ICEB 2012 Proceedings

International Conference on Electronic Business (ICEB)

Fall 10-12-2012

Maximizing the Information Authenticity in a Social Network

Liu Ning

Yaodong Ni

Maximizing the Information Authenticity in a Social Network

Liu Ning, Yaodong Ni
School of Information Technology and Management
University of International Business and Economics, Beijing 100029, China
yufuning@163.com

Abstract: Information often distorts during the process of transmission in a social network, which is very common in many real-life applications. In this paper, we study the problem of maximizing the information authenticity of a social network. We propose a new model to characterize information distortion during the diffusion of influence. In order to trade off between optimality and complexity, we design a framework of greedy algorithms. Finally, we carry out a numerical experiment to show the effectiveness of the proposed algorithms.

Keywords: social networks; information distortion; information authenticity; stochastic simulation; greedy algorithm.

§1 Introduction

A social network is a general graphic model that characterizes the relationships of a group of individuals. Social networks have been studied for many years in different areas, such as epidemiology [9], sociology [15, 35, 36], economics [4, 14, 16, 25, 31, 34], and computer science [3, 6, 8, 13, 18, 19, 24, 26, 30]. Recently, the research of information and influence transmission through social networks has attracted a lot of attention [6, 8, 26], which can provide suggestions for solving multitudinous problems in real life. Generally, practical problems where information transmission in social networks is involved can usually be modeled as optimization problems with various objectives, such as maximizing the amount of individuals who will receive the information [19, 20], maximizing the expected lift in the profit yielded by the information transmission [8, 30], minimizing the size of the initial target set of individuals such that the information is guaranteed to be transmitted to everyone in the network [6], minimizing the duration of information transmission until all individuals receive the information [28, 29].

In practice, we find that information usually changes during the process of transmission for some reasons, so it would be not the same as what it originally is, that is, information distortion happens. For example, by word of mouth, the most primitive way of information transmission, it is almost impossible to keep the spread information precise all the way. The game named "Happy Fax" provides good evidences, in which a number of people stand in a line and transmit a piece of message one by one. Except the one standing at the end of the line who read the message from a paper card, everyone hears the message from only the one behind her. Everyone tells the message to only the one in front of her, except the one at the head who will report what she thinks the message is. The game is usually funny because it is almost always that what the last one reports is totally different from what the message really is. For other popular online social networks such as Facebook, information distortion still happens. Although original message will stay the same all the way, due

Proceedings of the Twelfth International Conference on Electronic Business, Xi'an, China, October 12-16, 2012, 252-262.

to the function of “share”, users can still add their own comments to the message, which will influence other users’ understanding of the message when it is passed on and thus will lead to information distortion.

Although information distortion indeed exists in information transmission through social networks, the works mentioned above focus on only optimizing the process of information transmission, and none of them discusses information distortion in the transmission process. Information distortion has been widely studied in areas such as accounting [7], supply chain management [1, 21, 23, 27, 37], decision making [10, 32, 33], organization management [2, 5, 22]. However, to our best knowledge, little attention has been paid to information distortion in the area of information transmission in social networks. In this paper, we study the information distortion in information transmission through social networks.

The main reason for information distortion is due to the uncertainties in human communication, such as the vagueness in expression by human language and the diversity of the understanding of information. In the game of “Happy Fax”, because all the players express the message in their own words, errors in expression accumulate and large difference is yielded. In on-line social networks such as Facebook, subjective comments are added to the original message continuously, which results in different understanding of different users and thus leads to distortion. Another reason for information distortion is the oblivion that results from memory loss of human beings as time passes. One may not be able to express the message clearly enough, if the duration between the time she receives a message and the time she transmits it to others. In view of the above, we define a model to describe information distortion that incorporates the above two reasons for information distortion, and introduce the concept of information authenticity to describe the degree of distortion. Information authenticity is set as a real number between 0 and 1, which roughly measures the extent to which the information stays as what it originally is. The information authenticity of a piece of precise information is 1, while the authenticity of the information that is totally different from the original one is set as 0. As highly distorted information is meaningless for decision making, we set a threshold between 0 and 1, such that information with authenticity under the threshold is viewed as invalid and is not taken into account.

In this paper, we focus on the following decision-making problem: how to find a fixed number of nodes in a social network, to whom a piece of information is initially sent such that the information transmission with the minimum information distortion is triggered off. Such a problem is of great practical significance. For example, an environmental protection organization may want to advertise for a new low-carbon lifestyle through a social network by exploiting the word-of-mouth effect. With limited budget, the organization may have to advertise to only a limited number of individuals rather than all the people in the social network. Information distortion may be out of control of the organization, however its aim is to minimize the distortion.

In this paper, in order to solve such a decision-making problem, we adopt the incremental chance model [28] to characterize how information transmits. By measuring the information distortion by information authenticity, we aim at maximizing the total information authenticity of the valid information when information transmission finishes. We design a series of greedy algorithms in which different heuristic functions are embodied in order to alleviate computational burden. A numerical experiment is performed to show that the proposed algorithms can flexible trade off between optimality and complexity.

The remainder of this paper is organized as follows. In Section 2, we propose the concept of information authenticity and present a new model on basis of the incremental chance model to characterize information distortion during information transmission. Section 3 describes a series of greedy algorithms. We perform a numerical experiment in Section 4 to show the performance of the proposed algorithms. Conclusions are drawn in Section 5.

§2 Information Distortion

In this section, we review the incremental chance model, present the concept of information authenticity, and describe how information distorts in a social network.

We denote a social network by an undirected graph $G = (N, E, W)$. We let N be the set of nodes in G, in which each node corresponds to an individual in the population we consider. Throughout this paper, we denote by n the number of nodes in N. Let E denote the set of edges, in which the edge connecting any pair of nodes i and j can be written as either (i, j) or (j, i). Let W denote the weight function which assigns a positive weight to each edge to measure the relationship between the corresponding individuals the edge connects. For any edge (i, j), the associated weight $W(i, j)$ quantifies the relationship between node i and node j. A node j is called a neighbor of a node i, if there exists an edge (i, j) in E. We denote by $N(i)$ the set of neighbors of i.

In real life, information arrives at an individual usually at random. The chance one receives a piece of transmitted information in a given period of time is actually the probability that she meets and communicates about the information with her friends who have already known the information. Such a probability is believed to be proportional to the number of the individual's friends who have received the information and also to depend on how close friends they are. On the basis of the above observations, we assume that information transmits stochastically according to the incremental chance model [28]. At any time, nodes are categorized into two classes: *active* nodes who have received the transmitted information and thus are able to pass it to her neighbors, and *inactive* nodes who have not yet received the information. Each inactive node has a chance of turning active only if she has an active neighbor. The probability that an inactive node i receives the information at time t is defined by

$$p_t^i = \frac{\sum_{j\in N_t^a(i)} W(i,j)}{\sum_{j\in N(i)} W(i,j)},$$

where $N_t^a(i)$ is the set of i's active neighbors at time t. Specifically, the probability that an inactive node i gets the information from her neighbor j at time t is

$$\begin{cases} \dfrac{W(i,j)}{\sum_{k\in N(i)} W(i,k)}, & \text{if } j \text{ is active at time } t, \\ 0, & \text{otherwise.} \end{cases}$$

In the problem considered in this paper, we give the information directly to a given number of nodes at the very beginning. The set of nodes that we target, denoted by S, is set as the information source that will trigger off the information transmission. Throughout the paper, we denote by k the number of nodes in S. Throughout the process of information transmission, the value of p_t^i for each node i increases as time goes on until it becomes 1. The incremental chance model has been proved to have all the individuals in the social network receive the transmitted information with probability 1 [28].

We denote by t_i the time step when the transmitted information arrives at node i. We are particularly interested in how much of the transmitted information has not distorted from what it originally is until it has been received by each node. Therefore, the information authenticity of each node i is defined as a real number $a(i)$ in interval $[0, 1]$, which measures the extent to which the information received by i at t_i stays the same with the original. It is noticeable that the information authenticity is defined for only active nodes. According to Ebbinghaus [11], the information with only a very small authenticity is naturally viewed as unreliable, thus we define a threshold τ to indicate the level of reliability of the transmitted information and consider the information with an authenticity smaller than τ as invalid. Based on the threshold τ, we further classify active nodes at any time step t into two classes: *valid* nodes whose information authenticity $a(i) \geq \tau$ and *invalid* nodes whose information authenticity $a(i) < \tau$.

As information distortion almost always happens, we believe that the information authenticity decreases while information transmits in a social network for the following two reasons: (1) Due to the uncertainties in human communication, authenticity decreases when information passes from one individual to another. (2) Because of memory loss, authenticity naturally decreases as time passes by. In order to explain how the above two reasons are taken into account in our model, we assume that node i gets the information, at time t_i, from her neighbor j who got the information at t_j. It is notable that t_j is earlier than t_i, which means that $t_i - t_j \geq 1$. When the information transmits from j to i, we assume that i's information authenticity will decrease by a fixed rate of $\gamma \in (0, 1)$ due to the communication uncertainties. If we take only such communication uncertainties into account, the receiver's information authenticity is $1 - \gamma$ times that of the sender. On the other hand, to reflect how memory loss affects information authenticity, we assume that authenticity diminishes by a fixed rate of $\delta \in (0, 1)$ as each unit of time passes by. Since memory loss will never happen for the case of immediate transmission, information authenticity will not decrease when $t_i - t_j = 1$. For cases where $t_i - t_j > 1$, $a(i)$ will be equal to $a(j)$ times $(1 - \delta)^{t_i - t_j - 1}$, if communication uncertainties are not taken into account. By combining together both the factor of communication uncertainties and that of memory loss, the authenticity of node i is given as

$$a(i) = a(j) \times (1 - \gamma) \times (1 - \delta)^{t_i - t_j - 1}.$$

For each node i in the target set S in the problem we consider, we set her associated information authenticity $a(i) = 1$ and let the time when she receives the information $t_i = 0$. This assumption is natural because, as the information source, the nodes in S get the information directly without any distortion at the very beginning. It is noticeable that, for each node who has received the information, there is a chance that she may hear of the information again, perhaps from another neighbor. The late receipt of the information may update the authenticity that we have already assigned to the node. We presume that $\gamma = \delta$, such that late receipt of the transmitted information will not lead to a higher authenticity. Therefore, we can focus on the information authenticity that is initially assigned to each node.

According to Ebbinghaus [11], only information with high authenticity is reliable, thus we focus on only the valid nodes whose authenticity is higher than τ. In summary, the problem we consider in this paper is to find a set S consisting of a fixed number k of nodes such that the expected sum of the authenticities associated with all valid nodes is maximized. Formally, we aim at solving the problem

$$\max_{|S|=k} E\left[\sigma(S)\right] = \max_{|S|=k} E\left[\sum_{a(i)\geq\tau, i\in N} a(i)\right].$$

§3 A Framework of Greedy Algorithms

In this paper, given a connected social network G and a positive integer k, we focus on the problem of finding and targeting a set of nodes S consisting of k nodes, such that the expected total information authenticity $E[\sigma(S)]$ is maximized. A difficulty we face first is the lack of the analytical expression of $E[\sigma(S)]$. In order to deal with this problem, we adopt the stochastic simulation technique to estimate $E[\sigma(S)]$ as follows [12]: we independently generate M samples $\{\omega_1, \ldots, \omega_M\}$ and estimate $E[\sigma(S)]$ by $\sum_{i=1}^{M} \sigma(S)(\omega_i)/M$. To our knowledge, real social network is large-scale, such that n, the number of nodes in the network, is usually a large value. The problem we consider in this paper is difficult because we attempt to find the optimal one among all C_k^n possible sets of nodes, which is quite time-consuming. In addition, the time spent on stochastic simulation is also considerable, because the number of samples in simulation is required to be large to reduce estimation error. In this section, we design a framework of greedy algorithms to provide a flexible trade-off between performance and efficiency.

§3.1 The Framework

As we mentioned, in real-life applications, C_k^n is such a large number that it is not practical to employ brute-force search to solve the problem. In this view, we propose a framework of greedy algorithms by which a set of nodes is constructed incrementally. A greedy algorithm puts the nodes in the target set once a time, where each node we pick and add to the set is believed to lead to the best performance of the solution. Under the framework, greedy algorithms distinguish from each other by providing different ways of determining the node that is added to the set at each step.

The traditional greedy algorithm in the framework is named the value-based greedy algorithm, in which a node is added to the target set only if doing so leads to the largest increase of the value of objective function. Although the performance of the value-based greedy algorithm is relatively impressive, it suffers from the complexity of implementing stochastic simulation for a large number of times, which limits its scalability.

The other extreme in the framework is called the heuristic-based greedy algorithm, where we adopt a heuristic function to evaluate, at each step of the algorithm, the fitness of putting each node to the target set, and then pick the one with the highest fitness. This type of greedy algorithm indeed saves computational time because the heuristic functions are computationally cheap, however the performance is usually dissatisfactory.

In order to trade off between the value-based greedy algorithm and the heuristic-based greedy algorithm, we introduce an integer parameter r. At each step of the algorithm, we first evaluate the fitness of adding each node to the target set by some heuristic function and record the r nodes with the highest fitness; then by adopting stochastic simulation for evaluating the value of objective function, we add the node, among the r nodes, to the current target set if doing so results in the largest increase of the total authenticity.

Table 1 presents the algorithm framework. Given a social network G, the size of target set k, the trade-off parameter r and a heuristic function h, the algorithm returns a target set S. When $r = 1$, the algorithm is a heuristic-based greedy algorithm with heuristic function h; when r is set to be dependent on l as $r(l) = n - l$, it becomes the value-based greedy algorithm.

§3.2 Heuristic Function

Before we introduce the details of the heuristic functions, we first propose the concept of the distance network of a social network. The distance network is exactly the same with the original social network except that the weight function is replaced with one that characterizes the distances between nodes. Base on the weight function W in the original social network, we present the following alternatives of setting the weight function in the distance network.

Table 1 A Framework of Greedy Algorithms

```
Input: G,k,r,h;
Output: S;
  S = ∅;
  l = 0;
  while l < k
    R = ∅;
    c = 0;
    while c < r
      i_c = arg max_{i∈N\(S∪R)} h(S,i);
      R = R ∪ {i_c};
      c = c + 1;
    i_r = arg max_{i∈R}(E[σ(S ∪ {i})] − E[σ(S)]);
    S = S ∪ {i_r};
    l = l + 1;
  return S;
```

- $W^r(i,j) = \frac{1}{W(i,j)}$, whose reciprocal is the weight function in the original social network.
- $W^o(i,j) = \max\limits_{(i',j')\in E} W(i',j') - W(i,j)$, where a positive value is added to the opposite of W to keep the weights non-negative.

At each step of the greedy algorithms, given the current set of nodes $S \subset N$ and any node $i \notin S$, a heuristic function returns the fitness $h(S,i)$ of adding i to S. In this section, we propose three heuristic functions. The idea of the first two heuristic functions is to define the fitness of each node by its centrality. Different measures of centrality have been developed [17], each of which captures a particular aspect of how "important" the role a node plays in transmitting the information. The idea of the third heuristic function is to select nodes that are likely to get the transmitted information late, because delay in the receipt of the information may lead to large distortion.

§3.2.1 Degree Centrality (DC)

The degree centrality of a node is defined by its degree, i.e. the number of its neighbors. So we define the first heuristic function as

$$h_1(S,i) = |N(i)|.$$

Intuitively, we treat a node with large degree centrality as a social individual.

§3.2.2 Closeness Centrality (CC)

The closeness centrality of a node is defined as the inverse of the sum of the distances between the node and the other nodes. Note that the closeness centrality is defined on the distance network. As the weights on the distance network are all non-negative, a shortest path between any pair of nodes i and j exists. We denote the length of the shortest path from i to j by $SPL(i,j)$. By defining the value of the second heuristic function as the closeness centrality of i, we have

$$h_2(S,i) = \frac{1}{\sum_{j \neq i, j \in N} SPL(i,j)}.$$

§3.2.3 Maximin Path Length Reduction (MPLR)

By this heuristic function, we aim to put "the farthest point" in the target set in order to reduce information distortion by shortening the duration the information transmits. For any node i and a current target set S, we can define the distance between i and S in the distance network as $SPL(S,i) = \min_{j \in S} SPL(j,i)$. The maximin path length associated with S is defined as $\max_{j \in N} SPL(S,j)$. Given a node i and the current target set S, we let the value of the heuristic function be the reduce of the maximin path length if we add i to S, i.e.

$$h_3(S,i) = \max_{j \in N} SPL(S,j) - \max_{j \in N} SPL(S \cup \{i\}, j).$$

§4 Numerical Experiment

In this section, we perform a numerical experiment to show the effectiveness and robustness of the proposed algorithm framework. In the experiment, social networks are generated randomly. In order to construct a network, we set the number of nodes $N = 100$ and predetermine a parameter p as the probability of connecting any pair of nodes with an edge. The parameter p roughly indicates the density of the edges in the network. If p is close to 1, every node is connected to almost all the other nodes; while if p is small, the edges in the network are sparse and each node is connected to only a few of other nodes. After the network is generated, we will check whether the generated network is connected. If the generated network is not connected, we add as few edges as possible to make it connected. In the numerical experiment, we set $p = 0.002$ to generate the social networks. For each edge, we randomly generate an integer weight ranging from 1 to 5. The number of samples M is set to 5000 in the stochastic simulation. The experiment is performed on a Pentinum4 PC.

In the first experiment, we consider the results of a series of greedy algorithms with different heuristic functions, different weight functions in the distance network and different trade-off parameter r. Here, we set $k = 8$. By using the greedy algorithms, the results of the expected total information authenticity and the runtime are shown in Figure 1 and 2, respectively. In Figure 1 and 2, there are two extreme cases of r. When $r = 1$, the greedy algorithm is the heuristic-based greedy algorithm, and stochastic simulation is avoided; while when $r = |N| - t$, the greedy algorithm is the value-based greedy algorithm without using any heuristic function.

As shown in Figure 1, for all the greedy algorithms, the expected total information authenticity $E[\sigma(S)]$ increases with r increasing. Especially, when r is relatively small, $E[\sigma(S)]$ is improving fast as r increases. Besides, it is clear that heuristic function of "DC" generates worse results than the other two heuristic functions. In general, the weight function W^o turns out to produce better solutions than the weight function W^r when we set the heuristic function as "CC" or "MPLR". Figure 2 shows that the runtime of the greedy algorithms increases as r increases, because stochastic simulation takes more computational time for a large value of r. We can find that, compared to heuristic functions of "MPLR" and "CC", "DC" consumes a little more time for each setting of r. By combining both Figure 1 and Figure 2, we find that by properly setting the value of r, we can flexibly trade off between optimality and complexity by the framework of greedy algorithms we propose.

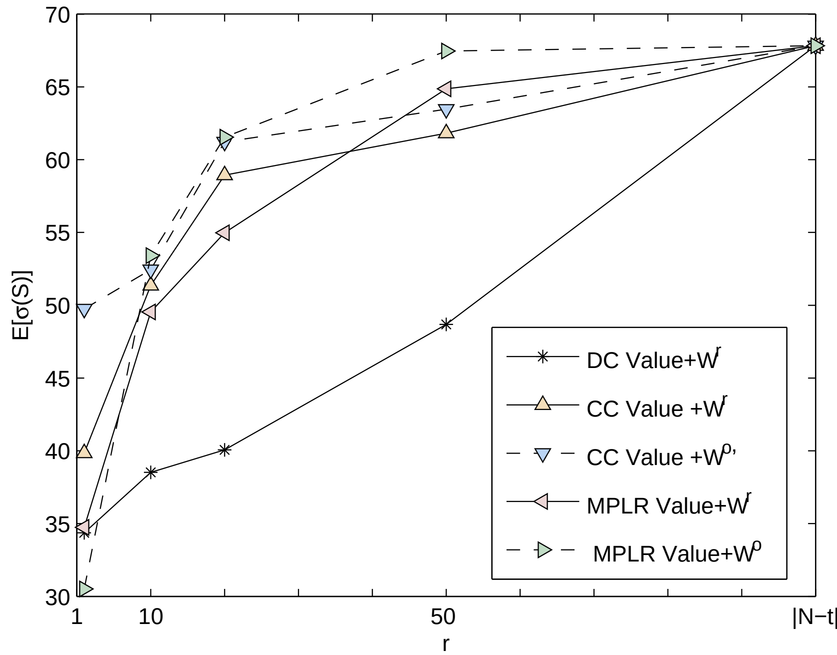

Figure 1 The expected total information authenticities obtained by different settings of greedy algorithms.

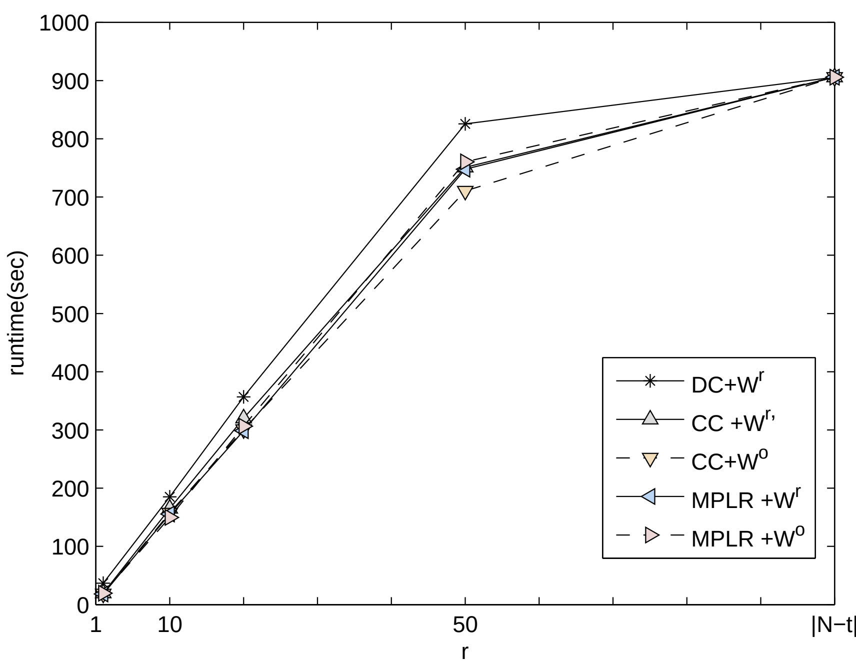

Figure 2 Running time of the greedy algorithms

§5 Summary

In this paper, we have studied the problem of maximizing the information authenticity of a social network. A new model has been proposed to describe the distortion of information when it diffuses through a social network. We have proposed a framework of greedy algorithms where different heuristic functions can be integrated in order to make a balance of solution performance and computational cost. We have performed a numerical experiment to show the proposed algorithms can flexibly trade off between optimality and complexity.

Acknowledgements

This work was supported by National Natural Science Foundation of China (No. 71101027), Program for Young Excellent Talents, UIBE (No. 12YQ08), and Research Funding of School of Information Technology and Management, UIBE (No. SIT2011001).

References

[1] S. Balan, P. Vrat, P. Kumar, Information Distortion in a Supply Chain and its Mitigation Using Soft Computing Approach, *Omega: The international journal of management science*, Vol. 37, pp. 553-558, 2007.

[2] D.A. Bella, Organizations and Systematic Distortion of Information, *Journal of Professional Issues in Engineering Education and Practice*, Vol. 113, No. 4, pp. 360-370, 1987.

[3] N. Berger, C. Borgs, J.T. Chayes, A. Saberi, On the Spread of Viruses on the Internet, *In: Proceedings of the Sixteenth Annual ACM-SIAM Symposium on Discrete Algorithms*, SODA'05, Vancouver, British Columbia, pp. 301-310, 2005.

[4] J. Brown, P. Reinegen, Social Ties and Word-of-mouth Referral Behavior, *Journal of Consumer Research*, Vol. 14, No. 3, pp. 350-362, 2007.

[5] K.M. Carley, L. Zhiang, A Theoretical Study of Organizational Performance Under Information Distortion, *Management Science*, Vol. 43, No. 7, pp. 976-997, 1997.

[6] N. Chen , On the Approximability of Influence in Social Networks, *In: Proceedings of the fourteenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD'08, San Francisco, California, pp. 1029-1037, 2008.

[7] D. Coffee, R. Roig, R. Lirely, P. Little, The Materiality of LIFO Accounting Distortions on Liquidity Measurements, *Journal of Finance and Accountancy*, Vol. 1, pp. 1-12, 2010.

[8] P. Domingos, M. Richardson, Mining the Network Value of Customers, *In: Proceedings of the Seventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco, California, pp. 57-66, 2001.

[9] Z. Dezso, A.L. Barabasi, Halting Viruses in Scale-free Networks, Physical Review E, Vol. 65, 2002.

[10] M.L. DeKay,, D. Patinño-Echeverri, P.S. Fischbeck, Distortion of Probability and Outcome Information in Risky Decisions, *Organizational Behavior and Human Decision Processes*, Vol. 109, No. 1, pp. 79-92, 2009.

[11] H. Ebbinghaus, A Supposed Law of Memory, *Mind*, Vol.os-XI, No. 42, pp. 300, 1886.

[12] G.S. Fishman, M. Carlo, Concepts, Algorithms and Applications, *Springer-Verlag*, New York, 1995.

[13] A. Ganesh, L. Massouli, D. Towsley, The Effect of Network Topology on the Spread of Epidemics, *In: Proceedings of IEEE INFOCOM 2005. 24th Annual Joint Conference of the IEEE Computer and Communications Societies*, pp. 1455-1466 , 2005.

[14] J. Goldenberg, B. Libai, E. Muller, Talk of the Network: A Complex Systems Look at the Underlying Process of Word-of-Mouth, *Marketing Letters*, Vol. 12, No. 3, pp. 211-223, 2001.

[15] M. Granovetter, Threshold Models of Collective Behavior, *American Journal of Sociology*, Vol. 83, pp. 1420-1443, 1978.

[16] N. Immorlica, J M. Kleinberg, M. Mahdian, T. Wexler, The Role of Compatibility in the Diffusion of Technologies through Social Networks, *In: Proceedings of the Eighth ACM Conference on Electronic Commerce*, EC'07, San Diego, California, pp. 75-83, 2007.

[17] M.O. Jackson, *Social and Economic Networks*, Princeton: Univ PR, pp. 61-69, 2010.

[18] M. Kearns, L. Ortiz, Algorithms for Interdependent Security Games, *In: Proceedings of the Seventeenth Annual Conference on Neural Information Processing Systems*, NIPS'03, Vancouver and Whistler, British Columbia, Canada, pp. 288-297, 2003.

[19] D. Kempe, J. Kleinberg, É. Tardos , Maximizing the Spread of Influence Through a Social Network, *In: Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD'03, Washington D.C., pp. 137-146, 2003.

[20] D. Kempe, J. Kleinberg, Tardos É, Influential Nodes in a Diffusion Model for Social Networks, *In: Proceedings of the 32nd International Colloquium on Automata, Languages and Programming*, ICALP'05, Lisbon, Portugal, pp. 1127-1138, 2005.

[21] H.L. Lee, V. Padmanablan, S. Whang, Information Distortion in a Supply Chain: the bullwhip effect, *Science*, Vol. 43, NO. 4, pp. 546-558, 1997.

[22] A.D. Level, Jr. , L. Johnson, Accuracy of Information Flows within the Superior Subordinate Relationship, *Journal of Business Communication*, Vol. 15, NO. 2, pp. 13-22, 1978.

[23] B.K. Mishra, S. Raghunathan, X.H. Yue, Information sharing in supply chains: Incentives for information distortion,*IIE Transactions*, Vol. 39, NO. 9, pp. 863-877, 2007.

[24] R. Monclar, A. Tecla, J. Oliveira, J.M. de Souza, MEK: Using Spatial-Temporal Information to Improve Social Networks and Knowledge Dissemination, *Information Sciences*, Vol. 179, No. 15, pp. 2524-2537, 2009.

[25] S. Morris, *Contagion*, Review of Economic Studies, Vol. 67, pp. 57-78, 2000.

[26] E. Mossel, S. Roch, On the Submodularity of Influence in Social Networks, *In: Proceedings of the 39th ACM Symposium on Theory of Computing*, STOC'07, San Diego, California, pp. 128-134, 2007.

[27] T. Niranjan, S.M. Wagner, V. Aggarwal, Measuring Information Distortion in Real-World Supply Chains, *International Journal of Production Research*, Vol. 49, No. 11, pp. 3343-3362, 2011.

[28] Y. Ni, L. Xie, Z.-Q. Liu, Minimizing the expected complete influence time of a social network, *Information Sciences*, vol. 180(13), pp 2514-2527, 2010.

[29] Y. Ni, Z.-Q. Liu, Heuristic Search for Optimizing Diffusion of Influence in a Social Network under the Resource Constraint, *Soft Computing*, vol. 15(2), pp 335-344, February, 2011.

[30] M. Richardson, P. Domingos, Mining Knowledge-Sharing Sites for Viral Marketing, *In: Proceedings of the Eighth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Edmonton, Alberta, pp. 61-70, 2002.

[31] E. Rogers, *Diffusion of Innovations*, Free Press, 1995.

[32] J.E. Russo, V.H. Medvec, M.G. Meloy, Information Distortion in Self-other Decision Making, *Organizational Behavior and Human Deci-*

sion Processes, Vol. 66, NO. 1, pp. 102-110, 1996.

[33] J.E. Russo, V.H. Medvec, M.G. Meloy , The Distortion of Information during Decisions, *Organizational Behavior and Human Decision Processes*, Vol. 66, NO. 1, pp. 102-110, 1996.

[34] T. Valente, Network Models of the Diffusion of Innovations, Hampton Press, 1995.

[35] D.J. Watts, S.H. Strogatz, Collective Synamics of 'Small-world' Networks, *Nature*, Vol. 393, pp. 440-442, 1998.

[36] S. Wasserman, K. Faust, Social Network Analysis, Cambridge University Press, 1994.

[37] J. Wang, J.D. Jia, K. Takahashi, A Study on the Impact of Uncertain Factors on Information Distortion in Supply Chains, *Production Planning and Control*, Vol. 16, NO. 1, pp. 2-11, 2005.