Research on Network Public Opinion Situation Awareness

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Abstract. In order to perceive the development of network public opinion effectively and provide technical support for the supervision of network public opinion, the incremental prediction model GG-ICP of information dissemination is constructed by integrating the structural and temporal characteristics of social networks. Firstly, the GCN is combined with the GRU to learn the dynamic network structure information and timing information together. Then, the time decay function is improved to more effectively reflect the value decay of public opinion information with the passage of time. By coupling the spatial and temporal characteristics, the historical and edge information can be captured more reasonably to improve the prediction accuracy of the model, and then make a scientific prediction of the increment of information forwarding. The results of comparison experiments on real datasets show that, the prediction accuracy of the information dissemination model proposed in this paper is significantly improved compared with the existing models.

Keywords: Online Public Opinion, Situational Awareness, Information Cascade, Temporal Characteristics

1. INTRODUCTION

Social networks not only provide people with convenient and quick information dissemination, but also have become a platform for the outbreak and dissemination of public opinions. The seemingly simple things, after a lot of forwarding and comments, may change into public opinion events in a short time and spread quickly over a large area. As a result, all kinds of irrational, negative, and even extreme emotions in the social network are overflowing, which seriously affects the normal ecology and healthy development of the social network, and destroys the harmony and stability of society [1].

Currently, the research on public opinion communication prediction in social networks can be divided into micro-prediction and macro-prediction according to the different research tasks.

Micro-prediction more focuses on modeling individual propagation nodes. The main idea is that, when the activation threshold of an inactive node is greater than or equal to the sum of the influence exerted by its adjacent nodes, the node will turn into an active node [2]. Micro-prediction can be regarded as a classification task, which is used to judge the behavior state of individual user nodes or predict the next node that will participate in public opinion communication behavior.

Macro-prediction focuses on estimating the increment of users participating in communication after a period of time, which gets rid of the limitation of the too fine division of individual nodes in micro tasks. For macro-prediction, it can be divided into methods based on the infectious disease model and methods based on the information cascade model.

The method based on the infectious disease model mainly depends on the assumption that the diffusion law of infectious diseases in the population is highly similar to the process of network public opinion transmission. The communication dynamic model established by using differential equations can describe the dynamics of information change with time, so as to find out the law of information transmission and the key factors affecting information transmission [3]. However, such methods mainly predict the trend of information dissemination from the perspective of groups and lack the analysis of the characteristics of users' individual communication behavior, so the popularization is poor.

The method based on the information cascade model is to learn the propagation mode of information in social networks by observing the diffusion sequence and topology of information [4], so as to predict the final scale of affected nodes in the next period of time. Information cascade refers to the cascade forwarding sequence and network relationship diagram of users identified in blogs, e-mail, and social networking sites [5]. Such methods can not only predict the size and breadth of affected nodes but also do not rely too much on the assumption of prior knowledge. They can be widely used in various scenarios, so they have become a research hotspot in the field of information dissemination prediction.

At present, the methods of information cascade prediction in social networks can be divided into three categories: feature-based method, generative modeling method, and deep learning method.

The feature-based method mainly uses the traditional machine learning model combined with multi-feature fusion technology for cascade prediction. The feature types include user, blog, structure, time, and so on. Weng et al. [6] considered the influence of early communication mode in the underlying social network, and found that the user's community structure is a more powerful influencing factor for cascade prediction through the comparison of various characteristics; Hong et al. [7] better predicted the text with higher forwarding volume in the future by integrating four characteristics: text content, time information, metadata composed of text and users, and users' structural attributes. However, the prediction performance of such methods depends too much on the particularity of application scenarios and the effectiveness of feature selection, so they lack practical significance.

The method based on generation modeling usually relies on the Hawkes point process to model the arrival intensity function of each message independently. Because the arrival intensity function of messages in different scenarios is quite different, the generalization of this method model is poor. Gao et al. [8] proposed an extended enhanced Poisson process model with a time mapping process to simulate forwarding dynamics and predict future popularity. Cao et

al. [9] proposed a new information cascade modeling generation process DeepHawkes, which uses end-to-end deep learning to simulate the Hawkes process. At the same time, the model has stronger predictability and higher interpretability. However, such methods have poor timeliness, and still can't make full use of the coding information in level linkage mechanics, so the prediction effect is still unsatisfactory.

Based on the method of deep learning, the data is embedded to extract the characteristics of nodes, and then the neural network is used to automatically learn the characteristics of nodes, and finally predict the output [10]. Considering the cross dependence phenomenon in the information cascade, Wang et al. [11] proposed an RNN model integrating attention mechanism and coverage mechanism to capture the cross dependence in the cascade, endow the model with memory ability through the coverage mechanism, and then calculate the weight of attention distribution more authoritatively in the modeling process. Li et al. [12] proposed a cascade model DeepCas, which automatically samples the cascade diagram and extracts the cascade timing features by random walk without manual feature selection. Wang et al. [13] introduced the diffusion topology model to fully describe the cascade structure, dynamically modeled the directed acyclic graph DAG, embedded the topology perception generated by each node as the model input, and proposed a new topology cyclic neural network Topo-LSTM. The method based on deep learning is the mainstream and the best prediction method at present, but most scholars focused on modeling cascaded topological features or time-series features alone. The research on information cascade prediction by fusing two or more features at the same time is still in the preliminary exploration stage.

It is found that although the current technology can detect public opinion, it can't effectively identify the development trend of public opinion, and it is difficult to meet the needs of public opinion supervision. Further analysis shows that the whole life cycle of public opinion can be divided into four stages: incubation period, growth period, maturity period and decline period. Through the analysis and prediction of the incremental public opinion data spread in social networks, it is helpful for the regulatory departments to accurately identify the stage of public opinion and grasp the development trend of public opinion in time. Then, corresponding control measures can be taken to provide scientific decision-making basis for public opinion supervision.

The overall idea is to combine the graph representation learning method with recurrent neural networks to capture the cascade potential information in an end-to-end manner. Then, the change of forwarding increment can be predicted, which can effectively identify the public opinion situation. The specific research schemes are as follows: Firstly, a graph convolution network is used to construct a graph structure representation of the forwarding relationship between users and the spatial characteristics of cascade evolution in social networks; Then, the gating loop unit is introduced to further extract the hidden timing features of the cascade sequence; Finally, the state vector, which combines the cascade spatio-temporal characteristics and the influence of the optimized and improved time attenuation effect, is input to the full connection layer to predict the increment of public opinion transmission.

2. PROPAGATION INCREMENTAL FORECASTING MODEL DESIGN

2.1 Overall architecture of the model

In the real social network environment, the dissemination of public opinion information is influenced by users' social relations and social behaviors and will show specific Spatio-temporal characteristics in space and time. At present, most of the existing research methods independently model cascade spatial features and temporal features, which leads to the lack of interaction between spatial domain and temporal domain, thus restricting the accurate prediction of propagation scale by the model.

Therefore, this paper proposes an information propagation prediction model GG-ICP, which combines the structural characteristics of social topological relations and cascade time series characteristics. Firstly, the forwarding relationship and cascade evolution spatial characteristics among users in social networks are constructed into graph structure representation by using GCN; Then, GRU is introduced to further extract the hidden time-series features of cascade sequences; Finally, the state vectors coupled with cascade spatial features and time-series features are input to the full connection layer, and the final prediction results are obtained. The information cascade prediction model combining topological relationship features and cascade time-series features is shown in Figure 1. It is mainly composed of node embedding layer, graph convolution layer, time-series layer, and cascade incremental prediction layer.

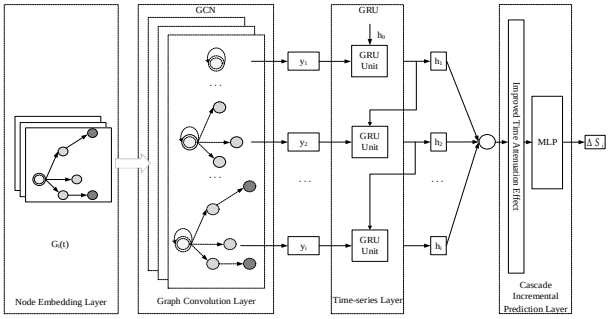


Fig.1 Cascade prediction model structure diagram

2.2 Node embedding layer

Firstly, the observation window [0, T] is divided into l disjoint fine-grained time intervals $\{[t_0,t_1),[t_1,t_2),...,[t_{l-1},t_l)\}$ with the same time interval. Then, the cascade graph $G_i(t)$ of message p_i is obtained into an evolution cascade subgraph G_i^T according to the divided time interval, $G_i^T=\{\zeta_i(t_1),\zeta_i(t_2),...,\zeta_i(t_N)\}$. $\zeta_i(t_j)(1\le j\le N)$ is transformed into the form of an adjacency matrix to describe the relationship between nodes. Therefore, all nodes of N cascaded subgraphs are embedded into space vector $\{x_v^N\in\mathbf{R}^K,\forall v\in V\}$ by One-Hot Code, where K is the dimension of node embedding and can be adjusted.

2.3 Graph convolution layer

The intention of the graph convolution layer is to capture the hidden spatial association of data streams in social networks, and convolution operation is the most effective means. However, CNN can only deal with data in Euclidean space (i.e., grid data), so it can't adapt to data in non-Euclidean space such as social networks. At the same time, learning the structural features of social network graphs is helpful to explain the potential relationship between information dissemination and social networks, and provide richer hidden feature information for the vector representation of user nodes. Therefore, this paper uses graph convolution network GCN to better depict the spatial topology structure in social networks.

GCN extracts high-level features from information transfer between nodes or some equivalent neighborhood aggregation functions by calculating Laplace feature decomposition of graphs, and then performs convolution operation in the Fourier domain, which improves the execution effect of various graph tasks. The information diffusion process is similar to the Markov process, that is, after diffusion for a period of time, it will converge to a stable distribution, similar to the P distribution [10]. Therefore, let the cascade Laplace matrix Δc conform to the random walk characteristics of cascade graphs, and let the Markov state transition probability matrix as eqn (1):

$$P = D^{-1}A_j \tag{1}$$

And, there is $\phi_i = \{\phi_1, \phi_2, .. \phi_n\}$ satisfying $\phi^T P = \phi^T$.

According to the graph theory, the spectral convolution results on the graph are obtained by convolution calculation of signal $x \in R^N$ and graph convolution kernel Θ. When calculating kernel Θ in graph convolution, the Chebyshev polynomial plays a more important role in approximation theory because of the high cost of graph Fourier cardinality operation. Therefore, the Chebyshev polynomial approximation strategy is adopted to overcome this problem. The convolution network calculation formula is as eqn (2):

$$y \approx g_\theta * Gx \approx g'_\theta(L)x \approx \sum_{k=0}^{K} \theta'_k T_k(\Delta\tilde{c})x \tag{2}$$

Where, $*G$ is the convolution operation of the graph, and $T_k(\Delta\tilde{c}) \in R^{N \times N}$ is the Chebyshev polynomial of order k.

Adjacency Matrix A_j and Laplace Matrix Δc of Cascade Subgraph $\zeta_i(t_j)$ are used as inputs of Graph Convolution Network, local feature correlation learning, and spatial feature extraction are carried out, and output y_i of Graph Convolution Network obtained by eqn (2) is used as input of the sequential coding layer.

2.4 Time-series layer

Because the graph convolution network is not sensitive to the time sequence of the cascade, it is easy to cause node dependency allocation errors in the modeling process. Therefore, this paper introduces GRU, which has a low computational cost and high prediction accuracy to model the cascade sequence. The temporal coding layer is similar in structure to the attention coding layer of the graph and is formed by stacking multiple temporal coding modules, which can fully consider the dynamic evolution process of the cascade graph and capture the temporal changes of nodes in multiple time periods.

The GRU module is introduced in the cascade prediction process in this paper. Therefore, the phenomenon of gradient disappearance and gradient explosion in the process of backpropagation is avoided, and at the same time, the historical information of nodes can be paid attention to, and the features with relatively high weight can be automatically screened and retained in the eigenvalues of different time periods, thus further improving the learning ability of the model for cascade time-series features.

2.5 Cascade incremental prediction layer

Literature [9] found that there is a time attenuation effect in the process of information cascade propagation, that is, the influence of one node on other nodes will decrease with time. However, in real life and social networks, the information exchange network between people is very complex, and the communication process will be affected by various factors such as the heterogeneity of communication subjects and objects and the media [16]. And because of the unique heterogeneity of human beings, the memory effect and forgetting amount of information is different for each person. After referring to the users' usage habits and actual usage of Weibo in real life, Considering the linear product of the time when the user forwards the message p_i, the average time interval τ when p_i is forwarded next time, and the weight φ_i of the corresponding forgetting gradient as the interference factor affecting forgetting, it is fused into the time attenuation effect introduced in the cascade propagation of information in literature [9]. In the process of information dissemination, the propagation forgetting probability function $f_i(t)$ caused by forgetting mechanism is as equation (3):

$$f_i(t) = \begin{cases} 0, a - e^{bt} + \varphi_i \tau \times 10^{-2} < 0 \\ a - e^{bt} + \varphi_i \tau \times 10^{-2}, 0 \le a - e^{bt} + \varphi_i \tau \times 10^{-2} \le 1 \\ 1, a - e^{bt} + \varphi_i \tau \times 10^{-2} > 1 \end{cases} \tag{3}$$

$a - e^{-bt}$ is the influence term of the forgetting mechanism, which means that the forgetting mechanism attenuates with $a - e^{-bt}$, where a is the maximum attenuation rate and b is the attenuation factor; $\varphi_i \tau$ is the interference factor Ω to prevent forgetting, which means that $\varphi_i \tau$ prevents users from forgetting in the forgetting process. τ is the average time interval when message p_i is re-forwarded, that is $\tau = \frac{\tau_1 + \tau_2 + ... + \tau_m}{m}$. τ_k is the average time interval between the time when the user forwards the message p_i and the time when p_i is forwarded again, $k \in (0, m)$. φ_i is the forgetting weight corresponding to the forgetting gradient of order i, $i \in [1,4]$.

Therefore, based on the research in reference [9], this paper uses the nonparametric time attenuation function $h_i^{''}$ fusing the improved forgetting mechanism to describe this time attenuation effect:

$$h_i^{''} = \sum_{j=1}^{R_T} \lambda_{f(T-t_j)} h_j^i + f_i(t) \tag{4}$$

$\lambda_{f(T-t_j)}$ is the influence time attenuation function proposed in reference [9], which can be calculated according to equation

(10); $f_i(t)$ is the improved attenuation function of the forgetting mechanism in this paper, which can be calculated according to equation (3).

The last part of the GG-ICP model consists of a full connection layer MLP. The $h_t^{''}$ obtained by equation (4) is used as its input for calculation, thereby obtaining a final information cascade propagation increment prediction result ΔS_i:

$$\Delta S_i = MLP(h_t^{''}) \quad (5)$$

After the prediction results are obtained, Adaptive Moment Estimation is selected to optimize the model parameters. The activation function uses the sigmoid function, and the final prediction result can be expressed as:

$$Y = sigmoid(W_y \Delta S_i + b_y) \quad (6)$$

Where, W_y is the weight matrix and b_y is the offset vector.

3. EXPERIMENT

3.1 Data set

In order to more objectively evaluate the effectiveness of the GG-ICP model in the information macro-cascade prediction task, this paper selects Sina Weibo [10], a public data set of Sina Weibo, to evaluate the performance of the model. Sina Weibo [10] recorded all the original data generated by Sina Weibo on June 1, 2016, and tracked the forwarding of each message in the next 24 hours. After filtering out messages with less than 10 forwarded messages, 119,313 messages remain in the dataset.

Each message_id message sample in the Sina Weibo [10] dataset corresponds to a forwarding path, and each forwarding behavior is divided by spaces in the following format:<root_user_id>/<retweet_user_id>:< retweet_time>. Among them, root_user_id is the unique user id of the message publisher, retweet_user_id is the user id that forwards the message sample message_id, and retweet_time is the timestamp forwarded by the user, counting in seconds, $1 \le retweet_time \le 86400$.

3.2 Experimental environment and parameter setting

The experiment environment is shown in Table 1.

Table. 1 Experimental Environment

Experimental Environment	Parameter
CPU	E5-2650 v4 x2 2.2GHz@48core
GPU	Tesla P100 16GB GP100GL x8

After many times of parameter adjustments and comparative experiments, the final model parameters are as follows: the number of hidden layers contained in the graph convolution network is set to 3; The number of units in the GCN coding layer and GRU time sequence coding layer is set to 64 to ensure that the dimensions of spatial and temporal feature matrices are consistent; The number of multi-layer sensing layer units is 64x32. In the training process, the Adam optimizer is used to optimize the parameters by gradient descent. The initial learning rate of the Adam optimizer is set to 0.0005, the number of iterative rounds is 2000, and the time step N is 12.

3.3 Experimental results and analysis

3.3.1 Model optimization experiment of improving time decay function

To verify the effectiveness of optimizing and improving the time attenuation effect proposed in reference [9], the DeepHawkes model proposed in reference [9] and GCN-GRU model which follows the traditional time attenuation effect in reference [9] are compared with this model. The observation time interval is set to 1h, and the observation period is selected to be 3h. The results of the MSLE and MAPE evaluation indexes of the three models are analyzed. The experimental results are shown in Table 2.

Table. 2 Comparison of experimental results on the effectiveness of optimizing and improving time decay function

Model	Evaluation Index	
	MSLE	MAPE
DeepHawkes[9]	2.731	0.344
GCN-GRU	2.305	0.326
GG-ICP	**1.989**	**0.315**

According to the comparative analysis in Table 6, the model in this paper is the best in both evaluation indexes. Compared with the DeepHawkes model and GCN-GRU model, we can see that the coupling model selected in this paper can significantly improve the prediction effect of forwarding increment when associating spatial and temporal characteristics and considering the dependence between computing nodes, which can effectively make up for the limitations of model selection and use under the current research status.

Comparing the GCN-GRU model with the GG-ICP model, we can see that the improved Ebbinghaus forgetting mechanism is introduced into the traditional time attenuation effect when the node embedding coding mode is the same as the coupling model structure, and the heterogeneity of individual memory benefit and forgetting benefit is considered. Starting from multiple dimensions, it helps to quantify the moderate fluctuation and dynamic change of public opinion information dissemination increment with time. Compared with the GCN-GRU model, the MSLE index has the most obvious improvement effect after optimizing the time attenuation effect, and the error is reduced by 13.8%, and the average absolute percentage error MAPE is also reduced by 3.37%. It effectively depicts the nonparametric attenuation characteristics of public opinion information value with the passage of time.

3.3.2 Comparative experiment of model performance

In order to test the effectiveness of the GG-ICP model proposed in this paper, the representative models are selected from the three mainstream cascade prediction methods for comparison. On the same Weibo data set, the observation time of the four models is set to 1h, and the forwarding increment in the next 1h, 2h and 3h is predicted by using the same parameter supernumerary setting. The specific results are shown in Table 3.

Table. 3 Comparison results of model performance

Evaluation Index / Model	MSLE Weibo/h			MAPE Weibo/h		
	1	2	3	1	2	3
Feature-Linear	2.995	2.891	2.711	0.385	0.362	0.349
DeepCas[12]	2.87	2.706	2.632	0.411	0.358	0.343
CasCN[18]	2.702	2.434	2.375	0.347	0.33	0.324
GG-ICP	2.615	2.3	**1.989**	0.332	0.326	**0.315**

As Table 3, when the observation period is 3h, the performance improvement effect of this model is most obvious. Compared with the Feature-Linear model and DeepCas model, MSLE error is reduced by 26.63% and 24.43% respectively. Compared with the excellent CasCN model at present, it is improved by nearly 16.25%. The optimization trend of MAPE is very similar to that of MSLE, and the prediction error decreases gradually with the increase of observation time. However, when the observation time is 1h, compared with the other three models, the average absolute percentage error MAPE has the most obvious reduction effect, and the performance is improved by nearly 13.77% compared with the Feature-Linear model.

Through above experimental results, it can be seen that the performance of this model is better in the downstream task of taking forwarding increment as cascade prediction. It can not only mine the spatial topology information of cascade graphs better but also alleviate the loss of part of time-series information when capturing spatial features caused by different sizes of cascade graphs. By quantifying the disturbance forgetting quantity which prevents individual forgetting due to re-stimulation at different time intervals, GRU units can be better used to dynamically capture cascade time-series features. While giving the model higher timeliness, the prediction accuracy is also improved, which is helpful to perceive the development trend of online public opinion and promote the monitoring and control of online public opinion. So that relevant departments can guide and intervene in public opinion in a timely and effective manner, ensure that the trend of public opinion develops in a sustained and benign direction, escort the development of social networks, and promote social harmony and stability.

4 SUMMARIZE

By scientifically predicting the increment of information forwarding, It is helpful to accurately distinguish the whole life cycle of public opinion evolution, that is, incubation period, growth period, maturity period, and recession period, so that microdata changes can be transformed into macro stage identification, which is convenient for public opinion supervision departments to accurately grasp the development trend of public opinion and provide decision support for public opinion supervision.

Therefore, this paper proposes an incremental prediction model of information dissemination GG-ICP, which combines the characteristics of social topological relations and cascade time series. This model avoids the shortcoming that the current research relies too much on artificial marking features, and fully considers the dynamics and uncertainty in the cascade propagation process. Optimizing and improving the time attenuation effect in the information cascade is helpful to describe the nonparametric attenuation law of public opinion information value with the passage of time.

The existing problem is that this paper has not considered the derivative risks in the evolution of public opinion communication, and has not conducted in-depth research on the business closed loop of network public opinion monitoring and early warning. In the follow-up, we will carry out further research on public opinion situational awareness from two aspects of technology and management.

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