Communications of the Association for Information Systems

Volume 36 Article 20

3-2015

How Rumors Spread and Stop over Social Media: a Multi-Layered Communication Model and Empirical Analysis

Zhiwei Qin
College of Engineering Peking University, China, qzw@pku.edu.cn

Jian Cai
School of Innovation and Entrepreneur Peking University, China

H.Z. Wangchen
College of Engineering, Peking University, China

Follow this and additional works at: https://aisel.aisnet.org/cais

Recommended Citation

Qin, Zhiwei; Cai, Jian; and Wangchen, H.Z. (2015) "How Rumors Spread and Stop over Social Media: a Multi-Layered Communication Model and Empirical Analysis," *Communications of the Association for Information Systems*: Vol. 36 , Article 20.
DOI: 10.17705/1CAIS.03620
Available at: https://aisel.aisnet.org/cais/vol36/iss1/20

This material is brought to you by the AIS Journals at AIS Electronic Library (AISeL). It has been accepted for inclusion in Communications of the Association for Information Systems by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

Communications of the Association for Information Systems

CAIS

How Rumors Spread and Stop over Social Media: a Multi-Layered Communication Model and Empirical Analysis

Zhiwei Qin

College of Engineering

Peking University, China

qzw@pku.edu.cn

Jian Cai

School of Innovation and Entrepreneur

Peking University, China

cai@pku.edu.cn

H.Z. Wangchen

College of Engineering,

Peking University, China

Abstract:

In this paper, we present a multi-layered communication (MLC) model that includes a trust-constructing procedure that can be used to explain how rumors spread and stop over social media. We define two structures in our MLC model: the social structure (SS) in the social layer, and the communication structure (CS) in the communicating layer. We propose two trust-building mechanisms (TBM): the social-based TBM (SBTBM) and the communicating-aimed TBM (CATBM). We discuss the trust-constructing procedure to demonstrate that an individual will sequentially decide to spread information based on three factors: the opinion environment, the individual's social influence, and the cost to confirm the information. The model predicts that individuals will tend to create links with others in social layers to extend their social structures (social clustering principle) when they use social media. Thus, a rumor will spread because a spreading core is formed in the CS. However, a rumor will be stopped by interactions that occur in the SS. Our empirical case supports this prediction. We analyzed the topology of CS to indicate how a spreading core forms and CS evolves, and how a rumor stops spreading because social behaviors in SS encourage the development of more accurate information based on reality.

Keywords: Social Media, Social Structure, Communication Structure, Trust-Building Mechanism, Rumor-Spreading; Rumor-Stopping.

Volume 36, Article 20, pp. 369-391, March 2015

The manuscript was received 11/03/203 and was with the authors 6 months for 3 revisions.

Communications of the Association for Information Systems

How Rumors Spread and Stop over Social Media: a Multi-Layered Communication Model and Empirical Analysis

I. INTRODUCTION

Since its development, social media has become new platform for supporting interactive communications that occur between individuals, organizations, and communities. Social media has exerted a significant impact on traditional media as demonstrated by its growing number of users. For example, as of September 2012, Facebook recorded over one billion active users (Fowler, 2012). In 2012, Twitter recorded over 500 million active users. It also recorded over 340 million tweets and 1.6 billion search requests per day (Twitter, 2011). By mid-2012, Sina's Weibo, a micro-blogging website in China, had registered 368 million users. Over 100 million messages are posted on Weibo daily (Cao, 2012).

However, because social media has seen such a significant rise in users, rumor spreading has become an increasingly serious issue. Specifically, We focus on rumor-spreading behavior over social media because: (1) extensive rumor spreading has deeply influenced the quality of information available on social media, and (2) The rumor behavior model illustrates a specific pattern of rumor spreading rather than normal information spreading. .

Therefore, determining the differences of users' information acquisition behaviors between social media and traditional media is important. Prior research has indicated that, in contrast with more traditional communication tools, social media allows firms to engage in timely and direct end consumer communication at lower costs and higher levels of efficiency (Kaplan & Haenlein, 2010). Generally, by an structured and targeted discussion on social media, topics and information are initially produced and rapidly spread by social contacts across networks.

How do rumors spread over these networks? In particular, how do rumors spread over social media? Many studies have discussed rumor spreading and information dissemination based on oversimplified social topology (e.g. Daley & Kendal, 1965). Additional studies have developed a new model for rumor spreading that occurs over the Internet. However, the Internet's topological structure seems far more similar to society's structure (Moreno, Nekovee, & Pacheco, 2004; Chierichetti, Lattanzi, & Panconesi, 2009).

To gain a better understanding of how rumor spreading begins and ends over social media, we propose a new theoretical framework entitled the multi-layered communication (MLC) model. The MLC can be used to analyze specific communication patterns. We developed a trust-constructing procedure to identify critical issues that might influence individuals' decision making. We discovered that individuals live in a combined social and communicating world created by social media. Information can spread from social layers to communicating layers when individuals attempt to determine whether a rumor is true. The trust-constructing procedure is able to identify trends in rumor spreading. It can also determine when a rumor might end. Empirical data collected from actual social media can be used to discover how these specific communication patterns can influence a rumor's spreading structure and its entire lifespan.

This paper is organized as follows: in Section 2, we define the research problem and discuss previous research to contextualize this study and clarify some basic concepts. In Section 3, we propose and explain a theoretical MLC model that might be used to analyze these specific communication patterns. We also discuss the trust-constructing procedure. In Section 4, we apply the MLC model and its trust-constructing procedure to determine how rumor spreading occurs and how rumors eventually end. In Section 5, we describe an empirical study we performed to examine this theoretical research model. Finally, in Section 6, we discuss this study's findings and limitations. We also provide suggestions for future research directions.

II. THEORETICAL BACKGROUND

Rumors can be defined as unverified accounts or explanations of events that circulate from person to person. These explanations might be related to objects, events, or issues that demand public concern (see Peterson & Gist, 1951).. On a social network, public concern will grow stronger when rumors are spread by extensive social links. The SIS model, a well-known model used to describe this phenomenon, was introduced by Daley and Kendall (1965)˙ The SIS model was inspired by the SIR model used in epidemiology (Pastor-Satorras & Vespignani, 2001). In the SIS model, homogeneously mixed populations are classified into three categories. "S" is used to represent spreaders (i.e., individuals who actively spread a rumor), "I" to represent ignorants (i.e., individuals who have not yet heard a rumor. Hence, they are susceptible to becoming informed), and the second "S" to represent stiflers (i.e., individuals who have already been informed of the rumor but have ceased spreading it) (Nekovee, Moreno, Bianconi, & Marsili, 2007). The SIS model has defined the research style of information dissemination at the societal level in recent research papers because it has been used repeatedly to determine topic flow in blogs, “word-of-mouth” in product marketing, and rumor spreading on social networks.

The SIS model’s determinations of the general spreading behaviors related to rumors are based on three main hypotheses: (1) the degree populations’ distribution is homogeneous, (2) the population is mixed homogeneously, and (3) the possibility of individuals’ removal due to death is not considered. Thus, the significant result for this model is the general prediction of a non-zero spreading threshold λ_c. The standard case states that, when the spreading rate is $\lambda \geq \lambda_c$, the rumor will spread persistently over time. When the spreading rate is $\lambda < \lambda_c$, the rumor will quickly die out exponentially. For quite some time, this model and its philosophical concepts have predominated among rumor-spreading theories.

However, one of the SIS model’s limitations is that it oversimplifies network topology. A significant number of empirical studies on social links, webpage links, and instant messaging networks clearly have demonstrated the highly right-skewed degree distribution of these topologies. They are far more complicated than homogeneously uniform networks (Nekovee et al., 2007). On the other hand, the SIS model completely equates the mechanism with epidemical spreading in a crude way that fails to describe rumor spreading over social networks (Balthrop, Forrest, Newman, & Williamson, 2004). Rumors are not viruses. Individuals can rationally decide whether they should believe or spread a rumor. Their decisions are based on their locations in the network, the layers in which those decisions were made, and the location(s) from which the information originated.

In fact, with respect to the social structure in which individuals engage in daily social interactions, and with respect to the virtual world in which individuals engage in “influential interactions” through their communicating links, the rumor-spreading process is determined by individuals’ sequential decisions made on different layers.

III. MULTI-LAYERED COMMUNICATION MODEL (MLC MODEL)

MLC Model for Knowledge Formation

Whether we discuss a social interaction or telecommunication system, we use the term “layered approach” to describe the way in which communicating entities are disjoined in the horizontal dimension of network space. Layering has always been considered a fundamental principle in system design and engineering because: (1) layering is the main principle used to comprehend a complicated system by examining its levels of abstraction, and (2) layering is the main principle used to decompose system architecture by examining its layers of service and functionality (Herzberg & Broy, 2004). Functional layered intelligence (FLI), a layered architecture reference model, is designed to enable the integration of human-like intelligence functions into technological systems to achieve specific desired functionalities (Dimkovski & Deeb, 2006).

Therefore, we propose the multi-layered communicating (MLC) model , which was inspired by the FLI model and the Internet’s TCP/IP layered network model, to explore the principles of human behavior inherent in disseminating information and forming knowledge (see Figure 1 for the MLC model). The upper two layers are generally defined as social layers. The lower two layers are generally defined as communicating layers. In these two layers, the single social layer, which is used for forming knowledge, and the single communicating layer, which is used for disseminating information, combine to form the applied layers. The interacting and connecting layers serve as the infrastructure for the applied layers that collect data and information. This layered approach to the communicating progress is consistent with the way people communicate with one another: People receive and publish opinions through their communicating links. However, they discuss and build long-term trust through their social links.

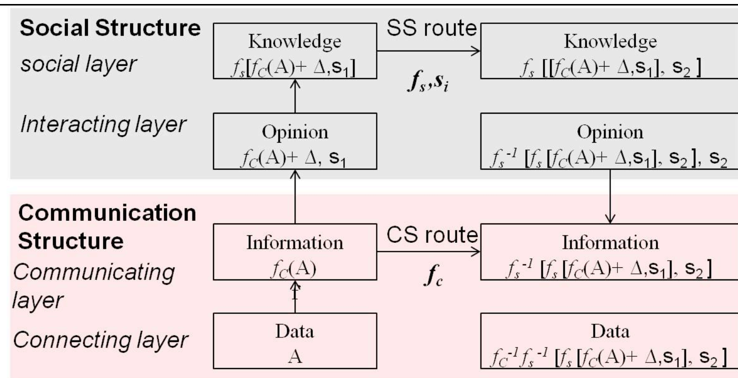

Figure 1. Multi-Layered Communication Model with SS Communicating Patterns

Specifically, creating knowledge through the MLC model can be explained by describing the following typical process. Man A (we use gendered terms for ease of reference) has to communicate with a huge system (media, online BBS, social media, and so on). He accesses a physical communication network to acquire data A. He uses his mobile device to receive information $f_C(A)$. The mobile device works by translating data A into signals Person A can understand. Person A may take one of two actions: 1) spread $f_C(A)$ out without making any revisions through the communication structure route, or 2) transfer $f_C(A)$ to his social layers to search for additional accurate opinions based on reality. He will then create knowledge and spread it through the social structure route (we discuss the two actions mentioned above in Sections 4 and 5). The trust-building mechanism primarily promotes the creation of links that connect physical and social levels. If man A prefers action 2, then we can state that he has chosen SS behavior (see Figure 3) because he adopted his own opinion when he revised $f_C(A)$ into $f_C(A)+\Delta$. Δ represents man A's opinion amendment. Then, the original information evolved as knowledge under a specific social state, and information $f_C(A)+\Delta$ was transformed into knowledge $f_S[f_C(A)+\Delta, s_1]$ because he made a social choice function (i.e., the function that maps each environment of available social states s_i for any given set of orderings). When man A decided to inform others, the inverse operation of social choice function f_S^{-1} under other specific social states will transform the knowledge in others' $f_S^{-1}[f_S[f_C(A)+\Delta, s_1], s_2]$. Then, the inverse technical function f_C^{-1} will transform the original $f_C(A)$ into information $f_C^{-1}f_S^{-1}[f_S[f_C(A)+\Delta, s_1], s_2]$. Simultaneously, when this information is received by others' physical layers, another turn of communication begins. Based on the MLC model, knowledge has been formed through other people's social value systems and through man A's social structure.

Connecting Layer

In this layer, people become physically linked when they transfer data. We consider the topology in this layer to be technical (e.g., the telephone-contacting network, the email-contacting network (Newman, Forest, & Balthrop, 2002), and so on). In this layer, the nodes represent terminals and the lines represent connecting ways. Links in this layer are responsible for the construction of physical links. However, they are not responsible for effective communication.

Communicating Layer

In this layer, people become physically linked when they transfer information through communicating activities motivated by information-acquisition behavior that allows people to decide with whom they want to connect and whom they want to observe (Celen & Hyndman, 2012). Information can be acquired through a trust-building mechanism (see the "The trust-building mechanism's effects on the multi-layered communication model" subsection below). Typical systems (e.g., the World Wide Web (WWW) webpage network, the author collaborative network, and the metabolic network) operate primarily in this layer. Fewer networks appear here rather than in the former layer because physical links that appear in the connecting layer that contain no information will be deleted in this layer. Effective communication is the focus in this layer rather than other details such as a link's strength or weakness. In fact, link properties are the key elements that influence the information dissemination's progress. However, they become the focus in the following layers.

Interacting Layer

In this layer, people become socially linked when they transfer opinions through random discussions. Long-term trust can solely develop when this layer operates effectively. Network structure is self-organized because optimal behaviors required for selecting interactions is decided by a Bayesian sequential link procedure (Celen, 2012). In general, debate results will be determined by the information itself rather than by the topological structure. A minority opinion spreading model that Galam (2002) introduced reveals that the minority opinion may finally dominate because of cultural tendencies or common knowledge. This fact is reminiscent of the interaction mechanism that indicates how people organize in this layer to engage in random discussions. It is also reminiscent of how common opinions that develop during a discussion eventually evolve into an individual's personal knowledge.

Social Layer

In this layer, people become psychologically linked when they create social trust links that eventually create knowledge. Knowledge becomes a stable reflection of reality in people's minds after it originates from data and is experienced as states of information and opinions. People construct their social structures based on knowledge-formation behaviors. This means that people are layered and structured to filter data, receive information, and form knowledge based on logical reasoning and rational analyses supported by the varied opinions that other peers in this system provide. Knowledge formation is based on the construction of social trust among people (see the "The trust-building mechanism's effects on the multi-layered communication model" subsection below).

Links based on social trust are more stable than those based on communication. For this reason, the topological structure of social layers is more reliable than that of communicating layers. Several well-known networks (e.g., the small-world network) (Watts & Strogatz, 1998) are based on the core mechanism of the social-topological structure. Barabási and Albert's (1999) scale-free network described the inner mechanism that operates in the communicating-topological structure.

Social Structure (SS) and Communication Structure (CS)

The MLC model essentially describes the different topological structures contained in each layer. These structures consist of people and their links. The definitions of SS and CS are best explained by the following example: man A communicates with woman B. Woman B is one of man A's social friends. This means that man A has constructed a (relatively stable) long-term trust link with woman B. Therefore, the communication route created between man A and woman B results in the creation of a specific structure known as a link of social structure. However, if woman B is the focus of man A only through man A's social media, and if man A is considered an entity in woman B's influential network but no social interactions occur between man A and woman B, then the communication method that develops between man A and woman B could be considered a link in the communication structure. To simplify, in our LC model, when one rumor spreads extensively, interactions that occur in social layers result in the emergence of many links. Figure 2 illustrates that these links eventually construct the social structure. Similarly, communications that occur in communicating layers motivate the emergence of self-organized links and construct the communication structure, which Figure 3 illustrates.

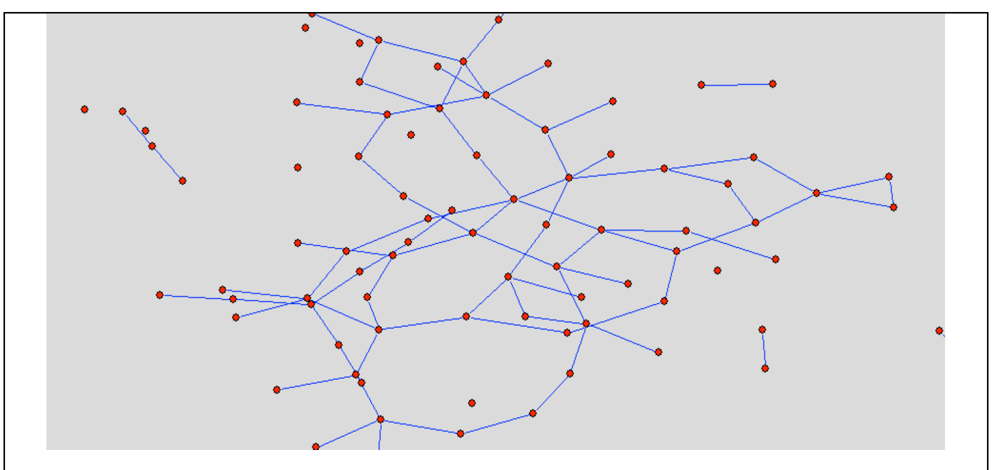

Figure 2. Topology of Social Structure

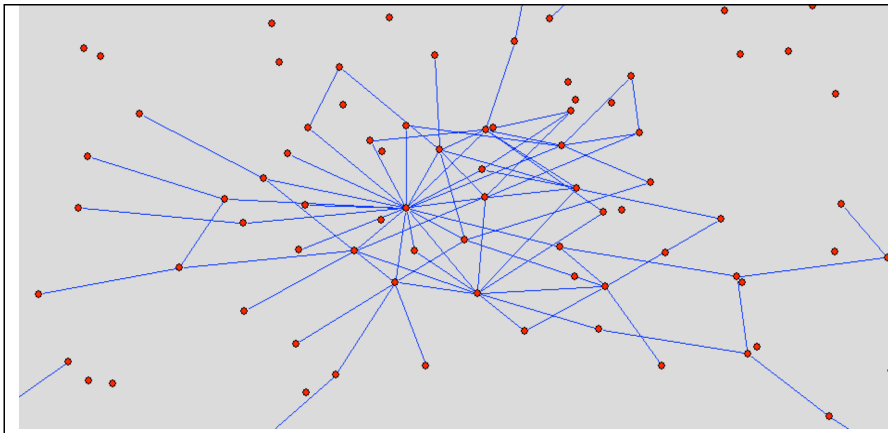

Figure 3. Topology of Communication Structure

Figure 2 illustrates a typical social structure in which each person maintains an average of two links. Locally formed links that appear in social layers lead to relatively large average distances between any two given persons. However, with respect to a limited number of long-distance links, the average distance of the entire network will be shortened dramatically. Figure 3 illustrates a typical communication structure in which some influential people can have more than 20 links. However, more than 50 percent of all people have no links at all. This “rich-get-richer” phenomenon reflects a distribution of the number of links owned by different people that strongly skews to the right. It is important to note that, although the distribution of links appears to be completely different, in Figure 3, people own an average of two links. These results are the same as the results shown in Figure 2.

At this point, it is important to review research related to SS and CS to examine how people’s decisions about individuals with whom they prefer to connect ultimately result in a very different topological structure.

In reality, people create gatherings in their social structures to discuss well-known issues in fragmented time. Then, these groups tend to produce fragile opinions because those opinions are based on discussions of information rather than on demonstrations (Galam, 2002). The WS model was introduced by Watts and Strogatz (1998). It was based on an ER random network model (Erdos & Rényi, 1960) that explored the inner mechanism that operates when a social structure that contains a small average distance forms. Basically, the structure consists of a uniform distributed network (Watts & Strogatz, 1998). They revised the ER model by creating relinks that offered some probability of improving the model’s strong hypothesis that people make links based on completely random opportunities. The WS model included one important rule known as high clustering or transitivity (Barrat & Weigt, 2000) in social interactions. This means that a heightened probability exists that two people will become connected directly to one another if they each possess another common neighboring friend. In addition, the WS model can predict the occurrence of one phenomenon, the small world effect. It relies on the reasonable explanation of “six degree of separation” that playwright John Guare proposed. It also relies on the results of a series of experiments performed by social psychologist Stanley Milgram in the 1960s (Milgram, 1967). In the essential mechanism that results in a small world phenomenon, only a limited number of long-distance links in the social structure will lead to a dramatic shortening of the average distance. However, they maintain the homogeneity of the overall distribution of networks. The main role of social interactions is to create local links among family, friends, or colleagues.

However, with respect to the Internet, many empirical studies have focused on networks’ observed degrees of distribution. These studies discovered that, for several contemporary systems, and, in particular, for the WWW, the Internet and email communication networks are typically asymmetrical networks. This means that the degree of distribution approximates a power law. This phenomenon occurs when a new communicating mechanism begins to operate. This results in the creation of a new communication structure that differs from the social structure. The Barabási and Albert (BA) model (Barabási & Albert, 1999) supposes that networks are not fixed. Rather, networks evolve over time. New people connect with *m* already existing people based on the preferential attachment (PA) rule. The so-called PA rule states that the probability that a new person will connect to an already existing candidate is proportional to the number of friends (degrees) possessed by each candidate. The BA model demonstrates that the degree of the BA network’s distribution follows a power law (Barabási, Albert, & Jeong, 1999) consistent with what can be observed in empirical studies. The BA network creates a scale-free property. Thus, in some studies, the BA network is also called a scale-free network, which implies that no average degree exists (e.g., the average height of people) that might represent an overall property of this network (Barabási, 2002). This is a main characteristic of communication structures because it focuses on influential communication and interaction. The citation network that Google uses, the author collaboration network that scientific papers use, and the metabolic networks that occur in biological organisms are good examples of the prominent nature of scale-free properties (Newman, Moore, & Watts, 2003) based on the PA principle's operation in communication structures.

Serge Galam introduced the minority opinion on the spreading phenomenon: he demonstrated how gathering and discussing principles affect social structure. In his model, repeated random-sized local discussions appeared to drive the majority reversal and the minority hostile view (Galam, 2003). For this reason, gathering discussions that occur in small groups are essentially important to producing common public opinions. Thus, social structure topology defines the dynamics of social discussions. Then, it defines the evolution of knowledge.

With respect to communication structures, the PA principle appears in search engines such as Google, in which the page rank algorithm first encourages a new webpage to connect with frequently cited webpages. As a result, this new webpage gains more and more point-in links and can be searched with greater probability (Page, Brin, Motwani, & Winograd, 1999).

In the subsection below, we examine social media such as Facebook, Twitter, and China's Weibo. Social media plays a very important role because it connects SS and CS. It constructs networks between social layers and communicating layers. It also combines social and communicating links. These links are used to make friends, discuss hot issues, and improve communication.

The Trust-Building Mechanism's Effects on the Multi-Layered Communication Model

Previous studies have reached limited conclusions about rumor-related behaviors because those studies solely focus on the network structures of lower layers and on a single layer in the MLC model. They examine the dynamics of rumor spreading on given topological structures (e.g., uniform network, small-world network, or scale-free network) based on mathematical modeling and simulation (Nekovee et al., 2007). These studies do not explain how rumors begin and end, where rumors originate, and why public opinion will change several times because they neglect the fact that people's social interactions occur in upper layers of the MLC model. For instance, the SIS model predicts that rumors spread when and only when their spreading rate is larger than the threshold. Rumors will ultimately end if the spreading rate decreases (Barabási & László, 2003). However, if the spreading rate remains unchanged, some rumors might suddenly die out, some might have relatively long lives, and some might even rise again after their demise.

Social interactions play important roles in communication. Generally, people acquire information through their communication structures. However, they form opinions, knowledge, or even beliefs through discussions and self-questioning. If an individual deeply believes a particular fact, that individual will tend to disseminate this information through their communication structure. Therefore, an individual's behaviors during communications are partially determined by decisions the individual makes in social layers. In fact, the evolution of communication structures is highly influenced by the development of an individual's social role. For instance, rumors may suddenly end with one individual because they were an eye-witness to an event and their role is acknowledged publicly in their social structure. Similar to the spread of an epidemic, a disease might not infect an individual because of social reasons. For example, the individual might be a doctor and they might know ways to avoid getting infected. This differs from a mathematical inference based on a calculated chance that the individual never touched any infected individuals. Unless the social structure is considered, some definite trends in spreading behaviors will remain misunderstood when special events occur that have very limited probability.

In terms of traditional media, the social layer is believed to create trust links between people based on a trust-building mechanism (TBM) that relies on existing social interactions. Alternatively, the lower communicating layer is solely responsible for reducing the noise that occurs during information dissemination. However, as the networked communicating infrastructure expands, a new TBM must begin to operate in communication layers to ensure the efficient spread of an individual's influence or public opinions at much lower costs. However, this must occur even if social interactions with opinion leaders or eyewitnesses do not occur. Generally, as we define it here, the new duty of communication layers in the network age is similar to what was once described, decades earlier, as the (traditional) media's responsibility. Readers' trust in traditional media is based on the accuracy of its reporting. Readers' trust in traditional media will be completely destroyed by inaccurate reporting. In other words, traditional media would incur a high risk by telling lies. Therefore, the public tends to believe media that maintain a lot of credibility. However, in this new social media era, all individuals can act as reporters. Together, they act as a type of media. Therefore, we must ask: do individuals continue to incur high risks if they tell lies? If the risk remains low, how will new trust in social media develop? How might social media ensure that individuals will agree to construct communication-layered trust?

In social structures, trust is based on repeated social interactions. Ultimately, social interactions produce general references that individuals can use to make decisions about whether to believe, spread, or transact. This mechanism is known as the social-based trust-building mechanism (SBTBM). The communication structure encourages individuals to build trust with other individuals who may not possess any social contacts. This new trust-building mechanism is known as the communicating-aimed trust-building mechanism (CATBM).

The CATBM encourages individuals to decide whether other individuals are trustworthy based on the number of individuals who have ever trusted those other individuals. In other words, individuals tend to believe in individuals who possess more believers. The BA model that Barabási introduced was based on this principle. It predicted the nature of scale-free distribution. In communicating activities, participants are motivated to make decisions based on the CATBM, provided they can observe the degrees of each node. For example, almost every e-commercial website provides customers with a particular type of order based on product sales volumes. Customers tend to generate trust based on several top products or stores because they believe those products or stores are trustworthy in general. This decision preference is referred to as a preferential trust (PT) strategy. It greatly reduces individuals' decision making costs. Each node's degree of trust (i.e., the number of people that ever trusted an individual) can reflect its general popularity during its historical evolution. Prices function as signals for the allocation of material resources in the market. Similarly, the signals of degrees of nodes guide the allocation of trusted-links resources in information networks.

The CATBM costs much less than the SBTBM. Without the CATBM, many people can find it relatively difficult to confirm what is real solely through electronic links. According to the CATBM, trust develops based an individual's belief in an average of a significant number of others' preferences. This can be easily achieved by technical means. However, according to the SBTBM, trust develops based on an individual's personal decisions. The individual makes those decisions based on historical interactions that require significant amounts of time for real interactions and significant amounts of space for historical data storage. Thus, the cost to develop social-based links is much higher than the cost to build communicating-aimed links.

The SBTBM continues to play an important role even when individuals have already developed relationships mainly through CATBM in social media. Evidence has revealed that information is derived from social reality when individuals create social links to extend discussions and update beliefs. With respect to social media, they include social-based links and communicating-aimed links. Let us imagine the following situation: an individual possesses several different principles that they rely on to decide whether to believe information they receive from social friends and from people they follow on Facebook. Let us suppose that this individual is well known and followed by thousands of people. (Thus, we can describe this individual as a "hub".) This individual receives information from social friends who may be unknown. This information is transmitted by hundreds of people. Ultimately, even if the individual and the individual's followers believe the same information, trust develops based on different motivations. The individual's trust is based on their personal social-based links because (1) they experienced interactions with their social friends, and (2) they maintained stable expectations of their credibility. However, the individual's followers solely believe in the individual because the individual has so many followers (the PT principle). In general, the individual is considered trustworthy. In other words, the individual's trust in their friends is constructed based on the SBTBM. Alternatively, the followers' trust in the individual is based on the CATBM. Note that, even though their trust originated in different places, ultimately, they accept the same information. In fact, although a rumor may originate with an unknown user, it might be spread by well-known people.

The Trust-Constructing Procedure

Based on the above discussion, individuals might naturally adopt a particular mechanism (either the SBTBM or the CATBM) based on the particular layer of the MLC model the information has reached. One can simplify this by discretely setting two groups of participants on network-hubs and non-hubs. Hubs have many more followers than non-hubs. In addition, hubs are located in the center of a radical communication structure. We clustered these two group nodes of hubs and non-hubs (see Section 5) to indicate that the public opinion environment is determined by the hubs' decisions. In other words, each non-hub has limited power to influence the overall conditions of spreading rumors. In our decision model, we assumed that:

- Nodes tend to transmit correct information to acquire more trust from followers. When a node transmits correct information, the node may obtain more followers as a benefit. Alternatively, if the node transmits a rumor, the node may lose the same number of followers as punishment.

- Hubs and non-hubs have different numbers of increasing or decreasing followers.

Thus, we set *N* as the variation per time of a hub's followers and n as that of a non-hub's followers. *N* and *n* are the functions of t. p_H or p_L is the probability with which an individual believes that information they have received is

Communications of the Association for Information Systems

true, where p_H represents a higher probability under the circumstance that the individual knows that information is confirmed by social-based links, and p_L represents a lower probability that the individual knows that information is solely spread through communicating-aimed links. Please note that p_H and p_L are continuously changing with time t.

Correspondingly, C_H, C_L, or 0 equal the cost to confirm information. C_H represents the higher cost when and only when the hubs spread information by the SBTBM. C_L represents a lower cost in the alternative situation that occurs if hubs fail to adopt the SBTBM. When two groups of nodes adopt the CATBM, the cost equals zero. Thus, we can write the expected benefit for each kind of nodes in each condition in the following strategic form (see Appendix A for details of the proof).

Table 1: Strategic Form

		Non-hubs	
Hubs		C.A.	S.B.
	CA	$(2p_L-1)N,(2p_L-1)n$	$(2p_L-1)N,(2p_L-1)n-c_H$
	SB	$(2p_H-1)N-c_H,(2p_H-1)n$	$(2p_H-1)N-c_L,(2p_H-1)n-c_L$

In general, $p_L \le 0.5$ and $p_H \ge 0.5$. The Nash equilibrium is only the strategic set:

Table 2: Two Stable Strategic Profile

Condition	**Strategic set**
$p_H - p_L \ge c_H/2N$	(SB, CA)
otherwise	(CA, CA)

This decision model intuitively explains how the nodes located in different positions react to others' decisions. Hubs tend to use their social links offline. This is a relatively reliable way to confirm information only when:

$$p_H(t) - p_L(t) \ge c_H/2N(t) \quad (1)$$

In addition, no matter what choices the hubs make, non-hubs will insistently occupy the CATBM because they are able to share benefits created by hubs without accruing any costs. Yet, when will hubs choose the SBTBM? We can show that hubs will adopt the SBTBM sooner or later depending on the opinion environment and on the hubs' own influence. When rumors begin to spread, $p_H(t) - p_L(t)$ is small enough to provide almost the same probability of p_H and p_L because only a limited amount of information has been spread. The two opinion environments constructed by the word-of-mouth method (social-based) and the word-of-click method (communicating aimed) are almost indifferent. In addition, $N(t)$, which represents risky benefits, is also too small to produce sufficient motivations for the hubs to confirm social layers. Thus, the Equation 1 cannot hold quickly. Therefore, because the rumor spreads faster and wider, the differences between the social-based opinion environment and communicating-aimed opinion environment become larger. This means $p_H(t) - p_L(t)$ becomes larger. $N(t)$ also becomes larger because more and more people begin to focus on this issue and follow this so-called influential node. Therefore, it is inevitable that at some point $p_H(t) - p_L(t) \ge c_H/2N(t)$ will hold. This means that the hubs will choose the SBTBM to ensure their acquired information can be confirmed by social links.

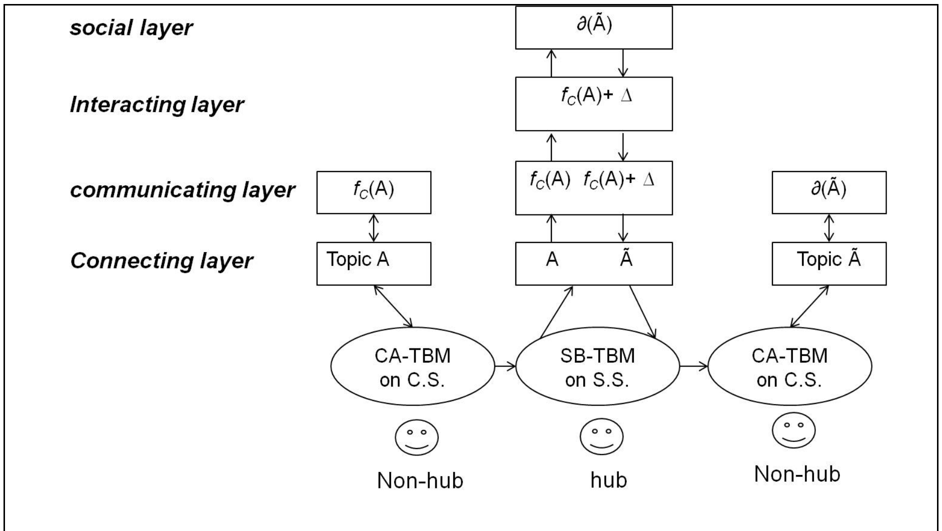

Figure 4. The Hub Makes Small Adjustments in Social Layers and Information Becomes Knowledge

Proposition 1: The optimal policy for a hub's decision-making procedure is characterized by a pair of (p_H, p_L, N, c_H, t) such that $p_H(t) - p_L(t) \geq \frac{c_H}{2N(t)}$; and the optimal policy for a non-hub's decision making procedure is to adopt the CATBM no matter what decisions hubs make.

The phenomenon in which a rumor spreads quickly and in which topics frequently change occurs because the development of social-based trust occurs more slowly than the development of communicating-aimed trust. When a rumor is transmitted by a star person, this person's followers tend to believe that individual at higher levels of probability. Thus, the area of spreading suddenly becomes extended. However, in social reality, it takes a relatively long time to confirm one rumor through social contacts such as calls or meetings. When new facts related to social-based trust emerge in a communication structure, the topic of the primary rumor may change and continue to spread rapidly through some star nodes.

Therefore, rumors spread very quickly. They can spread exponentially (Chierichetti et al., 2009) because many non-hubs who occupy the majority of nodes may have adopted a less-reliable mechanism (e.g., the CATBM). However, it is undeniable that social reality serves as the source of all rumors. Theoretically, any rumor can be stopped when a certain number of hubs become motivated to adopt the SBTBM. The SBTBM works in social layers. Therefore, the social structure evolves as a decentralized system in which individuals who are restricted by geographical locations tend to engage in social interactions frequently to build and rebuild their trust over social links. Although it is influenced by the CATBM, the communication structure evolves as a self-organized system to construct communicating links based on the PA principle. One advantage of self-organized mechanisms here is that geographical factors won't restrict the scale of network. On social media, the decision whether to choose the SBTBM or the CATBM defines the special communication structure that is self-organized by decentralized behaviors.

IV. RUMOR SPREADING AND RUMOR STOPPING IN THE MLC MODEL

Social Clustering Principle

The trust-constructing procedure can be inspiring. Thus, hubs who maintain the most believers may acquire a number of social-based links with other hubs (see Figure 5). The general property of this topological structure is scale-free. Many non-hubs are located in the periphery. They are linked with other hubs to form a communication structure. In addition, some hubs are connected with one another by social links to form a social structure.

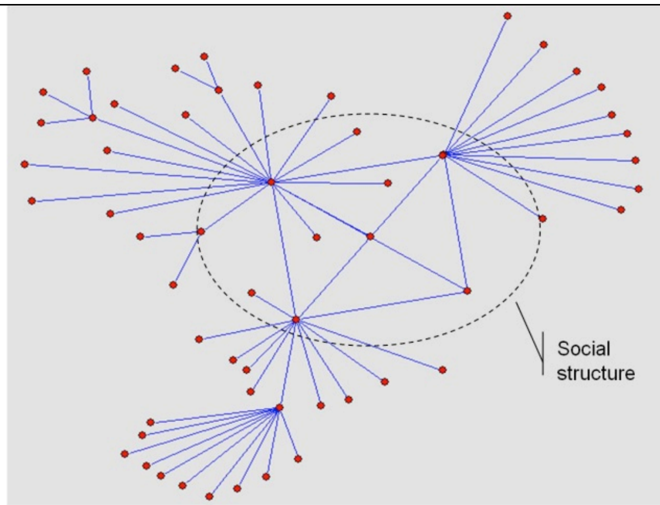

Figure 5. Spreading Topology of Social and Communication Structures

Proposition 2: The overall distribution is determined by the CATBM because few nodes (mainly hubs) apply to the SBTBM. Thus, the network evolves as a scale-free network. The probability density function of degrees for each node can be written as follows (where k represents the degree and m represents the initial parameter, assuming that $k_i(t_i) = m$) (Barabási et al., 1999) (see Appendix B for proof of equation):

$$p(k) = \frac{\partial P(k_i(t) < k)}{\partial k} = m \, {}^{1}\!/_{k^2} \qquad (2)$$

This indicates that (the term of "scale-free" also indicates) the structure of the network may become similar in both large and small scales, because $p(ck) = m \, {}^{1}\!/_{(ck^2)} = \frac{1}{c^2} m \, {}^{1}\!/_{k^2} \propto p(k)$.

Therefore, information spreads from one hub and then touches another hub by chance. On the large-scale network, rumors first spread across one local area (similar to a sphere). They spread to another area through a long-distance route. This progression is referred to as sphere-spreading on a small-world network (Moukarzel, 1999) (see Figure 6). Usually, it is possible to make the analogy that rumors spread quickly over long distances because rumors use wings to fly. However, our research indicates that these wings essentially originate in the CS.

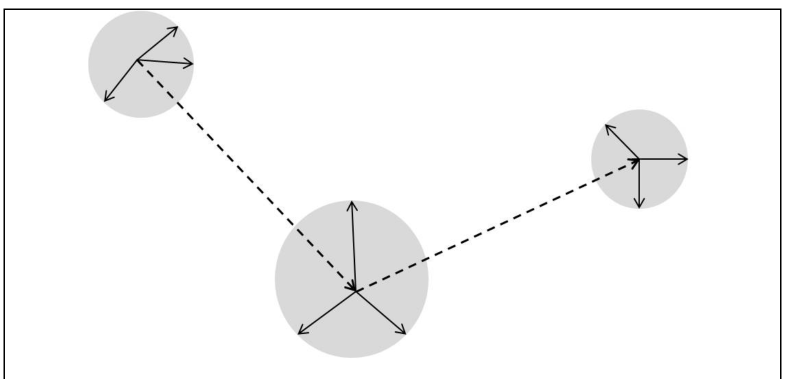

Figure 6. Sphere-Spreading on a Small-World Network

However, a limited number of links being social based and a limited number of nodes being influenced by the SBTBM can significantly change information-spreading behaviors. The structural pattern can be reorganized by a limited number of links formed by the SBTBM.

When spreading starts, a rumor spreads from one hub to another hub by way of a single link located in the communicating layer. This link is typically an information link because hubs are not motivated to confirm through social interactions ($p_H(t) - p_L(t) \le c_H / 2N(t)$). As the spreading trend grows, increasing numbers of nodes become involved in discussions of the topic. For hubs, random spreading becomes an increasingly risky action because it may result in the loss of many believers. For hubs, it can be quite difficult to reacquire these believers in such a low-cost manner. Therefore, some hubs will be cautious about spreading rumors. In addition to lower costs, a hub might make social interactions in a higher layer to obtain more accurate information from reality so the individual can update their beliefs based on the Bayesian method. This behavior will cause social links between several hubs on the social layer to emerge and result in the arousal of an extensive discussion environment. The structure will evolve as a new structure in which hubs tend to connect with one another. However, the primary distribution will not be destroyed (Figure 7 illustrates this process).

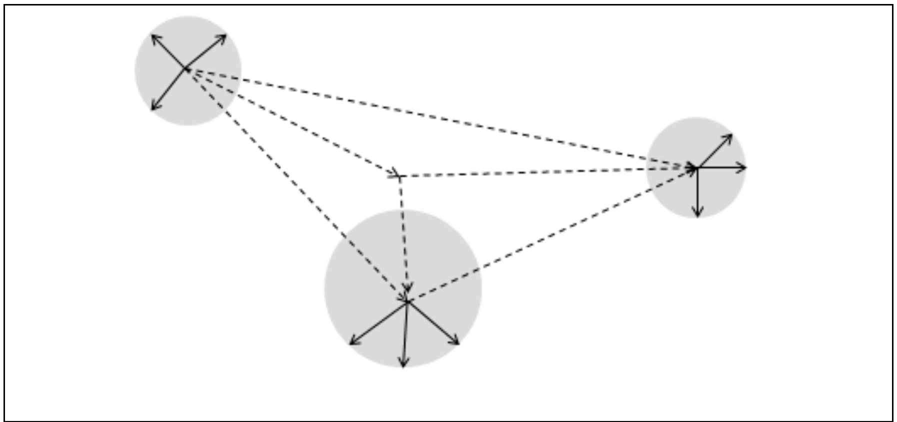

Figure 7. Sphere-Spreading with Social Clustering of Hubs

Dynamic Evolution of Rumor Spreading and Rumor Stopping

How does the "spreading core" emerge? Figure 8 illustrates its progression. The solid lines represent communicating links. The dotted lines represent social links. Note that the progress of spreading involves increasing amounts of social connections. As those increases occur, the hierarchy of the spreading progress becomes easier to observe.

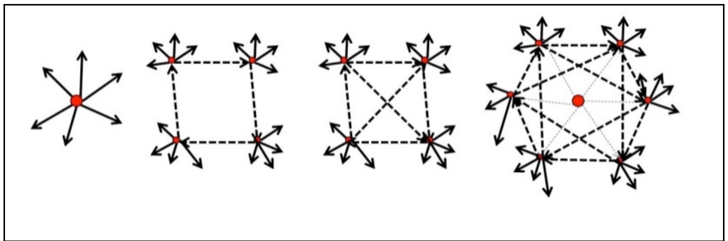

Figure 8. The Evolution of the Spreading Core

The social structure and the SBTBM motivates the emergence of a spreading core, depending on how we define each phase of the spreading process. In the beginning, hubs become involved when the core begins to spread. Then, the first non-hubs to receive the rumor become involved in the spreading structure, despite the fact that they are located in the outermost layers. This means these hubs are the farthest nodes that might be touched by the rumor. Because some active nodes continuously enter this structure, the spreading core becomes a sub-network that includes hubs and non-hubs. We can describe this as the self-organized discussion that is motivated by the trust-constructing procedure. The establishment of public discussions signals that the spreading process has entered into the second phase. In other words, the communicating pattern begins to form. Next, the social structure provides long-distance links (rumors' "wings") that spread extensively between the outer layer and the core. In this case, one can discover the source of the rumor the individual received in a limited number of steps. In turn, new information related to this rumor will spread from the core in a limited number of steps. This signals that the process has entered into the third phase. In this critical moment, rumors can end or new variants can spread. This might result in worsening conditions.

Table 2: Spreading Phases		
Phase	**Spreading core**	**Main character**
Emerging	Some hubs	Radical structure
Forming	Hubs and active non-hubs	Endogenous link
Spreading	Self-organized public opinion environment	Exogenous link

The social structure and the SBTBM join to stop the rumor. Rumor spreading includes two phases: in phase one, a rumor spreads. In phase two, new information spreads to enforce the idea that the previous information was a rumor. This second spreading process is referred to as rumor stopping. This process typically involves topic transformation for one rumor. The stopping process will begin if any hub who was expected to speak confirms the truth by contacting their personal social relations. Note that the social structure acts as a partial projection of all participants' links. On the one hand, the social structure carries another factual basis from our real world, rather than from the media network. This weakens the power of the scale-free structure that promotes the irrational spreading of rumors. On the other hand, the social structure can inspire nodes that act as potential "rumor clearers", even though this node has not declared any information related to their role. In all likelihood, this individual acts as a rumor clearer because of their social structure, rather than because of what they have stated. Their social structure can be observed by anyone in this network. An individual can decide to concentrate on the individual from whom they will acquire more accurate information based on their real-world experience.

V. EMPIRICAL DESIGN AND ANALYSIS

Background

In December 2010, a rumor spreads across China's micro-blogs that Jin Yong, a famous novelist born on March 22, 1924, had died of a midbrain infection and an accumulation of stagnant water in the corpus callosum. According to the rumor, his death occurred in St. Mary's Hospital, Hong Kong, on December 6, 2010. This piece of news spread to almost every corner of the Internet because it was spread by some certified users.

However, within two hours, this breaking news was confirmed to be a rumor. In fact, rumors cannot be disguised for long periods because they are usually inaccurate. For example, Jin Yong's birthday was incorrect. In addition, no hospital named St. Mary's Hospital exists in Hong Kong. When verification confirmed that Jin Yong was alive, people quickly realized that the reports of Jin Yong's death were simply a farce. This event became a classic example because only a brief amount of time passed between rumor spreading and rumor stopping.

We acquired 41320 micro-blog IDs and related contents that contained this rumor that spread between 19:55 pm and 23:00 pm on December 6 from the Sina database. We created a network of rumor spreading through data processing.

With respect to this case, we verify our two propositions (see Section 4) with the following empirical studies:

1. We use topological properties to illustrate the existence of scale-free CS and the emergence of hierarchies in CS.

2. We use the process of dynamic evolution to illustrate the existence of the spreading core and its three main phases.

3. We use the process of rumor stopping to explain how the social structure helped end this rumor.

Analysis of Topological Properties

We constructed a rumor-spreading topology in which the nodes represent the content of an individual's statement and directed lines represent spreading behavior. An individual receives a rumor from others and speaks out to create one rumor-spreading event.

To reveal the essential structure of the spreading core, we recursively deleted the node who possessed a degree equal to one until the roots of spreading trees could be clearly observed. We used the Kamada-Kawai algorithm (Kamada & Kawai, 1989) to rearrange node positions to construct a well-distributed layout. During the 12th run of the recursive reduction, the spreading branches separated clearly. Each branch represented the beginning of one community. in the six figures in Figure 9 refer to the process used to discover the core through recursive reduction. We performed this progression by inverting the order. In other words, we first drew the sixth figure—a complete topology of the spreading structure—and, second, simplified this original structure recursively until the core emerged (first figure)

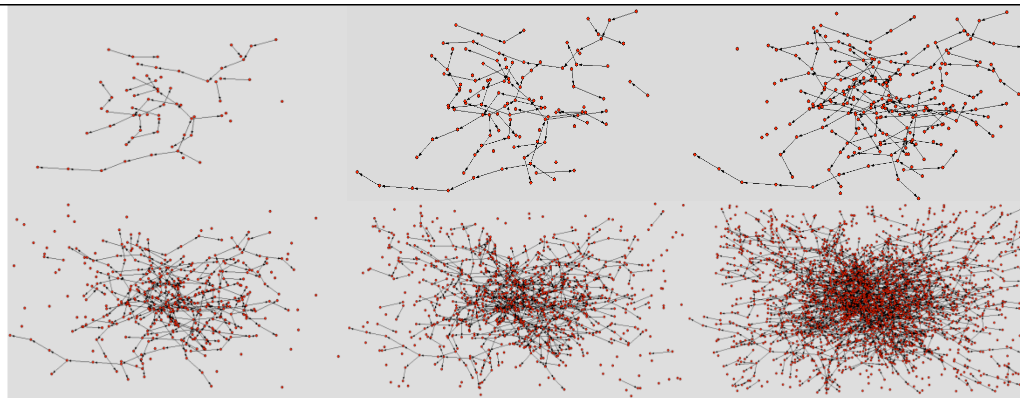

Figure 9. The Progression of Spreading Construction

The two figures shown in Figure 10 provide a comparison between the spreading structure and its core. Note that the core splits into many branches because of the social clustering of some key nodes.

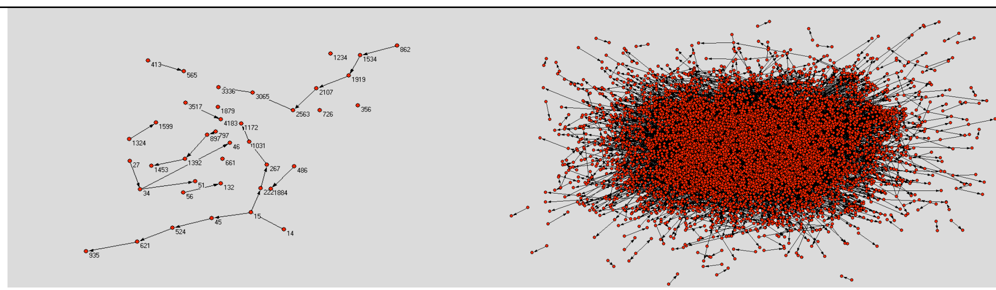

Figure 10. The Spreading Core and its Complete Structure

Next, we clustered all nodes. Nodes that possessed degrees in some specific scales demonstrated similar behaviors during rumor spreading. Thus, we can divide nodes into four categories: hub-nodes that possess degrees above 34, sub-hub-nodes that possess degrees between 8 and 34, active node-nodes that possess degrees between 1 and 7, and inactive nodes that possess degrees of 0. Nodes possess relatively greater probability to connect with nodes grouped in the same cluster. We created the nodes' degrees of distribution in clusters separately.

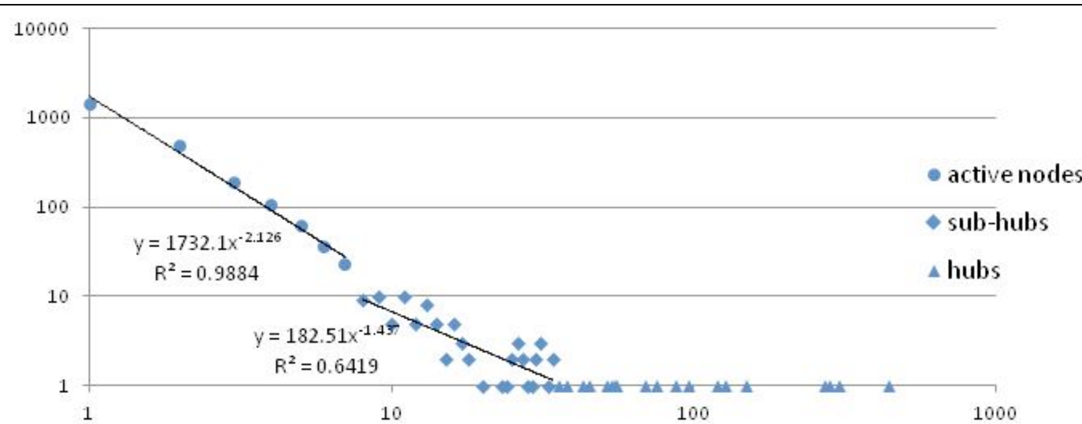

Figure 11. Separate Clustering of the Nodes' Degrees of Distribution

We present the results of the goodness-of-fit test below. Because the hubs' degrees spread over a wide range, only a limited possibility existed that hubs would possess the same degrees. This indicates that we were not required to perform a goodness-of-fit test on the hubs. Sub-hubs had a 64 percent goodness-of-fit, which means that they did not fit very well. This can be observed directly. Sub-hubs possessed random degrees because they were influenced by small probability events and by the scale-free mechanism. However, their degrees of distribution offered a power-law with an index of $\lambda = 1.43$. For active nodes, their degrees of distribution offered a power-law that demonstrated a dramatic 98 percent goodness-of-fit: $\lambda = 2.13$.

The key for why the behaviors of sub-hubs and active nodes differed during spreading lies in the power-law index that determines the rule for the structural growth of nodes. The threshold for phase transition in power-law index is 2 (Appendix C shows our attempts to prove this point and to analyze the mathematical property of the power-law index). When active nodes possess a power law index above 2, the variance of degrees diverges. However, the average degree converges. This suggests that nodes that possess greater degrees will increase very slowly when the total nodes increase. In addition, the degrees of these nodes will converge to an average value. Therefore, because active nodes will construct additional paths to improve communication between one another, the scale of the communication structure becomes enlarged. In contrast, when sub-hubs possess a power-law index above 2, the mean and variance of degrees diverge simultaneously. Therefore, sub-hubs will increase quickly when the total number of nodes increases. They will construct spreading paths, enlarge the communicating pattern directly, and enhance the level of network connectivity. Table 2 shows the clustering results for all nodes and discuss their details, (e.g., degrees of distribution and locations).

Table 3: Results of Node Clustering

Clusters	Quantity	Degree dist.	Location	Behaviors	Typical users
Hubs >= 34	0.2%	Completely random	Centered at the beginning of communication	Begin the emergence of communicating pattern	Verified star, grassroots star, influential media
Sub-hubs 8-34	1%	Randomly scale-free	Located mainly in the 1, 2, 3 layers	Promote increases in the communicating pattern	Star account, organizationa l account
Active nodes 1-7	50%	Approximately scale-free	Located throughout all layers	Continuously anticipate rumor spreading	Normal account
Inactive nodes 0	Almost 50%			Cannot be observed	Dead account

Second, we focused on the emergence of hierarchies in the communication structure. We discovered that 14 layers emerged during the spreading process. In other words, the largest diameter of the spreading area was 14. However, the average diameter was far less than 14 because of the significant asymmetry that the nodes distributed among the 14 layers.

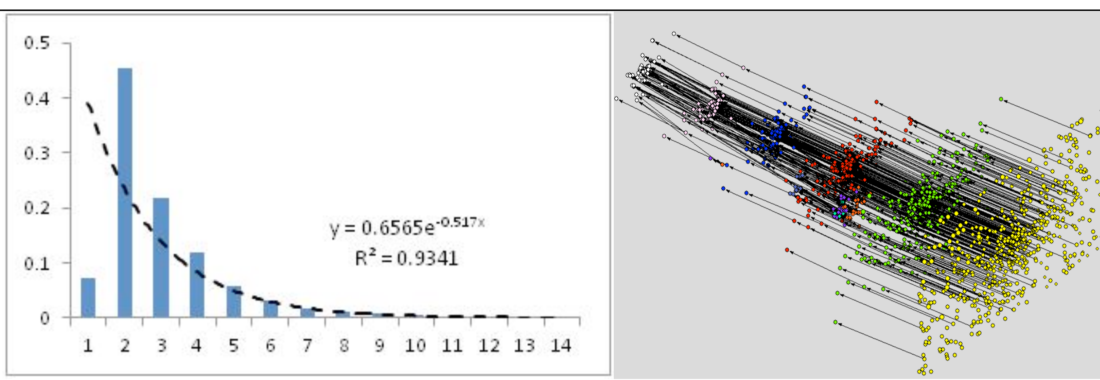

Figure 12. Goodness-of-Fit Test for Layered Distribution and the Phenomena Observed in the Structure

The left side of Figure 12 represents the mathematical analysis of the spreading hierarchies. The right side of Figure 12 provides the graphical results that occurred when we applied the mathematical results during spreading behaviors.

The number of nodes followed exponential distribution in the layers. We calculated the first moment of this distribution λ = 0.5 as the unbiased estimate of λ. In fact, the nodes primarily emerged in the second and third layers in which the number of nodes represented 60 percent of the total numbers.

Dynamic Evolution of Spreading

We used a Fruchterman-Reingold camera to take photographs for ten time plots to illustrate our communication structure (Fruchterman & Reingold, 1991). To achieve a symmetrical appearance in the topology, this heuristic algorithm rearranges all nodes to achieve a symmetrical appearance. The positions of nodes and their significance during evolution can be clearly observed in our photographs. These photographs helped us understand the dynamic evolution that occurred. The entire progression of rumor spreading can be divided into three phases.

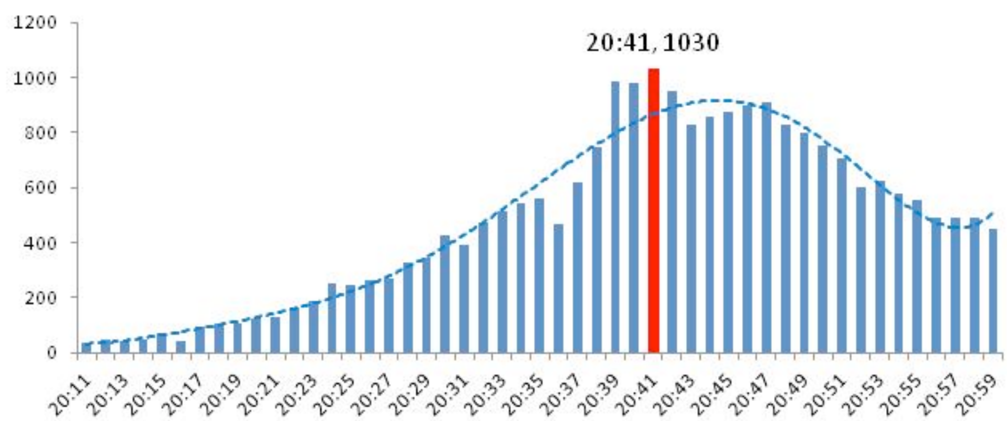

Figure 13. The Spreading Process (Number of Trust-Links Developed Over Time)

Figure 13 illustrates the total number of contents produced every minute. The red line shows the arrival of verified news. We included the emergent phase (20:11-20:21), the formation phase (20:21-20:36), and the spreading phase (20:36-20:41).

Emergent Phase

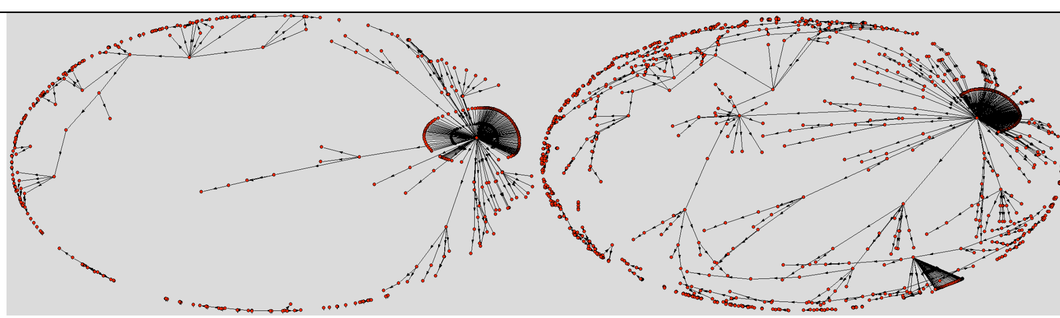

Figure 14. Topological Structure of the Emergent Phase

The hubs were losing their role as the core and a new core was emerging. Prior to reorganization, the communicating pattern remained in an unstable state because information content could be easily distorted and original leading power was lacking.

The hubs drove the communication structure's emergence. In the first graph in Figure 14, it is apparent that one hub initiated the development of a large radial structure. The sub-hubs led to the development of several small radiations. When a stable spreading structure later emerged, these radiations located around the spreading cores could not be observed. As the second graph in Figure 14 shows, this means the spreading core only contained these hubs during the emergent phase.

The sub-hubs and the active nodes constructed the outer layer of the communication structure and created an opportunity for the new core to move into the center. The original core was replaced by this core. At that moment, spreading information had a strong tendency to become distorted because participants were motivated to publish their opinions or facts. This offered participants opportunities to move to the center of the network. All distorted information would be tolerated during spreading.

Original hubs lost their spreading power during the transition phase. Based on connecting structures such as Weibo, the communicating pattern that overlaid the communication structure formed a tree in which any two nodes that already emerged were unable to form new links. Many newly formed nodes emerged continuously. These nodes were produced by nodes that operated in the inner layer. These inner nodes did not function as hubs because hubs were barely able to reemerge after the second spreading layer occurred. The intuited explanation is that newly formed nodes were not interested in who first published this information. These nodes only wanted to know whether the information was real. Original spreaders were barely able to provide persuasive answers. As a result, they lost the nodes' attention

Formation Phase

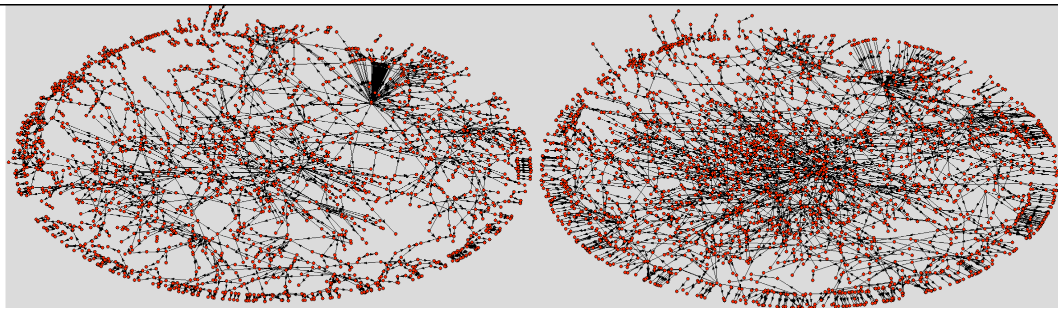

Figure 15. Topological Structure of the Formation Phase

In the graph that appears on the left side of Figure 15, a new core emerged and links between the core and the periphery began to form. The links were formed by active nodes moving to the center and forming a new core. This produced additional active nodes and, thus, newly formed links emerged. Because this core continued to grow, links between the core and the periphery slowly began to emerge.

Public discussions occurred during this phase. The development of a newly formed core implied a natural mechanism that pushed nodes interested in this rumor's topic into the center of this network. Then, opinions and facts were provided from different perspectives. This constructed a supplemental network to ensure that only effective information was allowed to spread. This represents a huge movement from "rumor spreading" to "fact and opinion spreading".

Spreading Phase

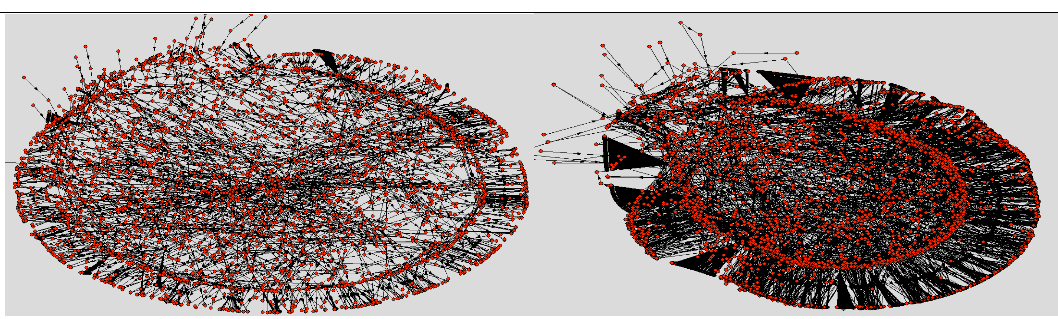

Figure 16. Topological Structure of the Spreading Phase

The spreading core constructed a barrier to separate active nodes that appeared in the core from other nodes that appeared in the periphery. The rumor-spreading rate remained stable because of this complete hierarchy structure. Inside the barrier, nodes became involved in full discussions of this rumor's topic. Outside the barrier, the discussion results spread continuously among nodes that appeared in the periphery.

It is apparent that rumor spreading failed to produce a new wave. In this case, this occurred because the new fact that emerged to clear this rumor was persuasive enough to close the discussion and stop spreading the core. Thus, the spreading process that proceeded from core to periphery naturally ended.

However, if this discussion had not closed, a new rumor might have begun to spread, along with stronger content and additional confused facts. Typically, this rumor would become a variation of the original rumor. However, it would spread more easily because routes for spreading were built earlier. In addition, the spreading structure had already been completed.

Rumor Stopping

To perform a deep study of how a rumor is cleared, we performed a semantic analysis on the contents of each micro-blog. We defined four attitudes that we employed to estimate whether speakers believed this rumor:

Attitude 1: Completely believable
Attitude 2: Hard to estimate
Attitude 3: Skeptical, hoping someone will clear it, and
Attitude 4: Unbelievable.

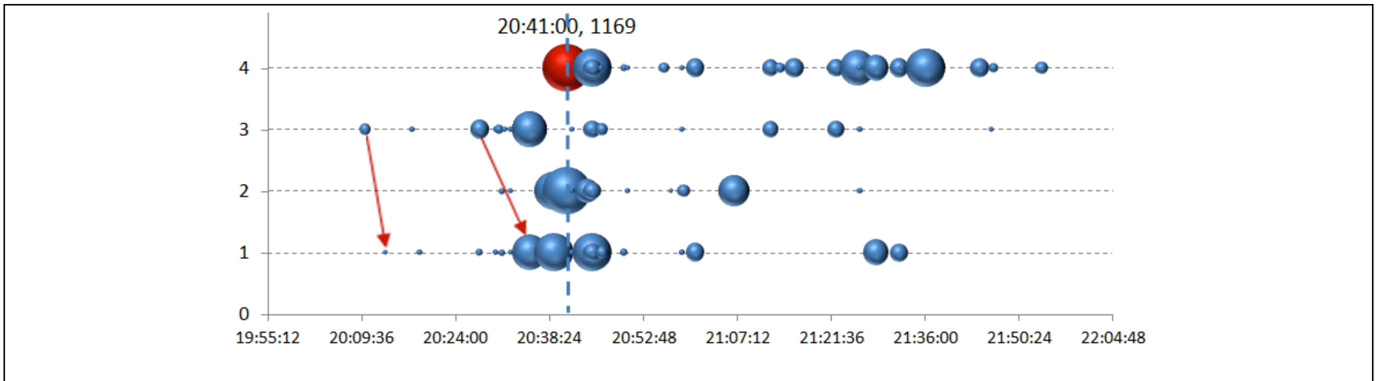

Figure 17. The Rumor-Stopping Process

The bubbles that appear in Figure 17 refer to one spreader. The diameter represents the spreading range. For example, spreader A's content spread 100 times. Spreader B's content spread 50 times. Thus, the diameter of the bubble that represents spreader A is two times larger than the diameter of spreader B's bubble. Therefore, spreader A's area will be four times as large as spreader B's area. This parameter setting helps construct a reasonable picture because we must consider the general influence of an individual's spreading and its direct influence on n infectors. It will also influence n^2 nodes directly because each infector has the potential to influence other n nodes. The horizontal axis is the timeline. The vertical axis refers to the four different attitudes listed above.

Notice the red arrow. It is obvious that the rumor originated from information that required verification. The red arrow that appears on the left signals the first transformation of normal news into absolute rumor. However, this beginning of a rumor influenced only a limited number of nodes. The red arrow that appears on the right signals the transformation that initiated large-scale rumor spreading. This illustration demonstrates how a rumor begins. The conclusion is consistent with our research on dynamic evolution. Information can easily be distorted because it is remains in an unstable state when spreading begins.

The spreading tendency of each attitude changed significantly after 8:41 pm, when the first clearing information arrived. Attitude 4 spread more intensely and lasted for a relatively long period. Attitude 1 almost ceased spreading. In particular, attitude 4 spread in a stable manner. This conclusion is consistent with our explanation of the spreading phase that occurs during dynamic evolution. If new information provides facts that are sufficiently persuasive, then discussions that began in the spreading core will end and the rumor will cease to spread.

VI. CONCLUSION AND FUTURE WORK

Because of the growing number of social media users, rumor spreading has become a serious issue that affects both the normal social order and the online world's public opinion environment. To better explain the rumor-spreading process, we propose a new multi-layered communicating model that includes a trust-constructing procedure in contrast to the oversimplification inherent in the traditional SIS model. In this MLC model, we decompose an individual's trust-or-not decision making process into four layers: the connecting layer, the communicating layer, the interacting layer, and the social layer. In this process, an individual can access data, transform data into understandable information, add personal opinions through social discussions, and form knowledge that reflects the real world. To distinguish between the different communicating patterns of real social and online links, we define the social structure (SS) and the communication structure (CS) to highlight the two different topological structures created by these communicating patterns. In SS, decisions to trust are built on the number of social interactions. An individual must decide whether to believe, spread or transact. We describe this mechanism as the social-based trust-building mechanism (SBTBM). In CS, an individual can also make the decision to trust another individual solely through communication on social media without making social contact. This mechanism is described as the communicating-aimed trust building mechanism (CATBM). Based on these concepts a major assumption that the loss or gain of followers can serve as both motivation and result, we create a game model that indicates that, because they understand that the SBTBM is more costly, nodes tend to choose the SBTBM despite the choices hubs make. Alternatively, hubs tend to employ the SBTBM when the Equation 1 holds, which inevitably occurs as the rumor-spreading process evolves.

With respect to rumor spreading and rumor stopping, the MLC model infers that hubs tend to connect with one another in social layers when they realize they require additional accurate information from a higher layer to perform Bayesian belief updating (the social clustering principle). Consequently, the social structure helps end the rumor. In addition, we can define the rumor-spreading phase by the variance of the spreading core, which is generated by the social structure.

To verify our model and to determine the explicit process involved in rumor spreading, we analyzed Jin Yong's "death", and illustrate the topological properties that describe the existence of communities and the emergence of hierarchies in communicating patterns, the process of dynamic evolution to illustrate the existence of the spreading core and the three main spreading phases, and the rumor-stopping process to explain how the social structure helps end the rumor. The results we achieved from the empirical study were consistent with the model. They provide specific details related to rumor spreading. As such, we can state that our model is complete. However, future efforts are required to improve this model. In practice, social media can be promoted in the social structure to accelerate rumor stopping.

REFERENCES

Editor's Note: The following reference list contains hyperlinks to the World Wide Web. Readers who have the ability to access the Web directly from their word processor or are reading the paper on the Web, can gain direct access to these linked references. Readers are warned, however, that:

1. These links existed as of the date of publication but are not guaranteed to be working thereafter.
2. The contents of webpages may change over time. Where version information is provided in the References, different versions may not contain the information or the conclusions referenced.
3. The author(s) of the webpages, not AIS, is (are) responsible for the accuracy of their content.
4. The author(s) of this article, not AIS, is (are) responsible for the accuracy of the URL and version information.

Fowler, G. A. (2012). Facebook reaches billion-user milestone. *The Wall Street Journal.* Retrieved from http://www.wsj.com/articles/SB10000872396390443635404578036164027386112

Twitter. (2011). The engineering behind Twitter's new search experience. *Engineering Blog*. Retrieved from https://blog.twitter.com/2011/engineering-behind-twitter%E2%80%99s-new-search-experience

Cao, B. (2012). Sina's Weibo outlook buoys Internet stock gains: China overnight. *Bloomberg Business*. Retrieved from http://www.bloomberg.com/news/articles/2012-02-28/sina-s-weibo-outlook-buoys-internet-stock-gains-in-n-y-china-overnight

Balthrop, J., Forrest, S., Newman, M. E. J., & Williamson, M. M. (2004). Technological networks and the spread of computer viruses. *Science*, *304*(5670), 527-529.

Barabási, A. L. (2002) *Linked: How everything is connected to everything else and what it means for business, science, and everyday life*. New York: Plume.

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

Barabási, A. L., Albert, R., & Jeong, H. (1999). Mean-field theory for scale-free random networks. *Physica A: Statistical Mechanics and its Applications*, *272*(1), 173-187.

Barrat, A., & Weigt, M. (2000). On the properties of small-world networks. *The European Physical Journal B-Condensed Matter and Complex Systems*, *13*(3), 547-560.

Brin, S., & Page, L. (1998). The anatomy of a large-scale hyper textual Web search engine. *Computer Networks and ISDN Systems*, *30*(1), 107-117.

Çelen, B., & Hyndman, K. (2012). Social learning through endogenous information acquisition: An experiment. *Management Science*, *58*(8), 1525-1548.

Chierichetti, F., Lattanzi, S., & Panconesi, A. (2009). Rumor spreading in social networks. *Theoretical Computer Science*, *412*(24), 2602-2610.

Daley, D. J., & Kendall, D. G. (1965). Stochastic rumours. *IMA Journal of Applied Mathematics*, *1*(1), 42-55.

Dimkovski, M., & Deeb, K. (2007). Knowledge technology through functional layered intelligence. *Future Generation Computer Systems*, *23*, 295-303.

Erdos, P., & Rényi, A. (1960). On the evolution of random graphs. *Publications of the Mathematical Institute of the Hungarian Academy of Sciences*, *5*, 17-61.

Fruchterman, T. M., & Reingold, E. M. (1991). Graph drawing by force‐directed placement. *Software: Practice and Experience*, *21*(11), 1129-1164.

Galam, S. (2002). Minority opinion spreading in random geometry. The European Physical Journal B, 25(4), 403-406.

Galam, S. (2003). Modelling rumors: The no plane pentagon French hoax case. *Physica A: Statistical Mechanics and Its Applications*, *320*, 571-580.

Herzberg, D., & Broy, M. (2005). Modeling layered distributed communication systems. *Formal Aspects of Computing*, *17*, 1-18.

Kamada, T., & Kawai, S. (1989). An algorithm for drawing general undirected graphs. *Information Processing Letters*, *31*(1), 7-15.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons*, *53*(1). 59-68.

Milgram, S. (1967). The small world problem. *Psychology Today*, *2*(1), 60-67.

Moreno, Y., Nekovee, M., & Pacheco, A. F. (2004). Dynamics of rumor spreading in complex networks. *Physical Review E*, *69*(6), 066130.

Moukarzel, C. F. (1999). Spreading and shortest paths in systems with sparse long-range connections. *Physical Review E*, *60*(6), 6263(R).

Nekovee, M., Moreno, Y., Bianconi, G., & Marsili, M. (2007). Theory of rumour spreading in complex social networks. *Physica A: Statistical Mechanics and Its Applications*, *374*, 457-470.

Newman, M. E., Forrest, S., & Balthrop, J. (2002). Email networks and the spread of computer viruses. *Physical Review E*, *66*(3), 035101.

Newman, M. E., Moore, C., & Watts, D. J. (2000). Mean-field solution of the small-world network model. *Physical Review Letters*, *84*(14), 3201-3204.

Page, L., Brin, S., Motwani, R., & Winograd, T. (1999*). The PageRank citation ranking: Bringing order to the Web* (Technical report). Stanford InfoLab.

Pastor-Satorras, R., & Vespignani, A. (2001). *Epidemic spreading in scale-free networks*. *Physical Review Letters*, *86*(14), 3200-3203.

Peterson, W., & Gist, N. (1951). Rumor and public opinion. *The American Journal of Sociology*, *57*(2), 159-167.

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

APPENDIX A: THE PROOF OF PROPOSITION 1

Each expected benefit in the strategic form can be represented in the following manner:
(*e = expected benefits*):

Hub: CATBM, non-hub: CATBM

$e(hub) = p_L N - (1-p_L)N = (2p_L - 1)N$,

$e(non-hub) = p_L n - (1-p_L)n = (2p_L - 1)n$.

Hub: CATBM, non-hub: SBTBM

$e(hub) = p_L N - (1-p_L)N = (2p_L - 1)N$,

$e(non-hub) = p_L n - (1-p_L)n - c_H = (2p_L - 1)n - c_H$.

Hub: SBTBM, non-hub: CATBM

$e(hub) = p_H N - (1-p_H)N - c_H = (2p_H - 1)N - c_H$,

$e(non-hub) = p_H n - (1-p_H)n = (2p_H - 1)n$.

Hub: SBTBM, non-hub: SBTBM

$e(hub) = p_H N - (1-p_H)N - c_L = (2p_H - 1)N - c_L$,

$e(non-hub) = p_H n - (1-p_H)n - c_L = (2p_H - 1)n - c_L$.

Then the one of Nash equilibriums (hub: SB; non-hub: CA) can be reached when and only when

$(2p_H - 1)N - c_H \geq (2p_L - 1)N$,

which means

$p_H(t) - p_L(t) \geq c_H / 2N(t)$.

APPENDIX B: THE PROOF OF PROPOSITION 2

First, the two steps based on BA model are:

1. Growth at constant rate. Starting with a small number of m_0 vertices, at every time step, we add a new vertex with $m\ (m \leq m_0)$ edges.

2. Preferential attachment. The probability $\zeta(k)$ that a new vertex will be connected to vertex i depends on the connectivity k_i of that vertex, such that

$$\zeta(k) = \frac{k_i}{\sum_{j=1}^{n} k_j}.$$

According to the mean field theory, the expected growth of i's out-degrees can be represented as:

$$\frac{\partial k_i}{\partial t} = \text{V}k\zeta(k) = \frac{k_i}{\sum_{j=1}^{m_0+t-1} k_j} = \frac{k_i}{t}$$

given that

$k_i(t_i) = m$,

Then

$$k_i(t) = m\frac{t}{t_i};$$

therefore,

$$p(k_i(t) < k) = p(t_i > \frac{mt}{k}).$$

Assuming that the growth of nodes is at a constant rate,

$p_i(t_i) = 1/t$

thus,

$$p(t_i > \frac{mt}{k}) = 1 - p(t_i \leq \frac{mt}{k}) = 1 - \frac{m}{k}$$

We can finally write the probability density function (pdf) of nodes' degrees:

$$p(k) = \frac{\partial P(k_i(t) < k)}{\partial k} = m \, 1/k^2$$ (Barabasi et al., 1999).

APPENDIX C: THE CALCULATION OF POWER-LAW INDEX OF RUMOR-SPREADING NETWORK

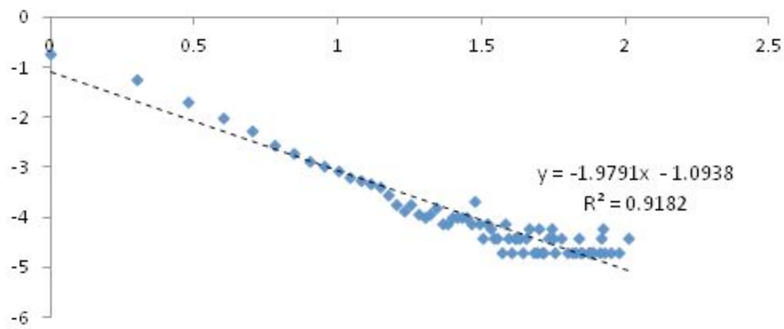

Figure 18. The Degree-Probability (Log-Log Plot) Distribution

We calculated that the power-law function of the rumor-spreading network in our empirical case is

$$p(k) = 12k^{-1.98}$$

and that the power-law index is $\gamma = 1.98(< 2, \approx 2)$. This means the variance and average of nodes' degrees diverge simultaneously.

Proof:

The first moment of degree distribution:

$$d_M = \sum_{k=1}^{N-1} kP(k) = m\sum_{k=1}^{N-1} k^{1-\gamma}.$$

The second moment of degree distribution:

$$d_{M^2} = \sum_{k=1}^{N-1} k^2 P(k) = m\sum_{k=1}^{N-1} k^{2-\gamma}.$$

When $1 < \gamma \leq 2$ And N is enough large,

$$\sum_{k=1}^{N-1} k^{-\gamma}$$ converges.

Therefore:

$$d_M = O(N^{2-\gamma})$$

$$d_{M^2} = O(N^{3-\gamma}).$$

ABOUT THE AUTHORS

Zhiwei Qin is an Assistant Research Fellow of Innovation Research Institute at Peking University. He holds the Master degree in Management Science and Engineering from Peking University. His primary research interests include social structure on mobile internet, the information and rumors' spreading over social media, and the trust constructing within individuals and communities on internet. His research has been published in several leading journals.

Jian Cai is the distinguished adviser of the School of Innovation and Entrepreneur at Peking University. He was the founding executive dean of innovation research institute and a professor of management science and engineering at Peking University. He is the founder of Urming and a member of the China council of World Economic Forum.

H. Z. Wangchen is a PHD candidate of management science in Peking University. She is dedicated to the research of marketing , evaluation of Internet companies, and Internet product design.

Copyright © 2015 by the Association for Information Systems. Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and full citation on the first page. Copyright for components of this work owned by others than the Association for Information Systems must be honored. Abstracting with credit is permitted. To copy otherwise, to republish, to post on servers, or to redistribute to lists requires prior specific permission and/or fee. Request permission to publish from: AIS Administrative Office, P.O. Box 2712 Atlanta, GA, 30301-2712, Attn: Reprints; or via e-mail from ais@aisnet.org.

Communications of the Association for Information Systems

ISSN: 1529-3181

EDITOR-IN-CHIEF
Matti Rossi
Aalto University

AIS PUBLICATIONS COMMITTEE

Virpi Tuunainen Vice President Publications Aalto University	Matti Rossi Editor, *CAIS* Aalto University	Suprateek Sarker Editor, *JAIS* University of Virginia
Robert Zmud AIS Region 1 Representative University of Oklahoma	Phillip Ein-Dor AIS Region 2 Representative Tel-Aviv University	Bernard Tan AIS Region 3 Representative National University of Singapore

CAIS ADVISORY BOARD

Gordon Davis University of Minnesota	Ken Kraemer University of California at Irvine	M. Lynne Markus Bentley University	Richard Mason Southern Methodist University
Jay Nunamaker University of Arizona	Henk Sol University of Groningen	Ralph Sprague University of Hawaii	Hugh J. Watson University of Georgia

CAIS SENIOR EDITORS

Steve Alter University of San Francisco	Michel Avital Copenhagen Business School

CAIS EDITORIAL BOARD

Monica Adya Marquette University	Dinesh Batra Florida International University	Tina Blegind Jensen Copenhagen Business School	Indranil Bose Indian Institute of Management Calcutta
Tilo Böhmann University of Hamburg	Thomas Case Georgia Southern University	Tom Eikebrokk University of Agder	Harvey Enns University of Dayton
Andrew Gemino Simon Fraser University	Matt Germonprez University of Nebraska at Omaha	Mary Granger George Washington University	Douglas Havelka Miami University
Shuk Ying (Susanna) Ho Australian National University	Jonny Holmström Umeå University	Tom Horan Claremont Graduate University	Damien Joseph Nanyang Technological University
K.D. Joshi Washington State University	Michel Kalika University of Paris Dauphine	Karlheinz Kautz Copenhagen Business School	Julie Kendall Rutgers University
Nelson King American University of Beirut	Hope Koch Baylor University	Nancy Lankton Marshall University	Claudia Loebbecke University of Cologne
Paul Benjamin Lowry City University of Hong Kong	Don McCubbrey University of Denver	Fred Niederman St. Louis University	Shan Ling Pan National University of Singapore
Katia Passerini New Jersey Institute of Technology	Jan Recker Queensland University of Technology	Jackie Rees Purdue University	Jeremy Rose Aarhus University
Saonee Sarker Washington State University	Raj Sharman State University of New York at Buffalo	Thompson Teo National University of Singapore	Heikki Topi Bentley University
Arvind Tripathi University of Auckland Business School	Frank Ulbrich Newcastle Business School	Chelley Vician University of St. Thomas	Padmal Vitharana Syracuse University
Fons Wijnhoven University of Twente	Vance Wilson Worcester Polytechnic Institute	Yajiong Xue East Carolina University	Ping Zhang Syracuse University

DEPARTMENTS

Debate Karlheinz Kautz	History of Information Systems Editor: Ping Zhang	Papers in French Editor: Michel Kalika
Information Systems and Healthcare Editor: Vance Wilson	Information Technology and Systems Editors: Dinesh Batra and Andrew Gemino	

ADMINISTRATIVE

James P. Tinsley AIS Executive Director	Meri Kuikka *CAIS* Managing Editor Aalto University	Copyediting by Adam LeBrocq, AIS Copyeditor