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Information diffusion through social networks: The case of an online petition

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ABSTRACT

People regularly use online social networks due to their convenience, efficiency, and significant broadcasting power for sharing information. However, the diffusion of information in online social networks is a complex and dynamic process. In this research, we used a case study to examine the diffusion process of an online petition. The spread of petitions in social networks raises various theoretical and practical questions: What is the diffusion rate? What actions can initiators take to speed up the diffusion rate? How does the behavior of sharing between friends influence the diffusion process? How does the number of signatures change over time? In order to address these questions, we used system dynamics modeling to specify and quantify the core mechanisms of petition diffusion online; based on empirical data, we then estimated the resulting dynamic model. The modeling approach provides potential practical insights for those interested in designing petitions and collecting signatures. Model testing and calibration approaches (including the use of empirical methods such as maximum-likelihood estimation, the Akaike information criterion, and likelihood ratio tests) provide additional potential practices for dynamic modelers. Our analysis provides information on the relative strength of push (i.e., sending announcements) and pull (i.e., sharing by signatories) processes and insights about awareness, interest, sharing, reminders, and forgetting mechanisms. Comparing push and pull processes, we found that diffusion is largely a pull process rather than a push process. Moreover, comparing different scenarios, we found that targeting the right population is a potential driver in spreading information (i.e., getting more signatures), such that small investments in targeting the appropriate people have 'disproportionate' effects in increasing the total number of signatures. The model is fully documented for further development and replications.

1. Introduction

Petitions are often formal letters or documents submitted to government organizations or public entities to convey requests on certain issues. Petitions represent the attitudes or opinions of petition initiators, as well as people who sign them. The initiators usually want to receive as many signatures as possible to raise awareness and maximize the impact of petitions. Traditional petitions collect handwritten signatures, but with the rise of the Internet and digital communications, online petitioning has become widespread. People regularly use email and social networks as platforms to launch their petitions due to their convenience, efficiency, and significant broadcasting power. For example, Care2, which was initiated in 1998, is a large petition website covering a broad spectrum of topics, such as animal rights, environment, politics, and human rights. Petitions on this site had received more than 373 million signatures as of September 2015. Many other sites provide similar services. People who want to launch petitions can follow simple processes to set up free online petitions and collect signatures. People interested in signing petitions visit the petition's webpage, fill in basic personal information, and submit the form. There is also an optional choice of sharing petitions with others through online social networks.

The spread of petitions in social networks raises various theoretical and practical questions: What is the diffusion rate? What actions can initiators take to speed up the diffusion rate? How does the behavior of sharing between friends influence the diffusion process? How does the number of signatures change over time? In order to address these questions, the mechanisms of the petition diffusion process need to be investigated and understood. In this research, we used system dynamics modeling to specify and quantify the core mechanisms of petition diffusion online. We used a case study to specify

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Table 1
Sharing, reminder, and forgetting variables.

Factor	Variables	Reference
Sharing	Satisfaction, length of relationship, novelty	De Bruyn and Lilien (2008)
Reminders	Familiarity, complexity, novelty	Tellis (1997)
Forgetting	Transience, absent-mindedness, misattribution, bias, socialization, interference	Percy (2004), Reitman (1971), Struben (2004)

the diffusion process of a petition, and based on empirical data, estimated the resulting dynamic model. Comparing different scenarios provided additional insights into the pragmatics of similar diffusion processes.

This article is organized as follows: Section 2 reviews the theoretical foundations of diffusion models; Section 3 presents the data and methods, including the case study and the developed model; Section 4 presents analysis, including model testing and calibration, comparison of our model with the Bass diffusion model, sensitivity analysis of the estimated model to different scenarios, and discussion on our modeling approach. The study is concluded in Section 5.

2. Theoretical foundations

2.1. Diffusion models

The phenomenon of diffusion has been widely studied due to its potential impact in various fields, such as epidemiology (Raj, Kuceyeski, & Weiner, 2012), marketing (Kim, Lee, & Ahn, 2006), and social behavior (Susarla, Oh, & Tan, 2012). Understanding contagion phenomena, product/service adoption and changing cultural features all depend on how people influence each other, which is the hallmark of diffusion models (Rogers, 2003). Better understanding can also enable decision makers to design policies that maximize benefits, minimize risks, and provide control over time. A basic diffusion process requires two main actors and one binding element. The transmitter (also called adopter and infectious) and receiver (also called potential adopter and susceptible) constitute the main actors, and various communication and contact channels establish the means to link them (Baran, 2010). Since the early 20th century (Kermack & Mckendrick, 1932), a vast literature has used such models to understand, predict, and control epidemics. In marketing applications, word of mouth (WOM) and advertisement are the key channels bridging early adopters and potential adopters of new products and services (Bass, 1969; Rogers, 1976). Various studies have looked at the spread of ideas and norms through diffusion processes (Centola, 2010).

The spread of online petitions on the Internet also follows a similar mechanism. Instead of purchasing products, signing petitions is the key choice that people may make in response to messages they receive from others. Potential adopters are defined as potential signatories, and the rate of diffusion can be measured by the number of new signatures per unit of time. Peer-to-peer word of mouth is one channel for spread of petitions. Parallel to the concept of advertising, first announcements followed by reminders may be considered, besides peer-to-peer mechanisms of spread.

2.2. Diffusion models in online social networks

Online social networks such as Facebook, Twitter and Google Plus are now integrated into people's daily lives. This magnifies the importance of studying mechanisms that affect the spread of information through these networks. Here we review diffusion models in two streams of research: marketing literature and expert and intelligent systems literature.

A large literature on marketing of products and services focuses on the effect of different factors, such as word of mouth, reminders, and forgetting on diffusion processes. These topics are mainly addressed from the business and psychological points of view (De Bruyn & Lilien, 2008; Percy, 2004; Tellis, 1997). De Bruyn and Lilien (2008) highlighted awareness and interest as the key factors in a diffusion process. Both of these factors influence the chances of adopting a product, service, or as in the case of this study, signing a petition, and as such should be further elaborated on. Tellis (1997) and Percy (2004) studied the influence of reminders and forgetting on awareness. Bentley and Earls (2008) discussed the nature of the diffusion process, whether it is a push process (a top-down form of diffusion) or a pull process (a bottom-up form of diffusion). De Bruyn and Lilien (2008) also proposed usefulness, trust, and customization as core elements of level of interest. Table 1 presents some of the relevant factors related to sharing, reminders, and forgetting. We benefit from these factors in our model.

A growing body of research in expert and intelligent systems also concentrates on information diffusion, which covers a wide range of theoretical and practical contributions. Here, we provide a brief overview of some of the studies and then discuss our contributions.

Li et al. studied the efficiency of information diffusion under information overload on Facebook-like (Li & Sun, 2014) and Twitter-like (Li, Li, Wang, & Zhang, 2014) social networks based on the structure of the network and user behavior. They proposed a metric to measure information diffusion efficiency and analyzed its values on simulated social networks with different characteristics. Yang et al. (2015) studied the effects of users' social roles on information diffusion through social networks. They proposed a role-aware information diffusion model, which can be used to predict whether a user will repost a specific message at the micro-level and the scale of a diffusion process at the macro-level. Taxidou and Fischer (2014b) introduced a system for real-time analysis of information diffusion on Twitter. They also analyzed information diffusion on Twitter based on social graphs (star-shaped vs. complex) and types of influence (Taxidou & Fischer, 2014a). Cheng, Adamic, Dow, Kleinberg, and Leskovec (2014) defined temporal and structural features of posts as key predictors of cascade size in information diffusion. Their findings showed that the breadth, rather than depth, of a cascade is a better indicator of large cascades. Network's degree, PageRank and k-core were also studied as other cascade size predictors by Pei, Muchnik, Andrade, Zheng, and Makse (2014). They found k-core to be the only factor influencing information spread on social networks. Liu and Zhang (2014) proposed a dynamic susceptible-infected-recovered (SIR) model for information diffusion through social networks in which individuals can break links and reconnect to their second-order friends. Their proposed strategy increases the speed at which information spreads on social networks. Kim, Newth, and Christen (2014) analyzed behavioral patterns of news diffusion through mainstream news websites, social networks, and blogs in terms of activity, reactivity, and heterogeneity. They found that mainstream news websites are the most active, social networks are the most reactive, and blogs are the most persistent. Li, Qian, Jin, Hui, and Vasilakos (2015) studied the efficiency of information diffusion on social networks of microblogs by studying 10 million user profiles from Sina Weibo (a Chinese microblog) and 41.7 million profiles from Twitter. Liu, Xie, Hu, and Chen (2014) explored the effects of affinity of information with people on information cascade size. They also discussed the effects of affinity, average degree of the network and the probability of people losing their interest in the information on the size of information diffusion.

In our study, we considered push and pull processes from the marketing literature such that sending announcements to a target