AI translation · View original & related papers at
chinarxiv.org/items/chinaxiv-201806.00096

Postprint of Research on Rumor Propagation in Social Networks Based on Network Structure Backbone Model

Authors: Wang Lubang, Li Shouwei

Date: 2018-06-19T00:00:00+00:00

Abstract

In social networks, nodes and their interrelationships constitute a network structure that forms support and supported relationships among nodes. By integrating structural support theory, we investigate several properties of nodal network structural support force, propose the aggregate consistency of total network support force and total supported force within social network structures, and further present a method for calculating nodal support force. Rumors, as a special type of information, exhibit distinct propagation characteristics across nodes with different support forces. Leveraging the PageRank calculation method from random walk models, we conduct simulation experiments on rumor propagation across nodes with varying support forces and the subsequent debunking outcomes. The results indicate that nodes with different support forces have a significant impact on both rumor propagation and debunking.

Full Text

Preamble

Rumor Spreading Based on Network Structural Supportiveness Model in Social Networks

Wang Lubang[1]*, Li Shouwei*[2]
(1. Zhejiang Wanli University, Ningbo Zhejiang 315100, China; 2. Shandong Normal University, Jinan 250014, China)

Abstract: The nodes in social networks and their relationships form a network structure that creates supportive and supported relationships among nodes. Combining structural support theory, this paper investigates properties of node network structural supportiveness, proposes the total consistency of network-wide supportiveness and re-supportiveness in social network structures, and further presents a method for calculating node supportiveness. As a special type of information, rumors exhibit different propagation characteristics among nodes with varying supportiveness. Drawing on the PageRank calculation method from random walk models, this paper conducts simulation experiments on rumor propagation across nodes with different supportiveness and the subsequent refutation status. Results demonstrate that nodes with different supportiveness have significantly different impacts on rumor spreading and refutation.

Keywords: social network; network structure; structural supportiveness; PageRank; rumor spreading

0 Introduction

Human behavior on social networks represents a mapping of real-world behavior, and the rapid propagation characteristics of networks can amplify certain behaviors to produce enormous negative effects, such as rumor spreading. Extensive literature exists on social network research. Watts and Strogatz transformed regular networks into small-world networks through random rewiring, demonstrating that social networks exhibit small-world characteristics [?]. Barabasi and Albert discovered the scale-free property of certain networks, where a few nodes have numerous connections while most nodes have very few, defining networks with power-law degree distributions as scale-free networks [?]. Real-world social networks and internet-based virtual social networks generally possess these scale-free features. Analyzing the topological structure of social networks provides an effective method for understanding their characteristics and patterns, with numerous scholars investigating network properties including degree distribution, clustering coefficient, community coefficient, vertex degree, and correlation coefficients [?, ?, ?, ?]. References [?, ?, ?] examine social networks from the perspective of node degree and influence. Reference [?] studies information dissemination effectiveness based on differences in out-degree and in-degree of social network nodes. Reference [?] demonstrates that information nodes in online social networks generally exhibit negative correlations. Reference [?] utilizes node influence in social networks for community detection, studying hierarchical privacy protection strategies based on community structure to enhance information availability and strengthen protection of core nodes. These structure-based research methods can profoundly characterize the underlying architecture of various information propagation phenomena, providing foundations for studying evolution patterns of information dissemination.

Information in social networks (including various public opinions) originates from so-called self-media individuals and subsequently spreads and evolves within friend circles. Among research on network information propagation, one question warrants further investigation: during information propagation, is success attributable to a node’ s inherent information advantages (such as personal charisma or authoritative interpretation), or to its important position within the network structure? Based on this question, some scholars analyze information propagation patterns from a network structure perspective.

Reference [?] proposes a random walk model for measuring relative importance indicators in graphs, defining an abstract PageRank function. PageRank has generated variants based on different network characteristics and analytical objectives, such as RWRS for measuring inter-node distances and topic-sensitive random walk models [?, ?]. In structure-related research, hypergraphs have also been employed as tools for studying public opinion diffusion. Real individuals exist within multiple closely related social networks, and their information propagation is constrained by various social relationships. Hypernetworks based on hypergraphs can characterize these multi-type network structures, and by introducing epidemiological propagation models, they can reveal patterns and trends of public opinion propagation in hypernetworks [?].

As special information, rumors exhibit different propagation characteristics and control methods compared to ordinary information. References [?, ?] utilize clustering coefficients in social networks to study rumor propagation patterns. Reference [?] investigates rumor spreading behavior on scale-free networks with power-law degree distributions and variable clustering coefficients based on the classic rumor propagation model, finding that higher clustering coefficients more effectively inhibit rumor propagation. Reference [?] conducts simulation studies on social network rumor propagation using complex network clustering coefficients as parameters, discovering that rumor propagation capacity and influence range increase with the degree of initial propagation nodes but are suppressed by increasing network clustering coefficients. Reference [?] constructs a two-stage A-SC1C2IR model and derives its dynamic equations, with simulation results showing that early authoritative intervention effectively controls microblog rumor propagation. Reference [?] analyzes information propagation patterns in virtual communities and blogs—environments with social network characteristics—treating blog networks as social networks based on blogger nodes. Reference [?] introduces user behavior analysis and contact nodes based on infectious disease dynamics models, proposing a user behavior analysis-based SCIR model to analyze node associations and evolution in microblog social networks. When considering network structure impacts on rumor propagation, Reference [?] constructs influence discrimination values based on community structure and K-shell node methods to analyze single-source infection problems. Recognizing that K-shell decomposition yields numerous identical ks values, they improve the method by proposing a ks value differentiation approach based on nodes' different community structures, defining a new node influence discrimination value (Nc value) to distinguish influence among nodes with identical ks values. SIR model simulations of single-source infection reveal that nodes with higher Nc values not only have larger final influence ranges but also faster propagation speeds [?]. Reference [?] proposes a network structural supportiveness model to characterize node importance in social networks, effectively quantifying and explaining influence degrees among network structure members. This paper explores social network node relationships based on network structural supportiveness theory, further investigating important properties of node supportiveness and examining rumor propagation characteristics across nodes with different supportiveness in social networks. This research provides reference value for studying, managing, and controlling rumor propagation.

1.1 Node Influence

Node influence reflects a node' s relative importance within a network. We define an abstract PageRank function. PageRank, based on probability transfer concepts, distributes a node' s PageRank value equally among nodes it points to. A node u' s PageRank value depends on the sum of transferred values it receives. Let $M(u)$ denote the set of nodes pointing to u, and $d(v)$ represent node v' s out-degree. The PageRank value is defined as:

$$PR(u) = (1-\varepsilon) + \varepsilon \sum_{v \in M(u)} \frac{PR(v)}{d(v)}$$

where ε is a damping factor. This value measures node u' s influence in network G. Generally, nodes with larger influence values have higher visitation probabilities. Drawing from Reference [**?**], we characterize node u' s influence function using this PageRank approach. Reference [**?**] similarly employs node importance scoring functions, using PageRank and TwitterRank to assign values to node u.

1.2 Individual Supportiveness Function

Using methods from Reference [**?**], we define and explain dependency, supportiveness, and K-supportiveness.

Definition 1 (Dependency). For graph $G = (V, E)$, the dependency function of node $v \in V$ on node $u \in V$ $(v \neq u)$ is defined as:

$$\omega_{v \to u} = \frac{\lambda(G) - \lambda(G \setminus \{u\})}{\lambda(G)}$$

where $\lambda(\cdot)$ represents a metric function. The dependency function indicates the relative change in metric λ for node v when node u is removed from the original graph G, reflecting the degree of support node v receives from node u in the original graph. The greater the change in λ after removing u, the more significant this support becomes.

Dependency can be understood as a measure of closeness between nodes. Greater dependency of v on u, or stronger support from u to v, indicates a closer relationship; conversely, it suggests a more distant relationship. For two nodes u and v, v' s dependency on u can be interpreted as u' s support for v. The degree to which a node is depended upon by other nodes represents its "supportiveness."

Let $N(v)$ denote node v' s nearest neighbor set. The reverse nearest neighbor set $RNN(v)$ can be defined as:

$$RNN(v) = \{u \in V \mid v \in N(u)\}$$

From this definition, $RNN(v)$ represents the set of all nodes for which v is a nearest neighbor.

Definition 2 (Supportiveness). In graph $G = (V, E)$, node $u \in V$' s supportiveness is expressed as:

$$SUPP_k(u) = \sum_{v \in RNN_k(u)} \frac{1}{|NN_k(v)|}$$

where $RNN_k(u)$ represents node u' s k-th order reverse nearest neighbors, and $NN_k(v)$ represents node v' s k-th order nearest neighbors. Supportiveness represents a node' s social energy; nodes with larger $SUPP_k(u)$ values generally exert greater influence in social networks.

1.3 Supportiveness Calculation

Calculating node supportiveness in social networks requires examining reverse nearest neighbor relationships, which presents certain difficulties. This section defines re-supportiveness, proves a theorem, and implements a supportiveness calculation method based on this theorem.

Definition 3 (Re-supportiveness). In graph $G = (V, E)$, node $u \in V$' s re-supportiveness is expressed as:

$$RSUPP_k(u) = \sum_{v \in NN_k(u)} \frac{1}{|RNN_k(v)|}$$

Re-supportiveness measures the degree to which node u is influenced by other nodes in the social network. Larger values indicate that node u is more frequently influenced by other nodes and is more likely to be affected by other nodes' information (or messages).

Theorem 1. In graph $G = (V, E)$, the total supportiveness equals the total re-supportiveness:

$$\sum_{u \in V} SUPP_k(u) = \sum_{u \in V} RSUPP_k(u)$$

Proof: By definition:

$$\sum_{u \in V} SUPP_k(u) = \sum_{u \in V} \sum_{v \in RNN_k(u)} \frac{1}{|NN_k(v)|} = \sum_{v \in V} \sum_{u \in NN_k(v)} \frac{1}{|RNN_k(u)|} = \sum_{v \in V} RSUPP_k(v)$$

Thus, the theorem is proved.

According to Theorem 1, calculating supportiveness can be achieved by computing re-supportiveness. This approach only requires calculating each node' s neighbors' support for it in $NN_k(u)$, rather than computing each node' s support for others in $RNN_k(u)$. Since node quantities generally require computer implementation, this method significantly reduces algorithmic complexity.

2 Simulation Analysis of Rumor Propagation Based on Supportiveness

2.1 Rumor Propagation States and Basic Process

Rumor propagation represents a special case of information dissemination in social networks. Due to their sensitive nature, rumors generally spread faster than ordinary information. When refutation information is published, rumor influence can be weakened and eliminated to some extent. Many studies on rumor propagation draw on the classic SIR epidemic model proposed by Kermack and McKendrick (1927), using S (susceptible), I (infective), and R (recovered) to represent three propagation states. The transition relationships among these states are shown in Figure 1 [Figure 1: see original paper].

However, rumor propagation characteristics differ significantly from infectious diseases, particularly regarding the transition from infected nodes I to recovered nodes R. Infectious diseases rely solely on individual immunity, with individuals transitioning probabilistically over time. Rumor propagation transitions generally require intervention from immunizing information (such as authoritative refutations). Additionally, the S-to-I transition process differs substantially: infectious diseases spread through spatial contact, while rumor propagation depends on inter-node associations. Combining these realities, we establish the following basic transition rules for social network rumor propagation:

a) If a healthy node S contacts a propagation node I, the healthy node transitions to propagation node I with probability p_1.

b) When a propagation node I encounters an immune node R, it transitions to immune node R with probability p_2.

c) A propagation node I can also transition directly to immune node R with probability p_3, independent of node topology.

Based on the SIR three-state rumor propagation relationship, the node state transition diagram is shown in Figure 2 [Figure 2: see original paper].

2.2.1 Construct Basic Network Structure

In microblogs or Twitter, bloggers serve as social network nodes. Information propagates through a "subscribe-distribute" model based on node following relationships. While node following and commenting behaviors don' t significantly amplify information influence, "retweeting" creates secondary information propagation, demonstrating amplification and "supportiveness" effects of information influence.

We construct a basic network structure as a bidirectional, unweighted attribute graph $G = (V, E, A)$, where $V = \{V_i | i \in N\}$ represents the node set, and $E = \{V_i \to V_j | V_i, V_j \in V, i \neq j\}$ represents edges indicating connectivity between V_i and V_j. When nodes have following or followed relationships, a directed edge exists between them: $V_i \to V_j$ indicates V_i follows V_j, $V_i \leftarrow V_j$ indicates V_i is followed by V_j, and $V_i \leftrightarrow V_j$ indicates mutual following. A represents the attribute set of nodes in graph G, defined as $A = \{S, I, R\}$, where S is the susceptible state, I is the infective state, and R is the recovered state. Thus, $G = (V, E, A)$ represents a network node set where nodes carry three possible attributes (S, I, R) and have directed edges between them.

2.2.2 Simulation Data Analysis

1) Scale-free network characteristics formed by numerous nodes

Using the method from the previous section, we selected 10,586 nodes from Sina Weibo and collected 26,836 retweets within a time period. Directed edges between nodes were determined based on following and followed relationships. From this data, we obtained the node degree distribution (combining out-degree and in-degree without distinction), shown in Figure 3 [Figure 3: see original paper].

Using the random walk model from Reference [**?**] to calculate nodes' PageRank values, we further implemented the node supportiveness calculation method from Section 1.3 for statistical analysis, shown in Figure 4 [Figure 4: see original paper].

The data analysis reveals that in Sina Weibo' s user relationships, both node degree and supportiveness follow power-law distribution characteristics: most nodes have small degree and supportiveness, while 极少数 nodes have relatively large values.

2) Propagation characteristics of top-K supportiveness nodes

We selected the 5 nodes with highest supportiveness (chosen for experimental convenience, not necessarily limited to 5) and injected rumors, setting these 5 nodes to state I at time step 0. Subsequently, nodes connected to these 5 nodes (nodes following them) transitioned from state S to I according to probability p_1, as shown in Figure 5 [Figure 5: see original paper]. In the figure, asterisks (*) represent the 5 high-supportiveness nodes, while plus signs (+) represent lower-supportiveness nodes.

After all nodes in the system became aware of the rumor, we injected refutation information by selecting the 10 nodes with highest supportiveness and setting them to state R at time step 0. Nodes connected to these 10 nodes (nodes following them) transitioned from state I to R according to probability p_2, as shown in Figure 6 [Figure 6: see original paper]. The figure shows that high-supportiveness nodes achieved significantly faster immune control over rumor information—the number of immune nodes increased more rapidly.

3 Conclusion

Based on the social network structural supportiveness model, this paper defines and analyzes system supportiveness and re-supportiveness concepts. By proving their equivalence across the entire system, we implement a method for calculating node supportiveness. Simulation experiments analyzing rumor propagation and refutation processes across nodes with relatively high versus low supportiveness in sample social network populations demonstrate significant differences in how supportiveness levels affect rumor spreading and refutation. Future research could further investigate propagation differences across all individuals, examining how supportiveness distribution characteristics create varying rumor propagation impacts. Additionally, more parameters in structural supportiveness-based rumor propagation models warrant deeper analysis, such as transition coefficients between various rumor states and potential intermediate states beyond the SIR framework.

References

[1] Watts D J, Strogatz S H. Collective dynamics of small-world networks [J]. Nature, 1998, 393 (6684): 440-442.

[2] Barabasi A L, Albert R. Emergence of scaling in random networks [J]. Science, 1999, 286 (5439): 509-512.

[3] Kumar R, Novak J, Tomkins A. Structure and evolution of online social networks [C]// Proc of the 12th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 2006.

[4] Hu H, Wang X. Evolution of a large online social network [J]. Physics Letters A, 2009, 373 (12-13): 1105-1110.

[5] Mislove A, Marcon M, Gummadi K P, et al. Measurement and analysis of online social networks [C]// Proc of the 7th ACM SIGCOMM Conference on Internet Measurement. 2007.

[6] Chun H, Kwak H, Eom Y H, et al. Comparison of online social relations in terms of volume vs. interaction: a case study of Cyworld [C]// Proc of the 8th ACM SIGCOMM Conference on Internet Measurement. 2008.

[7] 张凌, 罗曼曼, 朱礼军. 基于社交网络的信息扩散分析研究 [J]. 数据分析与知识发现, 2018, 14 (2): 46-57. (Zhang Ling, Luo Manman, Zhu Lijun. Analyzing information dissemination on social networks [J]. Data Analysis and Knowledge Discovery, 2018, 14 (2): 46-57.)

[8] Fu F, Chen X, Liu L, et al. Social dilemmas in an online social network: the structure and evolution of cooperation [J]. Physics Letters A, 2007, 371 (1-2): 58-64.

[9] 陆越, 陈秀真, 马进. 融合社团划分的社交网络分级隐私保护算法 [J]. 通信技术, 2018, 15 (2): 404-412. (Lu Yue, Chen Xiuzhen, Ma Jin. Hierarchical privacy protection algorithm for social network based on community division [J]. Communications Technology, 2018, 15 (2): 404-412.)

[10] Page L, Brin S, Motwani R, et al. The PageRank citation ranking: bringing order to the Web, Technical Report SIDL-WP-1999-0120 [R]. [S.l.]: Stanford University, 1999.

[11] Fujiwara Y, Nakatsuji M, Onizuka M, et al. Fast and exact top-k search for random walk with restart [C]// Proc of the 38th Very Large Data Base.

[12] Zhou Guangyou, Liu Kang, Zhao Jun. Topical authority identification in community question answering [C]// Proc of the Chinese Conference on Pattern Recognition. 2012.

[13] 索琪, 郭进利. 超网络中的舆情传播模型及仿真研究 [J]. 计算机应用研究, 2017, 34 (9): 2629-2632. (Suo Qi, Guo Jinli. Spreading model and simulation analysis of Internet public opinion in hypernetworks [J]. Application Research of Computers, 2017, 34 (9): 2629-2632.)

[14] 潘灶烽, 汪小帆, 李翔. 可变聚类系数无标度网络上的谣言传播仿真研究 [J]. 系统仿真学报, 2006, 18 (8): 2346-2348. (Pan Zaofeng, Wang Xiaofan, Li Xiang. Simulation investigation on rumor spreading on scale-free network with tunable clustering [J]. Journal of System Simulation, 2006, 18 (8): 2346-2348.)

[15] 朱张祥, 刘咏梅. 在线社交网络谣言传播的仿真研究——基于聚类系数可变的无标度网络环境 [J]. 复杂系统与复杂性科学, 2016, 13 (2): 74-82. (Zhu Zhangxiang, Liu Yongmei. Simulation study of propagation of rumor in online social network based on scale-free network with tunable clustering [J]. Complex Systems and Complexity Science, 2016, 13 (2): 74-82.)

[16] 宋之杰, 石蕊, 王建. 权威信息发布对突发事件微博谣言传播的影响研究 [J]. 情报杂志, 2016, 35 (12): 41-47. (Song Zhijie, Shi Rui, Wang Jian. Influence of authoritative information release on rumors spreading in emergency events [J]. Journal of Intelligence, 2016, 35 (12): 41-47.)

[17] Java A, Kolari P, Finin T, et al. Modeling the spread of influence on the blogosphere [C]// Proc of the 15th International World Wide Web Conference. 2006.

[18] 郑志蕴, 郭芳, 王振飞, 等. 基于行为分析的微博传播模型研究 [J]. 计算机科学, 2016, 43 (12): 41-46. (Zheng Zhiyun, Guo Fang, Wang Zhenfei, et al. Study on microblog propagation model based on analysis of user behavior [J]. Computer Science, 2016, 43 (12): 41-46.)

[19] 朱晓霞, 赵雪, 刘萌萌. 基于社团结构的节点的影响力分析 [J]. 计算机应用研究, 2017, 34 (9): 2582-2585. (Zu Xiaoxia, Zhao Xue, Liu Mengmeng. Analysis of influential node based on community structure [J]. Application Research of Computers, 2017, 34 (9): 2582-2585.)

[20] 韩毅, 许进, 方滨兴, 等. 社交网络的结构支撑理论 [J]. 计算机学报, 2014, 37 (4): 905-914. (Han Yi, Xu Jin, Fang Binxing, et al. Structural supportiveness theory on social networks [J]. Chinese Journal of Computers, 2014, 37 (4): 905-914.)

[21] Weng Jianshu, Lim E P, Jiang Jing, et al. TwitterRank: finding topic-sensitive influential twitterers [C]// Proc of the 3rd ACM International Conference on Web Search and Data Mining. 2010.

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.