technology 1 can be finally chosen by a majority of agents if the technology is seeded within targeted hubs. The explanation is that targeting hubs 1) enhances the spread of the firm's own technology and 2) halts or slows-down the adoption of the concurrent one. Comparison of the results for different network topologies leads us to the conclusion that the overall results are also affected by the distribution of number of connections (degree) of individual agents, mainly by its variance.

2 Related literature

Our work is connected to two main strands of literature. The first strand focuses on the technology adoption. Here authors explain observed regularities like path-dependency and lock-in effect through network externalities [Katz and Shapiro 1986], increasing returns [Arthur 1989], herding behavior [Banerjee 1992; Dosi, Ermoliev and Kaniovsky 1994], informational cascades [Bikhchandani, Hirshleifer and Welch 1992] and information contagion [Arthur and Lane 1991]. Many authors also describe micro-motives leading to the observed phenomena (see for example [Banerjee 1992], [Arthur and Lane 1991] or [Narduzzo and Warglien 1996]). [Vriend 2004] showed that information-contagious behavior can evolve in the population of artificial agents through self-organization and emergence. In our work we follow [Dosi, Ermoliev and Kaniovsky 1994] and assume that agents are govern by simple herding behavioral rule based on the information about choice of sample of agents. Contrary to [Dosi, Ermoliev and Kaniovsky 1994], this sample is not random but includes agents connected through social network.

The second strand of literature connected to the network theory. We are interested mainly in the studies focused on the importance of highly connected individuals (hubs) in the diffusion processes such as spread of contagious diseases [Moreno, Satorras and Vespignani 2006] and computer viruses [Lloyd and May 2001] in complex networks. As showed by [Moreno, Satorras and Vespignani 2006] hubs with large number of connections are the main cause of the absence of the epidemic threshold (below which major epidemic outbreaks are impossible) in scale-free networks. Therefore, it is very hard and costly to fight the spread of diseases in this type of networks even if the probability of transmission is very low. One way to halt epidemics spread in scale-free network is targeting of the treatment or prevention on the highly connected individuals. This strategy can restore finite epidemic threshold in scale-free network and potentially eradicate the virus [Dezso and Barabási 2002].

Targeting hubs is also used by [Alkemade and Castaldi 2005] who showed that more detail knowledge of consumer network can improve advertisement strategies. Authors proposed a model in which firms can learn directed advertisement strategy that takes into account both consumers' characteristics and topology of the social consumer network. Targeting advertisement to highly connected consumers outperform random advertisement strategies in their model.

In our model network topology and information about number of connections of individual agents also play important role. As proposed earlier our main goal is to examine if and how initial seeding of technologies – random or targeted to hubs, affects the resulting market share. We will argue that in the case of technology adoption targeting hubs 1) enhance the spread of the firm's own technology and 2) halt or slow-down the adoption of the concurrent one. We also show that the overall results are also affected by the distribution of number of connections (degree) of individual agents, mainly by its variance.

3 Network topologies

In our paper we analyze technology adoption in three most common types of networks – random graphs as defined by [Erdös and Rényi 1959; 1960], small-world networks model as proposed by [Strogatz and Watts 1998] and scale-free networks model of [Barabási and Albert 1999].

In 1959 Erdös and Rényi[1] published model of networks with undirected links with fixed number of nodes (N) and probability that two nodes are connected equal to p. This type of network characterized by binominal degree distribution (that for larger N takes the form of Poisson distribution $P(k) = \frac{e^{-\lambda}\lambda}{k!}$ where $\lambda = N\binom{N-1}{k} p^k (1-p)^{N-1-k}$) is called random graph or random network (see figure 2(a)).

Random graph network contains on average $p\frac{N(N-1)}{2}$ links and average degree of the network is $p(N-1)$.

Small-world networks as defined by [Watts and Strogatz 1998] have two characteristics often observed in real-world networks – "small" average shortest-path length and "large" clustering coefficient. One way to create small-world network proposed by Watts and Strogatz is to rewire links in regular lattice network. After

[1] See [Erdös, Rényi 1959]

creation of regular lattice (with number of nearest neighbors 4 and more) all links are in turn taken and with probability π rewired to randomly chosen node. For large π, the network is similar to random graph[2]. Figure 1 depicts construction of Watts and Strogatz small-world network through rewiring of links.

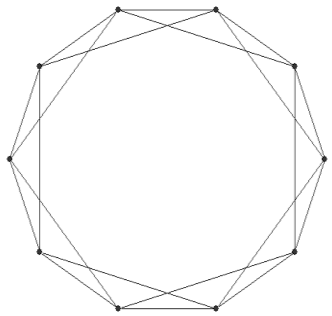

Figure. 1 Construction of Watts and Strogatz small-world network through rewiring of links with probability 0 (left), 0.2 (middle) and 1.0 (right).

The last type of the networks used in this paper is scale-free network as modeled by [Barabási and Albert 1999]. Scale-free networks are characterized by power-law form of degree distribution, $P(k) \approx k^{-\gamma}$, where $P(k)$ is the probability that a node in the network is connected with k other nodes, γ is called scaling exponent and ranges between 2 and 3 for most real-world networks. Barabási and Albert's network is characterized by two features typical for real world networks that lead to scale-free pattern of the network: growth and preferential attachment. The building of the network starts with small number of nodes (m_0). At every time step a new node with m ($\leq m_0$) links is added. New links connect the node to m different nodes already present in the system. The nodes to which new links are attached are not chosen randomly, the probability τ that a new link will be connected to node i depends on the degree k_i of that node, such that $\tau(k_i) = \frac{k_i}{\sum_j k_j}$. After t time steps we obtain a scale-free network with $N = t + m_0$ nodes, mt links, $\gamma = 3$ [3] and average degree $\langle k \rangle = 2m$ [4] (see figure 2(c)). Figure 2 displays examples of random, small-world and scale free network.

a) Random network b) Small-World network c) Scale-Free network

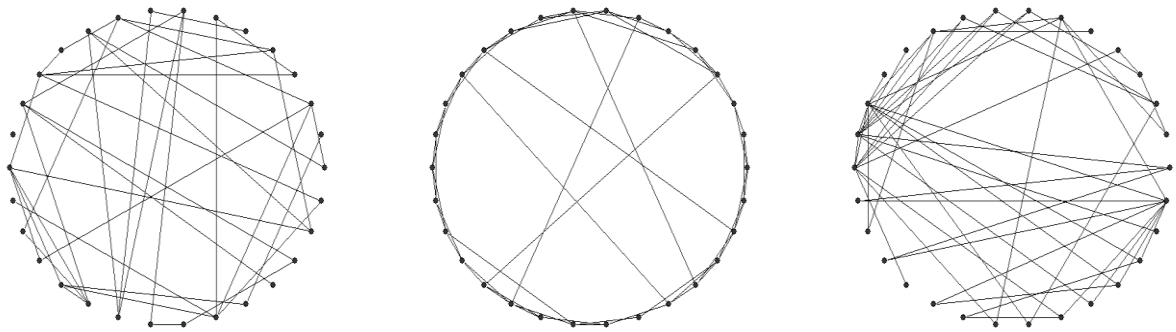

Figure. 2 Network topologies used in our work. Pictures were created using Pajek[5] software, tool for analysis and visualization of complex networks.

[2] See [Dorogovstev, Mendes 2001], pp.16.
[3] See [Barabási, Albert (1999].
[4] See [Pastor-Satorras, Vespignani 2006], pp.5
[5] http://vlado.fmf.uni-lj.si/pub/networks/pajek/

4 Model

The model is very simple. There is a population of N agents connected through social network. Network can have three different topologies: random network, small-world network and scale-free network. Agents sequentially choose between two technologies, Technology 1 and Technology 2. These two technologies are equal in all attributes, the only difference is that they originate from two different sources (firms, financial advisors etc.). In each step one agent is randomly chosen and has to decide which technology to choose. The choice of the technology made by the agent is ultimate and technology cannot be altered any more.

4.1 Initial seeding of technologies

Before the beginning of the sequential process of decision-making we choose two groups of agents that will not have the right to choose the technology. We set the choice of n_1 agents to Technology 1 and the choice of n_2 agents to Technology 2.

Number of agents in the first group is always fixed and set to 10 whereas number of agents in the second group varies, ranging between 10 and 100.

While agents in the second group (with predefined Technology 2 choice) were always chosen randomly, agents in the first group (with predefined Technology 1 choice) were either chosen randomly (*random seeding*) or targeted (*targeted seeding)*. In case of targeted seeding the agents with the highest number of links were chosen.

4.2 Agents' behavior

In number of experiments regarding technology adoption with real [Narduzzo and Warglien 1996; Chakravarty 2003] and artificial [Vriend 2004] agents, the observed behavior can be categorized into four main choice heuristics [Narduzzo and Warglien 1996]:

1. The mean rule – agents choose the technology with the highest mean value being the observed utility of other agents or whatever quantitative measure is used.
2. The highest minimum rule – agents choose the technology with the highest minimums value. As proposed by [Narduzzo and Warglien 1996] it can be seen as a extreme loss aversion.
3. The highest maximum rule – agents choose the technology with the highest maximum value. Contrary to the previous behavior, agents using this rule have tendency to believe that they can control or influence outcomes that they in reality cannot control or influence at all. This kind of cognitive bias is called *illusion of control* [Langer 1975].
4. The popularity rule – agents choose technology that has been chosen by the majority of other agents.

In our study we follow [Dosi, Ermoliev and Kaniovsky 1994] and we use popularity rule as a choice heuristic for our agents. Detailed description of the rule is as follows:

1. Agent observes the choice of her neighbors and finds out which technology was chosen by the majority.
2. Based on her observation, agent chooses between the two technologies. The rule is:
   a. If none of her neighbors has experience with any of these technologies she chooses randomly.
   b. If there is at least one experienced neighbor and there is majority of neighbors that have chosen Technology 1, resp. Technology 2, she chooses Technology 1, resp. Technology 2.
   c. If number of neighbors that have chosen Technology 1 equals number of neighbors that have chosen Technology 2, she again chooses randomly.

After that next agent is chosen randomly and the whole process continues until all agents have made their decision. It is important to note, that each agent can observe only the choice of her immediate neighbors and the number of neighbors differs for different agents.

We are interested in the resulting market share (which of the two technologies will be chosen by majority of agents). The main question is, given the behavior of agents, the topology of network and the initial number of agents with the choice set to Technology 1 resp. 2, how can different seeding strategies influence market share of the technology?

4.3 Implementation

To explore the model we use computer simulation implemented in JAVA object-oriented language and with the use of Repast[6] libraries. Repast libraries contain a lot of useful methods and predefined classes that allow researcher to focus more on the studied phenomena than on programming process. The computer code for the simulation can be obtained from authors upon request.

[6] http://repast.sourceforge.net/

5 Simulation setup and results

In this section we present detail results of our experiments with scale-free network but also briefly discus random and small-world network cases.

In all our simulations we fixed the number of agents in the network N to 1000. Each agent uses the same herding behavior described in the previous sections. The agents could differ in the number of interpersonal contacts, (created as undirected links). The distribution of the number of links attached to each agent depends on the network topology used in the simulation (exponential for the random and small-world network and power-law for scale free network) but the average degree or the average number of links was set to 4 for all the used topologies.

In our experiments we used several different initial seedings of the Technologies 1 and 2. First, while we fixed the value n_1 to 10 we varied the value n_2 from 10 to 100. This means that at the beginning the choice of 10 agents was set to Technology 1 while the number of agents with the choice set to Technology 2 ranged from 10 to 100 during experiments.

Second, rather than using only random seeding of technologies, we used both random and targeted seeding of Technology 1. In random seeding we randomly choose agents from the list with the probability of choosing equal for all agents. In targeted seeding, we sorted the agents based on the number of links attached to them and we set the choice of appropriate number of highest connected agents to Technology 1 (the seeding of Technology 2 was always random). For every parameter setting we run the simulation 1000 times and we averaged the results over all these runs.

Figure 3 shows simulation results for scale-free network, with n_1 always equals to 10 and n_2 ranges from 10 to 100. Horizontal axis shows n_2, vertical axis shows final market share of Technology 1 (in %). In this type of network, the difference in final shares in case of targeted and non-targeted seeding is most significant compare to other network topologies. The reason is that Technology 1 gets both the worst results in case of random seeding and best results in case of targeted seeding (compared to random and small-world networks). For example, in case of the greatest initial difference between n_1 and n_2[7], a scale-free network leads to the highest difference in the final shares of both technologies if random seeding is used. Under these circumstances, Technology 1 receives a market share of only 20%. Alternatively, under the targeted seeding model, the difference between Technology 1 and 2 in final market shares is lowest of all analyzed cases. In the end, Technology 1 gains a majority (51%) of the market, despite of being most seriously disadvantaged as concerns number of agents with predefined technology

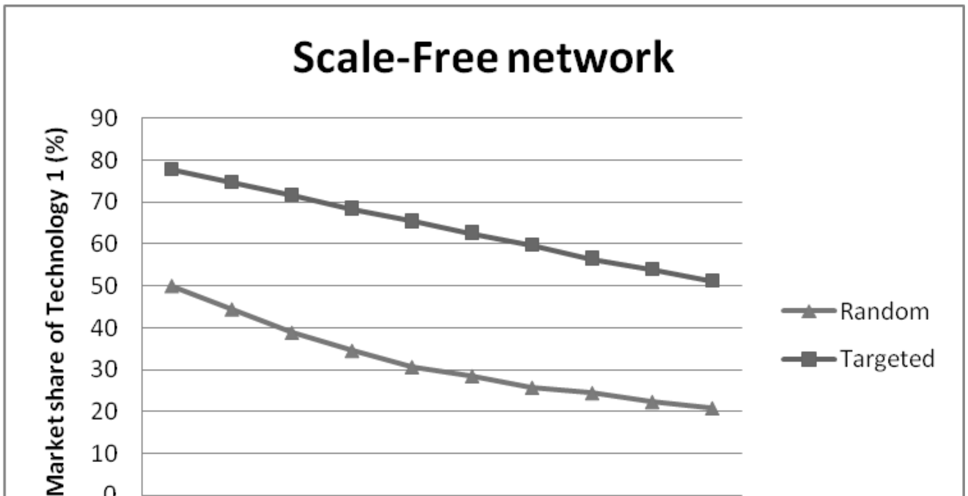

Figure 3 Final market share of Technology 1 for random network. Horizontal axis shows n_2, vertical axis shows final market share of Technology 1 (in %).

These interesting results stem from the following characteristics of hubs. On one hand, hubs are influenced by the greatest number of neighbors. This means that if there initially more agents with predefined Technology 2, the hubs themselves will display herbing behavior to adopt Technology 2 due to either their seeding or neighbor's influence. Hubs are then very effective in influencing other agents´ decisions, which leads to a high Technology 2 market share.

[7] This means $n_1 = 1$ and $n_2 = 100$.

On the other hand, even if initial seeding favors Technology 2 in number of agents (n_2), Technology 1 can finally prevail in case that it is targeted on hubs. Targeting the seeding of Technology 1 to hubs works in two ways. First, it is prevention. Targeting at hubs prevent them from choosing Technology 2 (which would otherwise take place due to herding behavior). Second, hubs are best suited for promoting adoption of Technology 1 because of large number of agents they influence.

For random and small-world network, the difference between random and targeted hub seeding were smaller compare to scale-free network but still significant. Furthermore, in small-world networks this difference was the smallest but it increases with the increase in rewiring probability (for rewiring probability close to 1 the results resemble that of random network). This observation leads to the conclusion, that overall results are also affected by the distribution of the degree of individual nodes.

6 Conclusions

As showed in previous studies, knowledge of the network topology can be very useful both in the case of stopping the spread of contagious diseases or computer viruses [Dezso and Barabási 2002] and promoting or enhancing the diffusion of new product or technology [Alkemade and Castaldi 2005].

In our paper we present similar results for the case of technology adoption in the population of agents governed by the simple herding behavior. We show that firm who is able to convince a few highly connected agents (hubs) to choose her technology at the beginning of the adoption process could significantly raise the overall number of agents choosing her technology. The explanation is that targeting hubs has two functions: 1) it enhances the spread of the firm's own technology and 2) halts or slows-down the adoption of the concurrent one.

When comparing the results for the three different network topologies – random, small-world and scale-free network, strategy of targeting hubs is most successful in case of scale-free network characterized with the highest variance of the degree of individual nodes. This leads us to the conclusion that the overall results are also affected by the distribution of number of connections (degree) of individual agents, mainly by its variance.

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