Hypernetwork Model Construction and Automated Key Node Identification for Semantic Social Networks (Postprint)

Authors: Zhang Lei, Ma Jing, Li Dandan, Shen Yang

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Abstract

[Purpose] Through modeling of semantic social networks, to discuss how to identify key nodes that play a core role in the evolution of public opinion propagation. [Method] Introduce hypernetwork theory to theoretically model Weibo semantic social networks, use sentiment ontology and LDA topic models to achieve node quantification of data, and propose a hyperedge ranking algorithm to calculate and rank user nodes to obtain key nodes. [Results] Implement the construction and quantification of the hypernetwork model programmatically using real Weibo network data, and demonstrate through results analysis the effectiveness and accuracy of the proposed key node identification method in practical application scenarios. [Limitations] The real-time application effects of the key node identification method and the effective guidance and intervention mechanisms after identifying key nodes have not been comprehensively addressed. [Conclusion] The key node identification method proposed in this paper can identify key nodes in Weibo networks, providing a solution for government monitoring and guidance of online public opinion, and reducing the impact of negative content and negative public opinion on the healthy development of the Internet.

Full Text

Hypernetwork Model for Semantic Social Network and Automatic Identification of Key Nodes

Zhang Lei, Ma Jing, Li Dandan, Shen Yang
(College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China)

Abstract

[**Objective**] This study investigates how to identify key nodes that play a central role in the evolution of public opinion propagation through modeling semantic social networks. [**Methods**] We introduce hypernetwork theory to theoretically model Weibo semantic social networks, employ emotion ontology and the LDA topic model to quantify nodes, and propose a hyperedge sorting algorithm to calculate and rank user nodes for key node identification. [**Results**] Using real Weibo network data, we programmatically implement hypernetwork model construction and quantification, with result analysis demonstrating the effectiveness and accuracy of our key node identification method in practical application scenarios. [**Limitations**] The real-time application performance of the key node identification method and effective guidance and intervention mechanisms after identifying key nodes are not comprehensively addressed. [**Conclusions**] The proposed key node identification method can excavate key nodes in Weibo networks, providing a solution for government supervision and guidance of online public opinion, thereby reducing the impact of negative content and passive public opinion on the healthy development of the Internet.

Keywords: Hypernetwork, Semantic social network, Key node identification, LDA model, Emotion ontology

Classification Numbers: C931, G35

With the development of information technology, social networks such as Weibo and WeChat have become primary means for information dissemination in daily life. A semantic social network is a new type of complex network composed of semantic information nodes and social relationships, which has become the main carrier of network public opinion propagation in the Internet era. The openness and convenience of the Internet make online public opinion expression more free, diverse, and difficult to control, with negative content and passive public opinion seriously hindering the healthy development of the Internet. Since semantic social network structures typically have one or more core nodes that exert greater influence on network structure and function—these are key nodes. According to the information propagation Pareto principle, a very small number of key nodes can influence most nodes in the network. For example, Weibo posts from the most influential "Big Vs" can quickly spread throughout the entire network. Therefore, research on network public opinion propagation, particularly for sudden public opinion incidents, often focuses on identifying key nodes to control and guide the spread of rumors and negative public opinion, making this research of significant practical importance.

Research on key node identification originates from social network analysis. Studies on identifying key nodes in network public opinion both domestically and internationally primarily approach from network topology structure and propagation dynamics. Node importance ranking methods based on network structure mainly measure from aspects such as local properties, global properties, paths, positions, and node removal or contraction. Klemm et al. propose that node importance in cluster dynamics is jointly determined by network structure and cluster dynamics mechanisms. Aral et al. found through studying the propagation behavior of 1.3 million Facebook users that user influence is affected by factors such as age, gender, and marital status. In summary, this paper argues that node importance is influenced not only by network topology characteristics but also by network propagation mechanisms and node-specific attributes.

Traditional network models mostly consist of single-attribute nodes (primarily user nodes), with limited consideration of other attributes such as semantics and emotion contained in these nodes. Particularly, semantic social networks contain complex associative relationships among multiple different elements, which single-node network models cannot accurately describe. American scientists Nagurney et al. were the first to define hypernetworks as "networks above and beyond existing networks," which are suitable for depicting real social networks with multi-layer structures, multi-level features, and multi-attributes, as well as interactions and influences between networks.

Currently, key node identification research based on hypernetwork theory has broad applications. Lin et al. applied it to electromagnetic compatibility problems to evaluate key nodes in electronic systems. Deng applied it to crowd importance modeling to assess the significant role of different groups in domains. Wu et al. used eigenvector centrality to evaluate the comprehensive information interaction capability of nodes in social hypernetworks. Ma et al. pioneered a four-layer hypernetwork model for forum application scenarios including social, environmental, psychological, and opinion layers. This paper improves the content and construction methods of subnet models for Weibo application scenarios where user behavior is easily influenced by topic and emotion attributes. Meanwhile, since previous research using manual summarization of forum corpora for semantic information construction and experimental verification is still in its infancy and time-consuming, this paper innovatively introduces emotion ontology and the LDA topic model for automatic identification and calculation of improved topic and emotion subnets, and proposes corresponding sorting algorithms to adapt to big data scenarios.

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2. Hypernetwork Modeling for Weibo Semantic Social Network

The research framework for automatic identification of key nodes in semantic social networks under hypernetwork environments is shown in [Figure 1: see original paper]. Based on summarizing Weibo propagation and user characteristics, we construct a hypernetwork model from four dimensions: social, content, topic, and opinion to depict the formation and evolution process of semantic social network public opinion. Drawing on emotion analysis and topic analysis methods, we propose an automatic quantification method for hypernetwork nodes based on emotion ontology and the LDA topic model, and present the HyperEdgeRank algorithm to sort hyperedges and identify key user nodes. Finally, we analyze feasibility through actual data. This paper elaborates using Weibo social network as the application scenario.

[Figure 1: see original paper] Research framework for automatic identification of key nodes in Weibo semantic social hypernetwork

2.1 Hypernetwork Construction

In the Weibo era, everyone is an event disseminator. Weibo centers on users, with content as the main body and network tools as the carrier, spreading viewpoints and information to society. Therefore, when constructing the model, we should include not only external characteristics—social subjects (users)—but also the content published by users and the topic and opinion information contained therein. The difference between this paper' s semantic social network and traditional social network research lies in the introduction of real-time semantic information, with the topic subnet being the core of its semantic information. Topic information is a high-level abstraction of Weibo semantic features and content information. Opinion information, as an abstract expression of the psychological motivation behind user behavior, plays a leading role in guiding public opinion, with opinions generally expressed through emotions. Therefore, this paper improves upon previous hypernetwork model research from the perspective of network attributes and propagation characteristics, constructing a hypernetwork model from four layers: social, content, topic, and opinion, and proposing the associative relationships between nodes within each subnet, as shown in [Figure 1: see original paper].

In Weibo social networks, social subjects (users) use content (published Weibo posts) to express opinions on certain topics. The intra-layer relationships are connections between elements within each subnet, while inter-layer relationships are connections between subnets.

(1) **Social Subnet (Social Network):** Uses social subjects participating in discussions in the social network, i.e., users, as nodes, with follow relationships between users building edges.

(2) **Content Subnet (Content Network):** Uses information content published by users in the social network as nodes, with forwarding relationships between Weibo posts building edges.

(3) **Topic Subnet (Topic Network):** Uses topics extracted from published content in the social network as nodes, with similarity relationships between Weibo topics containing the same keywords building edges.

(4) **Opinion Subnet (Emotion Network):** Uses emotion polarity and intensity extracted from Weibo posts as nodes, with the same emotion po-

larity indicating correlation and building edges.

The intra-layer relationships of the hypernetwork model are relationships between elements within each subnet, while inter-layer relationships are relationships between subnets. The mapping relationship between the social subnet and content subnet is that user nodes correspond to multiple Weibo content nodes, characterizing that Weibo users can publish multiple Weibo posts. The mapping relationship between the content subnet and topic subnet is that each Weibo content corresponds to related topics. The mapping relationship between the opinion subnet and topic subnet is users' opinions under topics (set as positive, negative, and neutral in this paper). Finally, the mapping relationship between the opinion subnet and social subnet is the opinion tendency of users publishing Weibo posts to participate in certain topics, which is an implicit mapping relationship.

The completed hypernetwork model can be represented as G(V, HE), where V represents the set of nodes, i.e., V = {social subnet nodes, content subnet nodes, topic subnet nodes, opinion subnet nodes}. HE represents hyperedges, which are vertical connections between nodes of four different subnets, representing that user s__i publishes opinion e__j about topic t__k through content c, used to characterize connections between different types of nodes, i.e., inter-layer relationships, as shown by HE1 in [Figure 1: see original paper].

2.2 Subnet Node Semantic Automation Quantification Method Design

Previous hypernetwork model research focused on theoretical construction of hypernetwork models, where abstract attributes such as psychology and opinion are difficult to measure quantitatively and mostly use manual corpus summarization identification methods. Since this paper improves the hypernetwork model for Weibo semantic social networks, for topic and opinion subnets containing abstract semantic and emotional information, we innovatively propose an automatic quantification method using emotion ontology and the LDA topic model.

(1) The social subnet and content subnet interpret the social network from external characteristics, representing the external features of Weibo propagation patterns, without obvious semantic connotations. Therefore, they are directly constructed from the dataset without requiring semantic quantification.

(2) To avoid the influence of subjective judgment in manual discrimination, we introduce the LDA topic model to conduct topic modeling on content subnet nodes, scientifically measuring the semantic connotations expressed by users. The number of topics set equals the number of nodes in the topic subnet. According to the prior assumptions of LDA, topics are independent of each other.

The LDA probabilistic topic model is the most commonly used topic mining model. Its basic idea is to assume that each document is a multinomial distribution over a set of topics, and each topic is a multinomial distribution over all words, expressing the prior parameter relationship of keyword-topic-text as a three-layer Bayesian model. Therefore, the LDA topic extraction algorithm can obtain the co-occurrence probability between keywords and text through repeated sampling based on the joint probability distribution formula of keywords and topics for known Weibo text and all vocabulary, and derive the joint probability distribution between text and topics, thereby achieving automatic extraction of topic nodes.

This paper extracts K topics through the LDA topic extraction algorithm, transforming the joint probability distribution of Weibo text over the topic set into the correspondence between Weibo content and topics, achieving the mapping relationship between the content subnet and topic subnet.

(3) Drawing on emotion analysis methods, we introduce the Chinese emotion lexicon ontology to extract Weibo opinion orientations, avoiding subjective judgment by evaluators and truly representing user opinion tendencies. After Chinese word segmentation of Weibo posts, we use the emotion lexicon ontology to annotate polarity, accumulating the emotion intensity and polarity of emotional words to achieve extraction of opinion nodes.

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3. Key Node Identification Algorithm Design

3.1 Hyperedge Sorting Algorithm (HyperEdgeRank)

This paper uses a hypernetwork model to describe how user propagation behavior is influenced by factors such as information, topics, and emotions. Therefore, unlike traditional node sorting methods that rank single user nodes, we sort hyperedges, transforming the calculation of single user node influence into the influence of all hyperedges containing the user, thereby achieving comprehensive consideration of multi-dimensional information. Meanwhile, the research goal is to identify key nodes—nodes whose published content exerts significant influence on other nodes in the network. According to Weibo propagation characteristics, users tend to forward Weibo posts about topics they are interested in and that align with their own opinions, i.e., they are easily influenced by such user nodes. Therefore, this paper argues that the higher the information propagation influence of a Weibo node contained in a hyperedge—meaning more users can access the Weibo information—the greater the probability that the hyperedge will be linked by other hyperedges. When the opinion category contained in a hyperedge in the opinion subnet is the same as that in other hyperedges with similar emotion intensity, and the greater the similarity of topic distribution between the topic contained in a hyperedge in the topic subnet and other hyperedges, the greater the score the hyperedge obtains when linked with other hyperedges. Therefore, based on the research of Ma et al., we modify the hyperedge sorting algorithm iteration formula from three dimensions: information propagation influence, topic similarity, and opinion consistency, obtaining:

$$\text{HyperEdgeRank}(HE_i) = \sum_{j=1}^{N} \text{HyperEdgeRank}(HE_j) \cdot e_{ij} \cdot \text{Sim}(t_i, t_j) \cdot L(HE_j)$$

where N represents the number of hyperedges, e_{ij} represents the consistency between opinion e_i and e_j, I(c_i) represents the information propagation influence of Weibo, Sim represents the similarity between topic t_i and t_j, and L(HE_j) represents the hyperedge connectivity of hyperedge HE_j.

From this, we obtain the formula for information propagation influence as:

$$I(c_i) = \frac{R(c_i)}{A(c_i)} = \frac{N}{N}$$

where s_N represents the number of users in the social subnet.

According to the definition of hypernetworks, we introduce two hypernetwork attributes:

(1) **Node Hyperdegree:** Represents the number of hyperedges containing the node.

(2) **Hyperedge Connectivity:** In hypernetworks, if two hyperedges contain the same node, it indicates that the two hyperedges are connected through that common node. Hyperedge connectivity is the number of hyperedges connected to a hyperedge through its contained nodes.

Since users are the core producers and disseminators of Weibo content, this paper argues that after sorting hyperedges containing multi-dimensional information using the hyperedge sorting algorithm, we should still focus on user nodes. We accumulate the scores of all hyperedges participated in by each user node in the social subnet and obtain the average score of the user node by dividing by the node' s hyperdegree. The node with the highest score is the key node, with the formula:

$$\text{Score}(s_i) = \frac{\sum_{\text{HyperEdge}(HE) \ni s_i} \text{HyperEdgeRank}(HE)}{\text{Hyperdegree}(s_i)}$$

3.2 Hyperedge Subnet Attribute Calculation

(1) Information Propagation Influence in Content Subnet

All Weibo posts published by users in the content subnet represent information nodes c_i ($1 \leq$ i $\leq$ N). The more users a Weibo post influences in network propagation, the higher its propagation influence; the more people forward a

Weibo post, the higher its propagation influence. Therefore, the information propagation influence I(c_i) of Weibo content mainly depends on the breadth and depth of propagation. Thus, we modify the definition of information propagation influence in Weibo semantic social networks based on the definition by Ma et al.:

Information Propagation Breadth R(c_i): The propagation breadth of a Weibo information node is measured by the ratio of the number of hyperedges containing the node P(c_i) to the total number of hyperedges N:

$$R(c_i) = \frac{P(c_i)}{N}$$

Information Propagation Depth D(c_i): The depth of Weibo information propagation can be understood as the number of users influenced after forwarding. This paper simplifies it to the ratio of the number of users influenced by the Weibo information node A(c_i) to the total number of users in the social subnet N_s:

$$D(c_i) = \frac{A(c_i)}{N_s}$$

(2) Topic Similarity in Topic Subnet

When calculating similarity between topic nodes, we introduce the commonly used Kullback-Leibler distance metric in statistical natural language processing. Since larger KL distance indicates lower similarity between topics, this paper defines semantic similarity Sim as inversely proportional to KL distance, with the formula:

$$\mathrm{Sim}(t_i, t_j) = \frac{1}{\mathrm{KL}(t_i||t_j)} = \frac{1}{\sum_i P(i) \log \frac{P(i)}{Q(i)}}$$

where P and Q are events of all words appearing according to topic distribution t_i and t_j respectively. P(i) represents the probability of the i-th word appearing in topic t_i, and Q(i) represents the probability of the i-th word appearing in topic t_j. Since each topic vector in the LDA model is a multinomial distribution over all keywords in the Weibo dataset, we can obtain P(i) and Q(i) through modeling results.

(3) Opinion Consistency in Opinion Subnet

Different users hold different emotion polarities on the same topic, and the published information has different emotion intensities. Therefore, opinion nodes contain different tendencies and intensities. This paper innovatively uses emotion ontology to obtain two dimensions of emotion information for information nodes: emotion intensity ED_i and emotion polarity EP_i. EP_i = 1 indicates positive opinion, EP_i = 0 indicates neutral opinion, and EP_i = -1 indicates negative opinion. We define that when the two emotion attributes are consistent –i.e., emotion polarity is the same and emotion intensity is similar–the consistency between opinion nodes is more obvious. Therefore, opinion consistency e_{ij} is determined by both emotion polarity and intensity and is inversely proportional to the difference in emotion intensity, defined as:

$$e_{ij} = \mathrm{sign}(EP_i \cdot EP_j) \cdot \left(1 - \frac{|ED_i - ED_j|}{|ED_i| + |ED_j|}\right)$$

where sign(EP_i EP_j) is the sign function. When EP_i EP_j > 0, sign(EP_i EP_j) = 1, indicating the same emotion polarity; when EP_i EP_j ≤ 0, sign(EP_i EP_j) = -1, indicating different emotion polarity.

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4. Experimental Results and Analysis

4.1 Data Processing

This paper mines key users who have significant influence on public opinion orientation in the propagation of Weibo hot topics. Therefore, the data verification phase must be based on hot topic data. However, the hot topic list on Sina Weibo does not provide open API access. Consequently, we extracted the top 5 topic keywords from Sina' s hot topic list: "food safety," "corruption," "civil service exam," "NBA," and "housing price," and used a self-developed crawler program to capture Weibo posts through the search box of Weibo' s mobile client.

After removing stop words, we filtered out Weibo texts shorter than 20 characters as overly short texts affect topic mining effectiveness. We obtained a total of 526 valid Weibo posts from April 30 to May 12, 2014, with 429 participating users. We used the open-source NLPIR word segmentation and new word identification toolkit to segment the Weibo texts based on new word discovery and remove high-frequency words without semantic connotations. Simultaneously, we utilized the Chinese emotion lexicon ontology from Dalian University of Technology' s Information Retrieval Laboratory and implemented hypernetwork node semantic information quantification, subnet similarity calculation, and hyperedge sorting algorithm using Java 1.6 and Matlab programming tools.

4.2 Automatic Construction of Hypernetwork Model

(1) Topic Subnet Node Quantification Results

The LDA modeling experiment parameters were set as $\alpha = 50/\mathrm{K}$, $\beta = 0.1$, with Gibbs sampling iteration times of 1,000. Since LDA topic modeling results are affected by the dataset and topic number settings, and this paper' s dataset is relatively small, we set the topic number to 5 to maintain consistency with the data source (top 5 topics from Weibo hot topic list). [Figure 2: see original paper] shows the LDA topic modeling results. Since LDA topic extraction results are joint distributions between topics and vocabulary, they can only be expressed through Topic_i. From the keyword sets of topics, we can infer that Topic1 represents the civil service exam topic, Topic2 represents the NBA sports topic, Topic3 represents the housing price topic, Topic4 represents the food safety topic, and Topic5 represents the corruption topic. Since the crawler program captured data through the Weibo search box, the LDA model results show that the captured keywords are similar to the obtained topic information, demonstrating that using the LDA model can reduce the ambiguity of manual topic information discrimination.

(2) Opinion Subnet Node Automatic Quantification Results

We preprocess the information nodes in the content subnet (i.e., Weibo texts) by deleting stop words to obtain candidate information texts. The Chinese emotion lexicon ontology contains emotion polarity and intensity, dividing emotions into 7 major categories and 20 subcategories, with emotion intensity divided into five levels: 1, 3, 5, 7, 9, where 9 represents the maximum intensity. lists the correspondence between content subnet Weibo nodes and their extracted opinion nodes. Our automatic identification method ensures the accuracy of opinion automatic identification through two-dimensional measurement of emotion intensity and polarity.

(3) Hypernetwork Model Results for Weibo Semantic Social Network

Based on automatic quantification of opinion and topic subnet nodes, we construct the hypernetwork model. In our hypernetwork model, the social subnet contains 429 user nodes, the content subnet contains 526 Weibo nodes, the opinion subnet contains 64 opinion attribute nodes, and the topic subnet contains 5 topic nodes. shows the correspondence relationships between nodes in the four-layer subnets, i.e., the composition of partial hyperedges.

4.3 Hyperedge Sorting Algorithm Results

(1) Content Subnet Attribute Calculation

The content subnet of the hypernetwork model contains 526 Weibo nodes. We obtain the information propagation influence of each information node according to formula (3), with results shown in (excerpt of 15 Weibo nodes).

(2) Opinion Subnet Attribute Calculation

The hypernetwork model contains 64 opinion nodes. We obtain the similarity between the 64 opinion nodes according to formula (4), with results shown in [Figure 3: see original paper] (excerpt of the first 10 opinion nodes).

(3) Topic Subnet Attribute Calculation

The hypernetwork model contains 5 topic nodes. We obtain the similarity between the 5 topic nodes according to formula (4), with results shown in .

4.4 Key Node Identification

We implement the hyperedge sorting algorithm using Matlab to calculate all hyperedges, obtaining scores for 526 hyperedges in the model. shows the top 19 hyperedges.

We calculate all user nodes according to formula (2), obtaining 10 key user nodes and their hyperedge average values: s159(0.19188), s195(0.19090), s338(0.19090), s132(0.19046), s19(0.19042), s189(0.19033), s6(0.19032), s164(0.19027), s87(0.19026), s173(0.19024).

As shown in , which excerpts hyperedge information with higher scores under each topic, users hold different emotion tendencies toward different topic nodes. They mostly hold neutral views on the civil service exam, negative views dominate topics on housing price, food safety, and corruption, while positive views are mainstream for the NBA sports topic. The experimental results align well with actual situations, demonstrating that network modeling based on hypernetwork environments has obvious advantages over traditional models in displaying multi-dimensional, multi-level, and multi-attribute information.

Since early network science research focused on networks with fewer nodes, survey methods could be used to compare and evaluate algorithm results with actual survey results as the standard. However, with the advent of the big data era, network scale has grown rapidly, making it extremely difficult to establish relatively objective node importance evaluation standards. Currently, the main approach for evaluating the advantages of various algorithms in key node identification research based on hypernetwork theory is to use algorithm-derived important nodes as research objects and examine their influence on overall network structure and function and other node states to judge 优劣.

shows the hyperedge composition of the top three key user nodes in our dataset, including published information content, opinion tendency, and topic content. It can be seen that the core topic discussed in the Weibo dataset is Topic4 (food safety issue), with key users mainly holding negative opinions. According to [Figure 2: see original paper], topic keywords such as “transgenic, America, food, China” frequently appear in . From the Weibo content of the top three key users, it can also be seen that the public has strong negative emotions toward food safety, particularly key node s159 with emotion intensity of 6. The results show that user node s159 can influence more nodes than s132 in the propagation process of Weibo topics and is more critical. Examining the data of these two nodes separately reveals that node s159’ s published Weibo content influenced 73 user-person-times’ opinions on the food safety topic, while node s132’ s published Weibo content only influenced 24 user-person-times. Although both hold negative views, the former has higher emotion intensity and stronger topic guidance, which aligns with experimental results. This demonstrates that our identification method can effectively identify key nodes that play a leading role in guiding public opinion and viewpoints in practical applications.

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Author Contributions

Zhang Lei: Designed the research plan, designed and conducted experiments, wrote the paper;

Ma Jing: Proposed research ideas and plan, revised and finalized the manuscript;
Li Dandan: Data crawling and processing;
Shen Yang: Provided partial revision suggestions.

Conflict of Interest Statement

All authors declare no conflict of interest.

Supporting Data

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

[1] Zhang L, Ma J, Li D D, Shen Y. JAVAprogram.rar. LDA modeling Java program.
[2] Zhang L, Ma J, Li D D, Shen Y. data.txt. Segmented dataset.
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Note: Figure translations are in progress. See original paper for figures.