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Research on Social Marketing Strategies with An Agent-based Propagation Model

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Abstract: Considering the increasing complexity of social networks and user behaviors, it is very challenging for advertisers to formulate their strategies of selecting proper initial seed users in their social marketing efforts. In this paper, we tackle this challenge by proposing an agent-based propagation model and injecting it into typical social networks with three types of structures, i.e., Erdős-Rényi random graph, Watt-Strogatz small world graph, and Barabási-Albert scale-free graph. We instantiate this agent-based model with demographic characteristics extracted from real-world census data collected in China. By investigating the diffusion process of advertising information in these social networks, we can analyze and compare the performance of advertisers' targeting and influencer strategies. Our experimental results indicate that advertisers adopting influencer strategies should manipulate the initial well-connected seeds to deliver information only to the potential customers instead of a wide range of generic users.

Keywords: social marketing, information diffusion, agent-based propagation model, seeding strategy.

1. INTRODUCTION

With the rapid development of social networking tools, and integration of online advertising and big data analysis, more and more advertisers now prefer to promote their products or services through the social marketing channels. In literature, social marketing is defined as the design, implementation, and control of programs calculated to influence the acceptability of social ideas, and it involves considerations of product planning, pricing, communication, distribution, and marketing research (Kotler & Zaltman, 1971), which is a much broader idea than social advertising and even social communication. Social marketing has a positive effect on the brand image, awareness and equity, which can contribute to a significant improvement in purchasing intention (Dehghani & Tumer, 2015).

Social marketing is closely related to viral marketing, where advertisers attempt to artificially create word-of-mouth advertisements among potential customers. Their main difference lies in the decay rate, which represents the rate to lose interests on sharing the given advertising information. Typically, there is one-time sharing in viral marketing as the advertising information is spread with little or no interaction. On the contrary, social marketing aims at persistent interests and growing sharing. When the decay rate increases above a certain threshold, social marketing tends to be viral marketing.

The social marketing process can be broadly modelled in terms of three components: a social network through which advertising information is propagated, a set of users that propagate the information, and a seeding strategy that activates the process by determining the initial set of targeted users chosen by advertisers (Bampo & Wallace, 2008).The seeding strategy is of particular importance, since a proper strategy can help advertisers to deliver the ideas to a wide range of target users. Generally, there are two popular seeding strategies for advertisers: selecting the best-matched users via Web cookie analysis, and selecting the influential users on the basis of their social activities (Li & Shiu, 2012). The former is called the targeting strategy, while the latter the influencer strategy.

For targeting strategies, advertisers identify the best-matched users on the basis of user profiles including gender, age, interests, purchase intentions and so on, and then launch campaigns or pass advertising information directly to them. Therefore, advertisers will have full control of the promotion process, and can manage the fine-grained audience targeting, and also can avoid the waste of limited budgets. However, those targeted users might not impose enough impacts to encourage the diffusion of the advertising information. Also, targeting advertising needs to access user profile to learn their traits, which may cause the problem of user privacy, and thus lead to the negative engagement of advertising systems (Wang et al., 2015).

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For influencer strategies, well-connected individuals in social networks will be chosen to maximize spread of advertising information. Since these influential users have powerful capacity to deliver social ideas and impose strong influence on others' acceptability, they can help advertisers build indirect connections with large amounts of users quickly, which improves both the effectiveness and efficiency of online promotions. The main disadvantage of this strategy is that some users receiving the advertising information are not the targeted ones, and will not create any values for advertisers. Generally, targeting strategies focus on the small-scale best-matched audience, while influencer strategies may broadcast advertisements to a large-scale generic audience.

It is a challenging task for advertisers to determine a proper seeding strategy in social marketing. Most advertisers are faced with budget limitations, which restrict them to select a finite number of users as their promotion targets. In addition to the complexity of social networks and user behaviours, generally advertisers are lack of ability to predict and control the diffusion process in social networks. Thus they are not able to estimate the marketing performance and further to select the proper seeding strategy.

The key to determine seeding strategies in social marketing is to figure out the diffusion mechanism of advertising information, as well as the social impact on users' purchasing intentions or behaviours in social networks. Social marketing is not a theory in itself but rather draws from many bodies of knowledge to understand how to influence people's behaviour (Kotler & Zaltman, 1971). Considering the factors of user preference, network influence, and propagation capability, Li & Shiu (2012) studied the diffusion mechanism to deliver advertising information over microblogging media. Todi (2008) proposed three criteria that successful advertising campaigns on social networks need to fulfil, which are unobtrusiveness, creativeness and engaging users. Psychological knowledge that is relevant and accessible to individuals is also very important for social marketing programs to foster sustainable behaviours (Mckenzie-Mohr, 2000). Stead et al. (2005) suggested that a theoretically sound framework, combined with the use of consumer research to help translate theoretical constructs into acceptable and persuasive interventions, is an important pre-requisite for the effectiveness of social marketing. Hinz et al. (2011) recommended influencer strategies for viral marketing based on empirical experiments.

The existing research efforts on the initial seeds selecting in social marketing are far from enough. However, selecting different initial seed set will not only result in different advertising information diffusion path and numbers of reaching out, but also different interventions on users' social behaviours and purchasing intentions, and thus will influence the final marketing performance and the advertiser's achievement. Therefore, there is a critical need to study the initial seeds selecting strategy in social marketing.

This paper is targeted at studying advertisers' decisions on seeding strategy in social marketing for influence maximization. Inspired from infectious disease research, we establish an agent-based propagation model to investigate the information diffusion and transition between user states during social marketing. Also, we design experiments in three typical social networks: Erdős-Rényi random graph (Erdős & Rényi, 1960), Watts-Strogatz small world graph (Watts & Strogatz, 1998) and Barabási-Albert scale-free graph (Barabási & Albert, 1999) to make further investigations of our research using real-world census data in China. Our research will provide reliable support for advertisers to determine their seed users in social marketing.

The remainder of this paper is organized as follows. In Section 2, we establish an agent-based propagation model for information diffusion in social networks. Section 3 conducts experiments to make further investigation of the model, and also gives detailed analysis of the experimental results. Section 4 discusses the management insights of our research. Section 5 concludes.

2. THE MODEL

2.1 Problem Statement

A social network is modelled as a directed graph G. The dynamics process of social marketing can be well represented as an information cascading process, during which decentralized nodes in a network environment act on the basis of how their neighbours act at earlier time (Yu et al. 2016). Given an influence diffusion model m and an initial seed set S, the final revenue is defined as the expected final number of active nodes, which is denoted by $R(G,m,S)$. A seed set S is initialized under a seeding strategy x. Due to budget constraints, the size of S is limited. The influence maximization problem is defined as finding the optimal seeding strategy x^* to maximize the final influenced size, which is denoted as the Equation (1).

$$\begin{aligned} &x^* = \underset{x}{\operatorname{argmax}}\, R(G,m,x(G)) \\ &s.t. |S|=|x(G)|=k \end{aligned} \tag{1}$$

In this paper, we consider the influence diffusion model of social marketing based on a propagation model inspired from the susceptible/infective/recovered (SIR) model (Saito et al., 2008). Due to similar patterns in the spread of epidemics and social contagion processes, existing research have adopted the SIR model to study on the information diffusion among social medias (Woo & Chen, 2016). And we will discussed the propagation model and also formulate the solution process for the model over the next sections.

2.2 The Propagation Model

Agent-based modeling is a powerful simulation modeling technique, which enables people to deal with complex individual behavior in complex systems. Even a simple agent-based model can exhibit complex behavior patterns and provide valuable information about the dynamics of the real-world system that it emulates (Bonabeau, 2002). Therefore we adopt an agent-based model for learning user behaviour in social marketing.

First, we define three states of these agents in social networks, i.e., infectible F, propagated P and immune I. And, the behaviours of these agents could be receiving, accepting or delivering advertising information. Infectible agents refer to those who are able to change to be propagated after receiving advertising information. Propagated agents are inclined to accept advertising information and have positive willingness to deliver it to connected nodes. As for immune agents, they will not be affected by any advertising information and will not have any follow-on behaviour after receiving advertising information.

The agents' states are not stationary, and will transit among these three states during the spreading process of advertising information in social networks. At the initial time t_0, all agents are initialized with the state F, and when the social campaign is launched, a certain number N of infectible agents will be chosen to receive the advertising information. At time t_1, some infectible agents start to transit into propagated ones while some may transit into immune ones. Considering that the interventions of social marketing cannot be continuous through all the period because of time decay, some propagated agents will also transit into immune ones in our research. However, only propagated users can bring revenues for advertisers, thus advertisers should select proper initial seeds to spark the diffusion of advertising information, and encourage more agents to be propagated. The transition of users' states in the social network is depicted in figure 1.

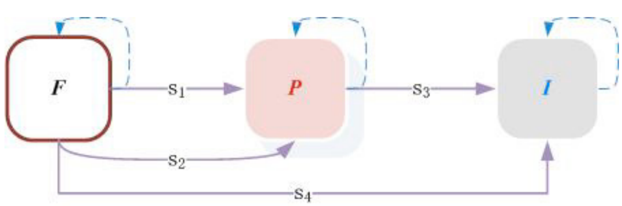

Fig. 1 Transition of users' states in social networks

$s_1: F \rightarrow P$ represents the external transition caused by the direct advertising displayed to the chosen users. There are two strategies for the advertiser to select proper infectible users. If the advertiser decides to display ads to the best matched users at initial time, user profiles, including income, gender, age and so on, should be taken into consideration to screen the best matched users. If the advertiser decides to select the most influential users in pursuit of better diffusion of social ads in the social network, they will value social factors above user profiles, including social activity, social connections, and so on.

For a specific user i chosen by the advertiser, we formulate the function $f_i = f(a_i, u_i)$ to describe the probability that he/she will transit to be propagated. Here, a_i represents user profiles, and u_i represents social factors, which means only those who are interested in this topic and active in the social network are willing to accept and deliver the advertising information.

$s_2: F \rightarrow P$ represents the internal transition caused by advertising information spread in social networks. When an infectible user i receives advertising information, there is a probability g_i that he/she will change to be propagated. The higher the similarity between the user i and his/her propagator k, the higher the possibility that he/she will accept the information. We define the similarity between user i and k as $g_{i,k}$, which can be formulated as $g_{i,k} = g(a_i, a_k)$. Also, in social networks, users are more likely to be affected by opinion leaders or influential users, therefore, we also consider the social power O_k of propagator k. Moreover, similar with the external transition, the social factor u_i of user i is also one of the deterministic parameters of g_i. Therefore, we have $g_i = g(g_{ik}, O_k, u_i)e^{-r(t-t_k)}$, where r is the decay rate of the information diffusion and t_k is the time when user k accepts the ad, since enthusiasm for many products or services naturally decays over time so that the willingness of user i to deliver advertising information in the network will decrease over time. When r is set to be infinite, social marketing tends to be viral marketing.

$s_3: P \rightarrow I$ describes that the propagator loses interest in advertising information and stops passing it to others any more. In this paper, we assume that the user profile is fixed during the promotion period, therefore the probability z_i of s_3 is considered to be only related to the time. Therefore, we have $z_i = 1 - e^{-r(t-t_i)}$. With time passing by, the desire of the user to deliver advertising information gradually diminishes or even vanishes.

For $s_4: F \rightarrow I$, some agents have original immunity, which means that even they receive advertising information at the initial time, they are not interested in it and will not spread it in the social network. The probability of this situation is given as $h_i = h(a_i, u_i)$, and $h_i + f_i < 1$.

2.3 Agent evolution

From the above, we can get that only the process of s_1 and s_2 can create revenues for the advertiser. Therefore we rewrite the Equation (1) as follows.

$$x^* = \underset{x}{\operatorname{argmax}}\, R(G,x) = \underset{x}{\operatorname{argmax}} \sum_t \left|\{i \mid i_{t-1} = F, i_t = P, i \in G\}\right|_x \tag{2}$$

The evolution of the agents' states is calculated using Algorithm I according to Figure 2. We conduct computational experiments to compare revenues of the two typical strategies in the next section.

3. EXPERIMENTS

In this section, we design experiments to make further investigation of our models and solutions. The agent-based propagation model will be validated in three typical network structures, namely Erdős–Rényi (ER) random graph, Watts-Strogatz (WS) small world graph and Barabasi-Albert (BA) scale-free graph.

Algorithm 1 Agent Evolution Algorithm

```
Input:
  the social network, G; the given seeding strategy, x;
Output:
  the final revenue, R;
initialize t_0 = 0, t_f = T, state(∀i ∈ G) = F,
the seeds set C ⇐ chooseSeeds(G, x), R = 0
for each i ∈ C do
  if random() < S_1(i) then
    state(i) ⇐ P, t(i) ⇐ 0, R ⇐ R + 1
  else {random() < S_4(i)}
    state(i) ⇐ I
  end if
end for
for t ∈ [t_0 + 1, t_f] do
  ps ⇐ {i|state(i) = P, i ∈ G}
  ns ⇐ {j|∃(j, i) ∈ G, i ∈ ps}
  for i ∈ ns do
    if random() < S_2(i) then
      state(i) ⇐ P, t(i) ⇐ 0, R ⇐ R + 1
    else {random() < S_4(i)}
      state(i) ⇐ I
    end if
  end for
  for i ∈ ps do
    if random() < S_3(i) then
      state(i) ⇐ I
    else
      t(i) ⇐ t(i) + 1
    end if
  end for
end for
return R
```

Fig. 2 Agent Evolution Algorithm

3.1 Experimental Settings

First, we build a group of agents according to a real-world census data of Beijing in China in 2000, in which the overall number of the sampled population is 13297. Each agent is randomly mapped to a real person's profile, which contains 74 features including gender, age, career information and so on. Furthermore, each agent is assigned with a random variable from a two-sided truncated normal distribution as the social factor. Specifically the distribution is given as $u \sim (0.5, 0.5^2), 0 < u < 1$.

Next, we construct 3 sets of randomly generated social networks.

- 10 ER random graphs

In the case of the ER graphs, there is an adjustable parameter p representing the probability of connecting between two nodes, which is set in the range from 0.001 to 0.01 at intervals of 0.001 in our experiments. Thus, we have 10 different random graphs.

- 15 WS small world graphs

In the WS graphs, each node is connected to k_1 nearest neighbours. The parameter k_1 is set to be an integer in $[2,16]$ with the interval of 1. So we have 15 small world graphs.

- 10 BA scale-free graphs

During the construction of the BA graphs, a new node is attached to k_2 existing nodes. The parameter k_2 is also set to be an integer in $[1,10]$ with the interval of 1 to build 10 scale-free graphs.

In all these social networks, each node refers to an agent and each edge refers to a social connection between agents.

Then, we study two strategies: the targeting strategy and the influencer strategy as well as their corresponding revenues in the experimental environment we set. The former selects agents in the top-100 s_1 ranking, while the latter selects agents in the top-100 degree ranking.

In each social network, we implement a group of experiments. Each group consists of 11 experiments performed under different decay rates, which fall into an interval of [0, 10]. For a pair of social network and decay rate, each experiment is run ten times and the final revenue is the mean value of these ten experimental results, considering stochastic decisions on information delivery of agents. Besides, the number of iterations during the period T of evolution is set to be 10.

3.2 Case I: Unrestricted initial seeds

In this case, the initial propagated agents are free to share advertising information to everyone in the neighbourhood. Experimental results are shown in Figure 4, 5 and 6, which describe the variations of total revenues in the ER graphs, the WS graphs and the BA graphs, respectively.

For both strategies in all types of social networks, the revenue increases significantly while the decay rate r decreases when $r < 1.5$, and there is no obvious change of the revenue with decay rates when $r > 1.5$.

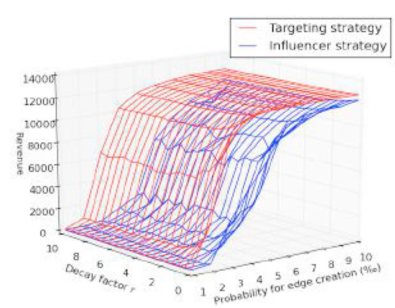

Fig. 4 Case I: Variation of final revenues in the ER graphs

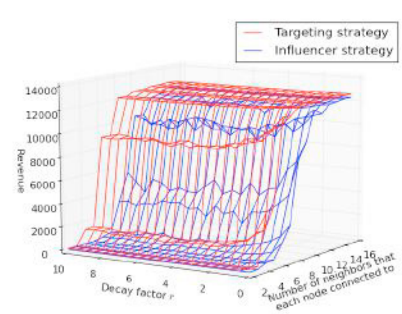

Fig. 5 Case I: Variation of final revenues in the WS graphs

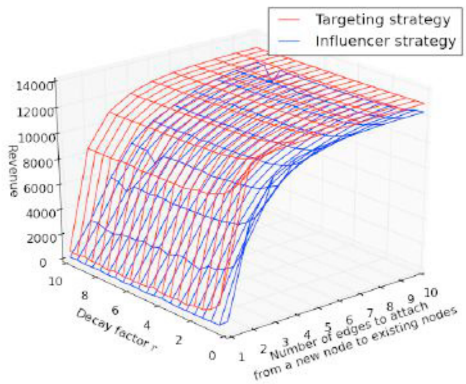

Fig. 6 Case I: Variation of final revenues in the BA graphs

Also the revenue increases when the connectedness of social networks increases along with the increase of p, k_1 and k_2. However, when the connectedness increases to reach a certain amount, its growth speed slows down. Thus we can draw the conclusion that the promotion effect is positively correlated to quantity of social connections, yet negatively correlated to the decay rate of advertising information. When $r > 1.5$, propagated agents will lose interests in a short time and transfer into immune with a high probability. Under these circumstances, most propagated agents share information only at the time when they are infected.

The targeting strategy outperforms the influencer strategy under almost every situation. It is due to that the influencer strategy selects seed agents with high degrees, which are willing to delivery information to a wide range of agents. In consideration of the random selection process of user profiles, we propose a reasonable assumption that the similarity with neighbor nodes follows a same distribution for every agent. Therefore, the higher is the degree, the more are the dissimilar neighbors. As a result, the broadcast-to-all behaviour performed by the initial seeds under the influencer strategy will cause negative effects to transfer a lot of infectible agents into immune thus reduce the number of infectible ones at the first few iterations of the evolution process. On the contrary, the targeting strategy can avoid this problem.

3.3 *Case II: restricted initial seeds*

In this case, the initial propagated agents are restricted to share advertising information only to similar infectible neighbours. Experimental results are shown in Figure 7, 8 and 9, which describe the variations of final revenues in the ER graphs, the WS graphs and the BA graphs, respectively.

The trend of revenue variation performs much the similar as that in Case I. For a pair wise of social network and decay rate, the revenue in Case I is generally larger than that in Case II under the targeting strategy, which is mainly caused by limitation of iteration times, as the diffusion rate is much slower in Case II than that in Case I. However, the revenues of the influencer strategy in these two cases show just the opposite conclusion to that of targeting strategy does, which benefits from the filtering of dissimilar agents.

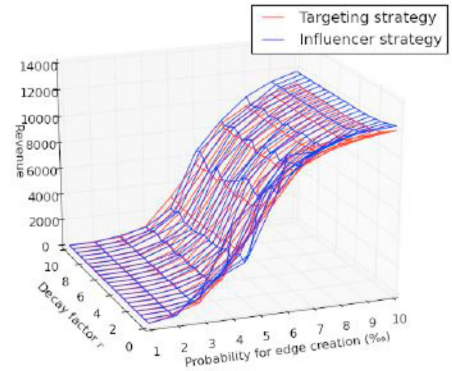

Fig. 7 Case II: Variation of final revenues in ER graph

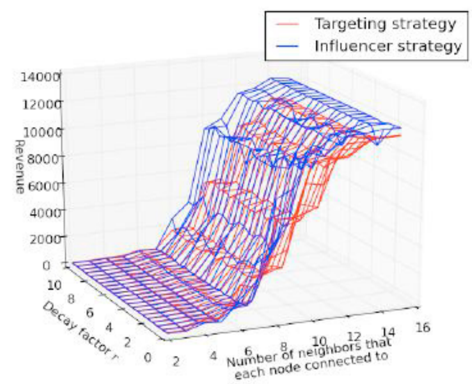

Fig. 8 Case II: Variation of final revenues in WS graph

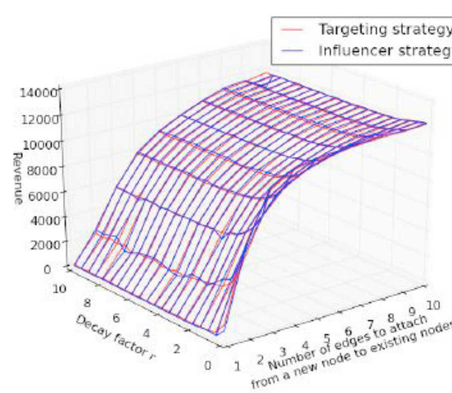

Fig. 9 Case II: Variation of final revenues in BA graph

In this case, the two strategies tie with each other in BA graph; moreover, the influencer strategy outperforms the targeting strategy in the other graphs, which indicates that manipulating sharing behavior of the most important nodes will greatly improve final revenues of the advertisers. For influencer strategies, although the restricted initial seeds will result in a smaller coverage of information diffusion, the effective delivery that makes receivers be interested in ads or even convert to keep delivering it may significantly increases. Under the assumption mentioned above that the similarity with neighbor nodes follows a same distribution for every agent, delivering advertising information to more similar people by the initial seeds under the influencer strategy will transfer more infectible agents into immune at the beginning of experiments than that of the targeting strategy.

4. MANAGEMENT INSIGHTS

Our research provides straightforward suggestions for the advertisers to select targeted users as initial seeds in social marketing. Intuitively, when adopting the social advertising, selecting influential users as the seed sets may be better than targeted users. However, our research proves that influencer strategy does not outperform the targeting strategy dominantly in all social networks, and both strategies show their superiorities under different situations.

Targeting strategy is a good choice when user profiles are perfectly accessible. However, in practice, due to the user privacy and technical difficulties, it is challenging for the advertisers to get accurate user profiles; while discovering influential users in online social networks is much easier, since the rapid growth of online social networks makes influential users powerful in information diffusion, e.g. VIP users in Microblog. However, as the widely applied broad-to-all approaches in social media, advertising information shared by influential users may not work well or even cause negative effects. Thus, the advertisers adopting influencer strategy should carefully manipulate the initial seeds and manage the promotion process to make sure that the advertising information is delivered to those potential customers.

From our analysis above, it can be concluded that the decay rate has a great impact on the revenue achievement; therefore the advertisers are suggested strongly to intervene in the promotion process to consolidate the advertising impressions to users. Also, they should pay enough attention to the selling process to maintain good relationships with existing customers and assure quality of products and services, since more satisfied customers and higher quality products will help keep smaller decay rates (Stephen & Berger, 2009).

5. CONCLUSIONS

In this paper, we investigate the diffusion of advertising information and transfer of user states in social networks with an agent-based model. We run experiments in three typical social networks using real-world census data of China. Our research can provide reliable support for the advertisers to determine the initial seeds in social marketing.

As decay rate is related not only to product but also to user characters (Stephen & Berger, 2009), we will introduce individual decay rate allowing for heterogeneity across agents in our future works. Besides, we plan to investigate more complex strategies, e.g. making direct advertising to users in stages.

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REFERENCES

Kotler, P., & Zaltman, G. (1971). Social marketing: an approach to planned social change. *The Journal of Marketing*, 3-12.

Dehghani, M., & Tumer, M. (2015). A research on effectiveness of Facebook advertising on enhancing purchase intention of consumers. *Computers in Human Behavior*, *49*, 597-600.

Li, Y. M., & Shiu, Y. L. (2012). A diffusion mechanism for social advertising over microblogs. *Decision Support Systems*, *54*(1), 9-22.

Wang, W., Yang, L., Chen, Y., & Zhang, Q. (2015). A privacy-aware framework for targeted advertising. *Computer Networks*, *79*, 17-29.

Todi, M. (2008). Advertising on social networking websites. *Wharton Research Scholars Journal*, 52.

Barbu, O. (2014). Advertising, Microtargeting and Social Media. *Procedia-Social and Behavioral Sciences*, *163*, 44-49.

McKenzie-Mohr, D. (2013). *Fostering sustainable behavior: An introduction to community-based social marketing*. New society publishers.

Stead, M., Gordon, R., Angus, K., & McDermott, L. (2007). A systematic review of social marketing effectiveness. *Health education*, *107*(2), 126-191.

Stephen, A. T., & Berger, J. A. (2009). 'Creating Contagious: How Social Networks and Item Characteristics Combine to Spur Ongoing Consumption and Reinforce Social Epidemics. *New York: Columbia University*.

Bampo, M., Ewing, M. T., Mather, D. R., Stewart, D., & Wallace, M. (2008). The effects of the social structure of digital networks on viral marketing performance. *Information systems research*, *19*(3), 273-290.

Erdos, P., & Rényi, A. (1960). On the evolution of random graphs. *Publ. Math. Inst. Hung. Acad. Sci*, *5*(1), 17-60.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world'networks. *nature*, *393*(6684), 440-442.

Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *science*, *286*(5439), 509-512.

Woo, J., & Chen, H. (2016). Epidemic model for information diffusion in web forums: experiments in marketing exchange and political dialog. *SpringerPlus*, *5*(1), 66.

Saito, K., Nakano, R., & Kimura, M. (2008). Prediction of information diffusion probabilities for independent cascade model. In *International Conference on Knowledge-Based and Intelligent Information and Engineering Systems* (pp. 67-75). Springer Berlin Heidelberg.

Yu, L., Cui, P., Wang, F., Song, C., & Yang, S. (2016). Uncovering and predicting the dynamic process of information cascades with survival model. *Knowledge and Information Systems*, 1-27.

Hinz, O., Skiera, B., Barrot, C., & Becker, J. U. (2011). Seeding strategies for viral marketing: An empirical comparison. *Journal of Marketing*, *75*(6), 55-71.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, *99*(suppl 3), 7280-7287.