# Research on Methods for Detecting Influential Users in Social Networks (Postprint)

**Authors:** He Jianmin, Yin Shu

**Date:** 2017-10-11T00:00:00+00:00

## Abstract

【Purpose】To maximize the performance of node-placed social network advertising, this study explores a novel method for identifying influential users in networks.

【Method】From the perspective of social capital measurement, inter-user relationships on social networks are described as a fundamental graph of social relationship networks. Based on this, a social capital measurement model for user influence is established. Influential users are identified and discovered through probability calculations of the likelihood of users' random walk behavior occurring within this fundamental graph.

【Results】The identified target users possess considerable discursive influence within their specific domains and can exert informational influence on other users. The validity and rationality of the method are verified through comparison with influential users tagged by the Sina Weibo platform.

【Limitations】The study does not consider the contribution of social network users' microblog content to their discursive influence.

【Conclusion】This study provides theoretical support and practical methods for enterprises to select influential users when placing social network advertising.

## Full Text

## Identifying Influential Users in Social Networks

**He Jianmin, Yin Shu**
(School of Management, Hefei University of Technology, Hefei 230009, China)
(Key Laboratory of Process Optimization and Intelligent Decision-making, Ministry of Education, Hefei 230009, China)

## Abstract

[**Objective**] This study explores a new method for selecting influential network users to maximize the performance of social network advertising placement. [**Methods**] From the perspective of social capital measurement, we describe user relationships in social networks as basic social relationship network graphs. Based on these graphs, we establish a social capital measurement model for user influence and identify influential users by calculating the probabilities of random walk behaviors among users under the basic graph structure. [**Results**] The identified target users possess considerable discursive influence in their specific domains and can exert informational influence on other users. The method' s effectiveness and rationality were verified through comparison with influential users identified by the Sina Weibo platform. [**Limitations**] The study does not consider the contribution of social network users' blog content to their discursive influence. [**Conclusions**] The proposed method provides theoretical support and a practical approach for enterprises to select influential users for social network advertising placement.


**Keywords:** Online advertisement placement; Social relationship graphs; Social capital measurements of users; Identification model of influential users

## 1. Introduction

On social networks, users publish and disseminate information on specific topics and interact with others based on "self-interested" or "altruistic" motivations, as well as needs for social connection and self-value realization, thereby obtaining and enhancing their online discursive influence. Users with influence have become important marketing resources for enterprises to deliver social advertisements. Compared with general online advertising, social network advertising offers advantages in audience attention and interactive influence, with intuitive performance metric feedback. Consequently, discovering and utilizing influential network users to maximize marketing performance has become a hot research topic in online marketing decision management.

User discursive influence in networks belongs to the category of social capital. Drushel argues that the social capital of opinion leaders is discursive influence, which can promote the dissemination of specific information and facilitate online advertising for enterprises. Lin views social capital as social resources embedded in social relationship networks that actors can access and utilize, including power, wealth, and prestige. According to social capital theory, the relationships formed through mutual attention among social network users constitute a social relationship network. Users can publish and disseminate information within this network, exerting informational influence on others through their information selection methods and behaviors, thereby obtaining and accumulating discursive influence. Social capital resources for user discursive influence consist of elements such as social prestige, professional background, and social skills, manifested as data on users' personal and social attributes.

Existing research on user influence describes online users and their information relationships as different types of physical structures and relationship networks, calculating user influence by computing characteristic attribute data and applying ranking or comprehensive calculations. Representative approaches include: the "user blog content–user social relationship" bipartite graph model method, user self-influence factor analysis method, and multi-interaction relationship network discovery method. Zhu et al., Ding et al., and Tang et al. utilized "blog content–user" bipartite relationships to determine connections between blog content nodes, user nodes, and their subgroups, discovering patterns of online blog dissemination and identifying influential users. Montangero et al., Tarokh et al., and Liu et al. used individual behavioral characteristics or comprehensive evaluation feature attributes of network users to calculate characteristic values and identify influential users. Ding Zhaoyun et al. described information "reading," "forwarding," "replying," and "copying" behaviors among users as single and multi-relationship network structures, using PageRank algorithms to calculate behavior occurrence probabilities under random walks to find influential users. Qi Chao et al. assigned weights to user behavior relationship attributes based on "forwarding," "commenting," and "mentioning" behaviors, then identified influential users through superimposed calculation of behavioral feature data.

In summary, scholars have employed various theoretical methods from different perspectives to explore the many attributes and features constituting user influence, mapping information attention relationships among users into physical structures and relationship networks. When calculating user influence, they primarily rely on users' social relationship graphs within network structures and identify information publishing capability as another factor of user influence social capital. This study designs a calculation method for random walk information selection behavior occurrence probabilities under user social relationship network graphs, and uses product calculation and comprehensive ranking of feature data under users' multi-relationship attributes to obtain influential users on social networks, thereby forming a set of social capital-based methods for discovering influential users on social networks.

## 2. User Social Relationship Network Graphs and Their Influence

User influence is formed and enhanced alongside the evolution of their social relationships. The utility of user influence is related not only to their own personal attribute feature data but also to the combined effects of personal and social attribute feature data. User influence emerges from the joint action of multiple attribute feature data including personal and social attributes. From the perspective of social capital theory, this paper describes user attention behavior relationships on social networks as social relationship networks, and characterizes information "browsing," "replying," and "sharing" behaviors among users as single social relationship graphs. We identify users' information interaction capability as a social capital factor of user influence. Under the single social relationship network graph, we describe the combined effects of users' personal attributes and information interaction behavior attribute feature data as multi-relationship graphs. Based on PageRank algorithm rules that allow users to randomly select any behavior during information selection, we calculate the fused probability of user nodes' social behavior occurrence to obtain discursive influence under a certain state. For the entire social network, comprehensive ranking of each user node' s discursive influence composite values yields all user nodes with different discursive influence, thereby discovering influential users suitable for enterprise online advertising placement whose marketing goals match their discursive influence.

**2.1 Basic User Social Relationship Network Graph** In a social network, assuming user node i publishes or disseminates a valuable piece of information on topic T, other users (such as node j) will notice node i' s information and interact with node i through "browsing," "replying," and "sharing" behaviors, forming attention relationships (hereinafter referred to as relationships) and thus constituting a social relationship network. In fact, there are three forms of attention relationships between user node i and node j:

(1) **Browse**: When node j "browses" the information text published by node i, nodes i and j establish a "browse" relationship.

(2) **Reply**: When node j uses the tag "reply" to respond to the information text sent by node i, nodes i and j establish a "reply" relationship.

(3) **Share**: When node j forwards the information text sent by node i, nodes i and j establish a "share" relationship.

The basic graph of the social relationship network formed by mutual user attention is shown in Figure 1 [Figure 1: see original paper].

**2.2 User Social Relationship State Transition Graph** In social networks, assuming any two users form one or more social relationships, the result of user information attention behavior must be one of the state forms in Figure 1. In Figures 1(a), (b), and (c), to describe the possibility of user node i and node j transitioning from an existing social relationship state to another new relationship state, this paper uses probabilities $\alpha$*{Read},* $\alpha$\{Reply\}, and $\alpha$*{Share} to represent the likelihood of node j changing behavior between any two social relationship states. For example, if user node j has "browsed" the information sent by node i, nodes i and j are in the "browse" state. When node j transitions from the "browse" state to the "reply" state, the possibility of node j' s social relationship state change is represented by* $\alpha$\{Reply\}, as shown in Figure 2 Figure 2: see original paper. Similarly, from different states in Figure 2, we can determine node j' s relationship transition probabilities $\alpha$*{Read} and* $\alpha$\{Share\}.

Figure 2 describes user nodes' relationship transition behaviors under different social relationship states. It shows that node j will only transition social relationships when interested in or valuing the information provided by node i.

That is, node i' s information has utility value for node j and exerts discursive influence on node j, meaning node i has discursive influence over node j. When a user node' s discursive influence gradually increases, it can be considered that the node has formed multiple social relationships with n other user nodes. Zuo Wenming et al. found that user discursive influence is positively correlated with related information publishing and social relationship capabilities. Therefore, user influence is determined by their information publishing and social interaction capabilities, described respectively as information publishing capability and information interaction capability. Information publishing capability refers to a user' s ability to use their social resources to publish valuable information with viewpoint tendencies to exert informational influence on others, which can be calculated from the frequency of information sent and the intensity of attention from others. Information interaction capability refers to a user node' s ability to frequently engage in social interaction and communication with other nodes to exert informational influence on others, calculated from the weights of social behavior relationships between users. User discursive influence results from the combined action of information publishing capability and information interaction capability, obtained by multiplying these two capability values. The higher the user' s discursive influence, the greater the possibility of establishing social relationships with others. For example, if node j has "browsed" node i' s information, the possibility of this social relationship occurring is represented by "social behavior occurrence probability from j to i," obtained by calculating the sum of discursive influence values of all nodes interacting with node j and comparing this value with node i' s discursive influence value.

Figure 1 shows the social relationship network graph between any two users. Based on this, we can calculate according to PageRank algorithm rules, which allow users to randomly select any behavior during information selection. By calculating the fused probability of user nodes' social behavior occurrence, we obtain discursive influence under a certain state. For the entire social network, comprehensive ranking of each user node' s discursive influence composite values yields all user nodes with different discursive influence, enabling the discovery of influential users suitable for enterprise online advertising.

**2.3 Multi-Relationship Graph of User Social Relationship Network**
Under topic T information, assuming the set of node users is V and the set of texts published by V is C, and users in V maintain one or more social relationships with each other, then all node users in the entire social network form a large social relationship network graph G, where G = (V, E) and E represents the set of relationships between any two nodes in G. Figure 1 shows all situations where attention relationships exist between any two user nodes. Thus, the graph G_f can be understood. For example, in Figure 1(a), (V, E_{Reply}, E_{Share}) represents the "browse" relationship graph G_{Read} between any nodes, where V_{Read} is the set of all nodes maintaining "browse" relationships, E_{Read} is the set of directed edges maintaining "browse" relationships between nodes, and W(E_{Read}) represents the weight of "browse" relation-

ships between nodes, reflecting the node' s information interaction capability over other nodes. Similarly, the graph for "reply" relationships is G_{Reply} and for "share" relationships is G_{Share}.

In social networks, since node users' "browse" relationships with other nodes are random and lack tag identification, the information interaction capability under this social relationship is uncertain, making it impossible to calculate node weights under the "browse" relationship. However, when user nodes have "reply" and "share" relationships with other nodes, the results are deterministic and can be identified through information tags. Therefore, when calculating user nodes' information interaction capability under "reply" and "share" relationships, we can compute W(E_{Reply}) and W(E_{Share}) based on the number of "replies" and "shares."

**2.4 Social Capital-Based User Influence Discovery Model** The social capital-based user influence discovery model is shown in Figure 3 [Figure 3: see original paper]. This model reveals the patterns of occurrence and transformation of social relationships among users. Based on this, we can comprehensively calculate users' social behavior occurrence probabilities and relationship transition probabilities through random walks according to users' social behavior patterns, obtain the ranking values of user nodes' discursive influence, and rank them across the entire social network to discover influential online users.

## 3. Social Capital Calculation of User Discursive Influence

In social relationship networks, user discursive influence is social capital. The acquisition and enhancement of user influence require continuous publishing and dissemination of valuable information texts to attract others' attention, while also engaging in information interaction with other users who follow their information to exert informational influence on others. This paper defines the degree of attention received by a user node' s information texts as the sum of comments and forwards on the texts published by the node, averaged appropriately. We define the degree of information activity of a user node as the number of information texts published by the node within a unit time, thereby calculating the user' s information publishing capability.

**3.1 Measurement Calculation of User Information Publishing Capability (1) Measurement of User Information Attention Degree**
Assume user node i publishes n_i information texts within time t, the total number of comments on i' s n_i information texts is c_i, and the total number of forwards is r_i. Then the information attention degree q_i of user node i is calculated as shown in formula (1).

**(2) Measurement of User Information Activity Degree**
Assume user node i publishes n_i information texts within time t, and the information activity degree of user node i is a_i, then:

**(3) Measurement of User Information Publishing Capability**
Based on formulas (1) and (2), the information publishing capability d_i of user node i is calculated as shown in formula (3).

### 3.2 Measurement Calculation of User Information Interaction Capability (1) Under User "Browse" Relationship

When user node i participates in discussions on topic T information, its information is browsed by user nodes in G as soon as it is published, indicating that node i' s information can attract others' interest and has value, thus node i may receive attention from others. The higher the frequency of others browsing node i' s information, the greater the influence node i' s information exerts on others. From G_{Read} = (V_{Read}, E_{read}, W(E_{Read})), we know that the information interaction capability of user node i is w_{Read}.

When user node j has "browsed" node i' s information, it indicates that node j has experienced the value of node i' s information and has been influenced by it. In this process, node j users have two scenarios: Node j lacks the professional knowledge necessary to understand and participate in discussions on T information, or node j is new to the social network and participates in T topic discussions under the influence of node i' s information; Node j understands T topic information and has independent opinions, is willing to participate in discussions on T topic information, and also willing to express independent views.

Under the basic "browse" social relationship graph, the method to distinguish these two types of users is: first assume that the information publishing capability threshold of all user nodes in G is $\delta$, and the information publishing capability of any user node i is d_i. When d_i $\geq \delta$, node i can be classified as type user; when d_i $\leq \delta$, node i can be classified as type user. For type user j, if node j has "browsed" node i' s information and adds node i as a "friend" to follow, the decision factors stem from node i' s "popularity" and the "quantity of information texts published" by node i. Assuming user node j has browsed the information sent by node i, node i' s information interaction capability can be defined as:

w_{Read}→i = _i × d_i

where _i represents node i' s popularity, which can be calculated as node i' s "number of followers/number of followings."

For type user j, node j is interested in T topic-related information sent by friend node i. Based on formula (4), we must also consider the focus degree of user node j' s "browsing" of friend node i' s information on T topic content. The higher the focus degree of user node i' s published information on T topic information, the greater the possibility that other users such as node j will "browse" node i' s information texts. Assuming user node i publishes an information text p_i(s), the closeness degree between this information text and T topic information is $\beta$_i(s), which can be calculated according to keyword TF-IDF detection technology and text cosine similarity. Assuming the closeness threshold between node i' s published information text and T topic information is , when $\beta_i(s) \geq$ , it indicates that node i' s information text $p_i(s)$ is related to T; otherwise, it is unrelated. By calculating the total number of T-related texts published by user node i within time t and comparing it with the total number of texts published during this period, the ratio $\lambda_i$ is obtained as the focus degree of user node i' s information. Thus, the information interaction capability of user node i under the "browse" relationship is:

$$w_{Read} \to i = \ _i \times \lambda_i \times d_i$$

**(2) Under User "Reply" and "Share" Relationships**
Social relationships of "reply" and "share" between user nodes can be confirmed through tag detection. In the "reply" relationship graph $G_{Reply} = (V_{Reply}, E_{Reply}, W(E_{Reply}))$ and the "share" relationship graph $G_{Share} = (V_{Share}, E_{Share}, W(E_{Share}))$, the information interaction capability $w_{Reply} \to i$ of user node i is determined by the total number of text messages "replied" or "shared" by other user nodes it follows. When user node j has "reply" and "share" relationships with its friend node i, node i' s information interaction capability under "reply" is $w_{Reply} \to i$ and under "share" is $w_{Share} \to i$.

**3.3 Social Capital Calculation of User Discursive Influence** In Figure 2, user node discursive influence is jointly determined by its own information publishing capability d and information interaction capability w, where w is the synthesis of $w_{Read}$, $w_{Reply}$, and $w_{Share}$. The calculation method for node i' s discursive influence is the product of d and w values. Assuming nodes i and j are any one of the relationship scenarios in Figure 1, node i' s discursive influence F can be calculated through formulas (6)-(8) to obtain the social capital measurement of user discursive influence:

$$F(Read) = w_{Read}(v_j \to v_i) \times d_i$$
$$F(Reply) = w_{Reply}(v_j \to v_i) \times d_i$$
$$F(Share) = w_{Share}(v_j \to v_i) \times d_i$$

## 4. Composite Calculation and Comprehensive Ranking of User Discursive Influence

**4.1 Single Social Relationship** In Figures 1(a), (b), and (c), after calculating user nodes' discursive influence, we must examine the possibility of node social behavior occurrence under Figures 1(d), (e), (f), and (g), mainly calculating nodes' social behavior occurrence probabilities. Assuming user node j, after "browsing" node i' s information, goes on to "browse" other nodes' information, a new multi-relationship is established, namely a "browse-browse" relationship. Let the probability matrix of this node j' s "browsing" behavior be $A_{read}$, then the social behavior occurrence probabilities of node users for "browsing," "replying," and "sharing" are:

**(1) Social behavior occurrence probability of any user node v_j randomly "browsing" node v_i' s information text:**

A_{Read}(v_j→v_i) = F_i(Read) / Σ_{v V} F_v(Read)

**(2) Social behavior occurrence probability of any user node v_j randomly "replying" to node v_i' s information text:**

A_{Reply}(v_j→v_i) = F_i(Reply) / Σ_{v V} F_v(Reply)

**(3) Social behavior occurrence probability of any user node v_i randomly "sharing" node v_j' s information text:**

A_{Share}(v_i→v_j) = F_i(Share) / Σ_{v V} F_v(Share)

where v V represents all nodes "browsed," "replied," or "shared" by v_j.

**4.2 Multi-Social Relationship** Under the relationships in Figure 1, besides nodes interacting with other nodes in forms (a), (b), and (c), they can also interact in forms (d), (e), (f), and (g). Therefore, a new type of social relationship needs to be established, namely a multi-relationship graph.

Assuming a node user' s social relationship state belongs to any one of (a), (b), and (c) in Figure 1, let the social relationship transition probabilities from any relationship state to "browse (reply, share)" relationship states be $\alpha$*{Read},* $\alpha${Reply}, and $\alpha$*{Share}, respectively, satisfying* $\alpha${Read} + $\alpha$*{Reply} +* $\alpha${Share} = 1. Besides exerting discursive influence on others through random walks under the states in Figures 1(a), (b), and (c), nodes can also use these as starting points to build new social relationships with any other nodes, as shown in Figures 1(d), (e), (f), and (g). Thus, we can calculate the possibility of node behavior changes in the next step under random walks in a given social relationship graph, then integrate it with the possibility of node social relationship state transitions to obtain all possibilities of the node exerting discursive influence on other nodes, i.e., calculate social behavior occurrence probabilities under multi-social relationships.

Under topic T information, assuming $\gamma$ is the possibility of nodes establishing social relationships with other nodes in any of the forms (a), (b), and (c) in Figure 1. From the multi-relationship graph shown in Figure 2, the social behavior occurrence probabilities between nodes are B_{Read}, B_{Reply}, and B_{Share}. Here we consider nodes' social behavior occurrence possibilities A_{Read}, A_{Reply}, and A_{Share} in Figure 1, while also considering probability calculation methods for nodes' multi-social relationship state transition possibilities $\alpha$*{Read},* $\alpha${Reply}, and $\alpha$_{Share} in Figure 2.

**(1) Social behavior occurrence probability of user node j after "browsing" i:**

B_{Read}(v_j→v_i) = $\alpha$*{Read}* - $\gamma$ × *A*{Read}(v_j→v_i)

**(2) Social behavior occurrence probability of user node j after "replying" i:**

$B_{Reply}(v_j \rightarrow v_i) = \alpha\{Reply\} - \gamma \times A\{Reply\}(v_j \rightarrow v_i)$

**(3) Social behavior occurrence probability of user node j after "sharing" i:**

$B_{Share}(v_j \rightarrow v_i) = \alpha\{Share\} - \gamma \times A\{Share\}(v_j \rightarrow v_i)$

where all user nodes participating in topic T interactions are included.

**4.3 Iterative Ranking of User Discursive Influence** Under topic T information, assuming the number of participating user nodes is n, and the vector composed of these users' discursive influence ranking values is P. The discursive influence ranking value of any user node i in P is $p(v_i)$. According to the PageRank algorithm, calculating $p(v_i)$ involves calculating the ranking values of node i' s followers in Figure 2, then multiplying all followers' ranking values with their social behavior occurrence probabilities and accumulating them to obtain node i' s total discursive influence ranking value. The $p(v_i)$ calculation formula is:

$p(v_i) = \Sigma_{v_j V} [B_{Read}(v_j \rightarrow v_i) \times p(v_j) + B_{Reply}(v_j \rightarrow v_i) \times p(v_j) + B_{Share}(v_j \rightarrow v_i) \times p(v_j)]$

where moving $p(v_j)$ out of the brackets shows that the formula inside the brackets is exactly the sum of transposes of behavior occurrence probability matrices $B_{Read}$, $B_{Reply}$, and $B_{Share}$, multiplied by vector P to obtain the $p(v_i)$ value in row i.

Assuming the composite behavior occurrence probability matrix of user node i in Figure 2 is B, where $B = B_{Read} + B_{Reply} + B_{Share} = 1$. According to the PageRank power iteration calculation method, we can calculate the ranking values of n nodes' discursive influence to obtain the ranking value vector matrix P. Based on the Markov chain and its finiteness theorem, the result of this vector matrix P converges. The iteration formula is:

$P_k = B^T \times P_{k-1}$

where the initial value of k is 0, the initial ranking value vector is set as $P_0$, and $P_k$ and $P_{k-1}$ are the vectors of n nodes' discursive influence ranking values obtained after the k-th and (k-1)-th iterations, respectively.

## 5. Experiments and Results Discussion

The experimental platform is the Sina Weibo social network platform. Data collection was performed automatically through the API programming interface provided by Sina Weibo, with the data collection period from October 1, 2014, to October 31, 2014. From the obtained user data packages, we selected the user discussion topic "#Where Are We Going, Dad?#" as the T topic information.

The collected Weibo user node data mainly includes node self-characteristic attribute data, interactive behavior relationship attribute data, and daily records of blogs published and disseminated by nodes and their interactions and forwards. After eliminating invalid ID user node numbers, we obtained a total of 106 users participating in T topic information publishing, browsing, replying, and forwarding, with a total of 1,301 blog information records. User data record attribute items include: user nickname (A0), whether verified (A1), number of followings (A2), number of followers (A3), total number of Weibo posts (A4), number of Weibo posts within the data collection period (A5), and sum of comments and forwards on Weibo posts (A6). The above Weibo user data collection was imported into a basic information database, with a partial list of data attribute items shown in Table 1 . Meanwhile, based on the attention relationships among these users, a user node attention relationship database was established in "0-1" matrix form, as shown in Table 2 .

### 5.1 Experimental Steps and Results Discussion (1) Calculation of Weibo User Nodes' Information Publishing Capability

In the Weibo user basic information database, the information publishing capability d of Weibo users can be calculated using formulas (1)-(3). For example, the user with nickname "CaiCai_{JiaYouXiaoXiaoCai}" has an information publishing capability value of 2.6777. Calculating all Weibo users' information publishing capabilities yields their values. Assuming the information publishing capability threshold is $\delta = 1$, based on whether a Weibo node' s information publishing capability is greater than or less than $\delta$, we can determine whether the Weibo node belongs to type or type user as defined in Section 3.2. The calculation results are shown in Table 3 .

**(2) Calculation of Weibo Users' Social Behavior Occurrence Probability Matrix in Figure 1**

Based on the Weibo user node attention relationship database, and according to the user type determination conditions and calculation formulas (4)-(6) and (9), we can calculate Weibo users' social behavior occurrence probabilities under the "browse" relationship. The calculation results are shown in Table 4 . Similarly, we can obtain Weibo users' social behavior occurrence probabilities under the "reply" and "share" relationships.

**(3) Calculation of Weibo Users' Social Behavior Occurrence Probability and Matrix in Figure 2**

From step (2), we calculate the social behavior occurrence probabilities in Figure 1, then use formulas (12)-(14) to calculate Weibo users' social behavior occurrence probabilities under Figure 2. First, set the node social relationship transition probability as $\alpha$. When a Weibo user has "browsed" a friend user' s blog post, it is considered that the Weibo user has been influenced by the friend' s information, but the influence is not as strong as when the Weibo user replies to or forwards the friend' s blog post. Therefore, $\alpha\{Read\} < \alpha\{\text{Reply}\}$ and $\alpha\{Read\} < \alpha\{\text{Share}\}$. Set $\alpha\{Read\}$, $\alpha\{\text{Reply}\}$, and $\alpha\{Share\}$ *as 0.2, 0.4,* *and 0.4, respectively, and set $\gamma$ as 0.15 based on empirical values. From this, we calculate nodes' social behavior occurrence probabilities* $B${Read}, B_{Reply}, and B_{Share} in Figure 2. Taking B_{Read} calculation as an example, the results are shown in Table 5 . Similarly, we obtain social behavior occurrence probabilities for B_{Reply} and B_{Share}.

**(4) Weibo Users' Discursive Influence Ranking Values and Comprehensive Ranking**
From step (3) and formulas (15) and (16), we calculate Weibo users' discursive influence ranking values and comprehensive ranking, as shown in Table 6 .

Based on steps (2)-(4), we can calculate the comprehensive ranking of Weibo users' discursive influence, thereby discovering Weibo users with discursive influence under topic T. Assuming an enterprise' s marketing theme content is consistent with the content discussed in topic T, Table 6 can help enterprises recommend top-ranked users as alternative influential users for delivering T-themed advertisements, providing theoretical support and practical methods for enterprises' social marketing advertising placement.

The results of Weibo users' discursive influence in Table 6 show that the method provided in this paper differs from the Weibo user influence recommendation method provided by Sina Weibo' s official platform. Sina Weibo platform judges user influence based on the number of followers or whether a user is verified. In fact, which social circle a Weibo user belongs to is determined by their domain knowledge, interests, and abilities. Evaluating a user' s influence utility requires comprehensive consideration of elements such as their network prestige, professional background, and social skills in the social circle. The user discursive influence ranking provided in Table 6 demonstrates users' expertise and capabilities in the above three aspects, providing decision support for enterprises to select users' areas of expertise and capabilities. This can help enterprise advertising dissemination, making advertisements easier for target audiences to notice, generating interest, searching, and taking action, thereby promoting purchase and sharing value to form word-of-mouth. Exploring the relationship between user discursive influence factors and advertising performance factors to select appropriate advertising placement users is a new attempt to maximize enterprise advertising performance.

## 6. Conclusion

Social networks and users' discursive influence are important strategic resources for enterprise online marketing. Leveraging user discursive influence can provide enterprises with better promotion efficiency and effectiveness than general online advertising when placing social network advertisements. How to discover users with discursive influence on social networks is a hot research issue in the field of maximizing social marketing performance.

From the perspective of social capital theory, this paper studies the formation and enhancement process of user influence and its utility on social networks, explores users' information selection behaviors and relationships, user social relationship networks, and the formation patterns of users' social capital. It aims to identify the components of social capital elements of user discursive influence on social networks, discovers that users' information publishing capability and information interaction capability are the main contents of their social capital, defines the characteristic data of personal attributes, social attributes, and behavioral relationship attributes of user discursive influence social capital, and uses probability theory methods to calculate relevant data of influence attribute features to identify influential users on social networks, thereby forming a set of social capital-based methods for discovering influential users on social networks.

Research shows that social relationships among users on social networks are essentially social relationship networks. User influence consists of information publishing capability and information interaction capability, which are the main manifestations of users' social capital resources, represented by users' personal and social attribute feature data. We establish single-relationship and multi-relationship social relationship graphs, define users' social relationship behavior occurrence probabilities and random walk behavior and relationship transition probabilities, calculate the possibility of users exerting informational influence behaviors on other users (i.e., influence utility), build a social capital-based influential user discovery model describing user social behavior occurrence probabilities and relationship transition probabilities under different social relationships, and use PageRank random walk thinking to calculate the social capital ranking values and comprehensive ranking of user discursive influence to discover influential users. This ultimately forms a set of social capital-based methods for discovering influential users on social networks. Experiments on Sina Weibo user data verify the method' s rationality and effectiveness. This method can serve as an approach for enterprises to select influential users for placing social advertisements, which is of important value for helping enterprises achieve maximized social marketing performance. Future research will focus on the relationship between information content published by social network users and its contribution to influence growth.

## References


[1] He Jianmin, Zheng Zhe. Study of "Motivation-Behavior"Model of Consumers' Complaints on Social Network [J]. Journal of Hefei University of Technology: Social Science, 2015, 29(1): 1-9.

[2] O' Connor L G, Dillingham L L. Personal Experience as Social Capital in Online Investor Forums [J]. Library & Information Science Research, 2014, 36(1): 27-35.

[3] Drushel B E. HIV/AIDS, Social Capital, and Online Social Networks [J]. Journal of Homosexuality, 2013, 60(8):

[4] Lin N. Social Capital: A Theory of Social Structure and Action [M]. Cambridge University Press, 2002.

[5] Tang Xiaobo, Fang Xiaoke. Research on Microblog Ranking Strategy with the Social Relations [J]. New Technology of Library and Information Service, 2013(9): 74-81.

[6] Subbian K, Sharma D, Wen Z, et al. Finding Influencers in Networks Using Social Capital [C]. In: Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. 2013: 25-28.

[7] Zhu Z, Su J, Kong L. Measuring Influence in Online Social Network Based on the User-Content Bipartite Graph [J]. Computers in Human Behavior, 2015, 52: 184-189.

[8] Ding Z, Wang H, Guo L, et al. Finding Influential Users and Popular Contents on Twitter [C]. In: Proceedings of the 16th International Conference on Web Information System Engineering, Miami, FL, USA. Springer International Publishing, 2015: 267-275.

[9] Tang B, Lu T, Gu H, et al. Measuring Domain-Specific User Influence in Microblogs: An Actor-Network Theory Based Approach [C]. In: Proceedings of the 19th International Conference on Computer Supported Cooperative Work in Design. IEEE, 2015: 314-319.

[10] Montangero M, Furini M. TRank: Ranking Twitter Users According to Specific Topics [C]. In: Proceedings of the 12th Conference on Consumer Communications and Networking, Las Vegas, NV, USA. IEEE, 2015: 767-772.

[11] Tarokh M J, Arian H S, Speily O R B. Discovering Influential Users in Social Media to Enhance Effective Advertisement [J]. Advances in Computer Science: An International Journal, 2015, 4(5): 23-28.

[12] Liu N, Li L, Xu G, et al. Identifying Domain-Dependent Influential Microblog Users: A Post-Feature Based Approach [C]. In: Proceedings of the 28th AAAI Conference on Artificial Intelligence. AAAI, 2014: 3122-3123.

[13] Ding Z, Jia Y, Zhou B, et al. Mining Topical Influencers Based on the Multi-relational Network in Micro-blogging Sites [J]. Communications, 2013, 10(1): 93-104.

[14] Ding Zhaoyun, Zhou Bin, Jia Yan, et al. Topical Influence Analysis Based on the Multi-Relational Network in Microblogs [J]. Journal of Computer Research and Development, 2013, 50(10): 2155-2175.

[15] Qi Chao, Chen Hongchang, Yu Hongtao. Method of Evaluating Microblog Users' Influence Based on Comprehensive Analysis of User Behavior [J]. Application Research of Computers, 2014, 31(7): 2004-2007.

[16] Zuo Wenming, Wang Xu, Fan Chang. Relationship Between Electronic Word of Mouth and Purchase Intention in Social Commerce Environment: A Social Capital Perspective [J]. Nankai Business Review, 2014(4): 140-150.

[17] Wu X, Kumar V. The Top Ten Algorithms in Data Mining [M]. Chapman and Hall/CRC, 2009.

[18] Mao Jiaxin, Liu Yiqun, Zhang Min, et al. Social Influence Analysis for Micro-blog User Based on User Behavior [J]. Chinese Journal of Computers, 2014, 37(4): 791-798.

[19] Russell M A. Mining the Social Web: Data Mining Facebook, Twitter, LinkedIn, Google+, GitHub, and More [M]. O' Reilly Media, 2013.

[20] Li L, Sun L, Ning G. Deterioration Prediction of Urban Bridges on Network Level Using Markov-Chain Model [J]. Mathematical Problems in Engineering, 2014, 9(1): 129-145.

## Author Contribution Statement

He Jianmin: Proposed research ideas, designed research plan, revised final version of paper; Yin Shu: Collected, cleaned and analyzed data, conducted experiments; He Jianmin, Yin Shu: Drafted paper.

## Conflict of Interest Statement

All authors declare no conflict of interest.

## Supporting Data

Supporting data can be found in the online version of the journal at http://www.infotech.ac.cn.

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