User Behavior Prediction Of Social Hotspots Based On Multi Message Interaction And Neural Network

Tirumani Navyasri, Miss G.Keerthana, Sri.V.Bhaskara Murthy
MCA Student, Assistant Professor, Associate Professor
Dept Of MCA
B.V.Raju College, Bhimavaram

ABSTRACT— In network public-opinion analysis, the diversity of messages under social hot topics plays an important role in user participation behavior. Considering the interactions among multiple messages and the complex user behaviors, this article proposes a prediction model of user participation behavior during multiple messaging of hot social topics. First, considering the influence of multimessage interaction on user participation behavior, a multimessage interaction influence-driving mechanism was proposed to predict user participation behavior more accurately. Second, in the view of the behavioral complexity of users engaging in multimessage hotspots and the simple structure of backpropagation (BP) neural networks (which can map complex nonlinear relationships), this study proposes a user participant behavior prediction model of social hotspots based on a multimessage interaction-driving mechanism and the BP neural network. Finally, the multimessage interaction has an iterative guiding effect on user behavior, which easily causes overfitting of the BP neural network. To avoid this problem, the traditional BP neural network is optimized by a simulated annealing algorithm to further improve the prediction accuracy. In evaluation experiments, the model not only predicted the user participation behavior in actual situations of multimessage interaction but also further quantified the correlations among multiple messages on hot topics.

Keywords— Backpropagation (BP) neural network, multimessage interaction, social hotspots, user behavior.

I. INTRODUCTION

WITH the emerging of the Internet era, online social networks such as Twitter and Face book continue to be popular. People's communication and lifestyle have brought about tremendous changes. The generation and dissemination of hot topics in social media are constantly affecting the daily lives of people. The social hotspots refer to news or topics that are concerned or interested by the public at present. The social network topology and the user's reads and replies to messages in the network promote the dissemination and evolution of information related to the hot topic, that is, the propagation of the network topics [1].

Therefore, mastering user-forwarding participation behavior is important for evaluating the influence of a microblog topic [2], monitoring public opinion through networks [3], [4], and information retrieval [5]. At present, the prediction of user behavior in social networks mainly includes the following two approaches. The first approach analyzes the structural topology map used for information dissemination in social networks. This approach predicts the path and range of the information propagation [6] and, hence, the user's participation behavior. Which users will participate in the micro blog is commonly predicted by dynamic propagation [7] or an infectious disease model [8], [9].

Such predictive models typically classify network nodes as unknowns, communicators, and immunizers [10], [11]. However, this modeling has two main shortcomings. First, it creates a complex topology diagram requiring a large number of calculations. Second, it considers only the

relationships of interest among the users, ignoring the differences among users and the frequent changes of topics in social networks. The second modeling approach considers user activity, the number of fans, and the number of messages [3], [12], [13]. Some scholars also make predictions based on the user's micro blog interest and micro blog information [14]–[16]. The influence of social media platforms (such as Weibo) and the behavior of users are then predicted by machine learning.

The forwarding behavior of online social networks has been extensively studied in recent years. Focusing on the different aspects of the predicted content, prediction models using both approaches have been established. However, despite significant progress in this area of research, there are still some challenges. 1) The Complexity of the Multi message Interaction: Most studies predict either the micro participation behavior during single messaging or the macro popularity perception during multi message topics. These studies ignore the complexity of interactions among multiple messages under hot topics that occur in actual situations. 2) The Ambiguity of Multi message Mutual Impact Metrics:

The user participation behavior is closely related to the multi message interaction under a topic. Traditional micro participation behavior mostly starts from a single message, generally, only analyzes user attributes or network topology, and does not accurately measure the interaction of multiple messages. 3) The Accuracy of the Predicted Model: Traditional mod models cannot correctly capture the nonlinear relationship between the topic data input and user behavior prediction output. In addition, ordinary neural networks are usually over fitting and prone to local minimums, thus reducing the accuracy of predictions. When predicting user participation behavior, the model should consider the personal characteristics of users. In addition, the interactions among multiple messages under the same hot topic are vital for improving the prediction results. Multi message interaction mechanisms and nonlinear relationships can be handled by a back propagation (BP) neural network model. The BP neural network is a multilayer feed forward network trained by an inverse error propagation algorithm. It can learn and store a large number of input–output mode mapping relationships, without the need to derive mathematical equations for the relationship in advance. However, as mentioned earlier, multiple messages exert an iterative guiding effect on user behavior, which causes over fitting of the neural network.

To avoid the over fitting problem, this article applies a simulated annealing algorithm to the BP neural network, which assists the local miniaturization solution of the algorithm and greatly improves the accuracy of the prediction results. The simulated annealing algorithm is derived from the principle of solid annealing and has greatly improved the prediction results in many past instances [17]. The main innovation of this article is that we study the user behavior of social hotspots from the perspective of multi message interaction at the micro level. The specific contributions of this article are as follows.

1).A user participation behavior prediction model based on multi message interaction is constructed. Based on the mapping relationships between the basic user information and participation behavior under the traditional single message, the multi message interaction-driving mechanism improves the completeness of the prediction results. Meanwhile, it is more realistic to describe the process of message dissemination. 2) A quantization mechanism based on multi message interaction is proposed. This article can more accurately measure the multi message selection process within the user community by quantitatively evaluating the mutual influence of messages from the perspective of topics. Meanwhile, the hidden influence under the same topic can be qualitatively measured, which leads to user's participation behavior. 3) The BP neural network was improved by the simulated annealing algorithm. This method fits well with the nonlinear relationship between the topic data input and the user behavior prediction output. Moreover, the neural network over fitting problem is solved by the simulated annealing

algorithm, and the prediction accuracy is further improved. This article is organized as follows. This section introduces the background and status of the research. Section II discusses the work related to our study, and Section III formalizes the research question. Section IV describes the proposed method and its learning algorithms. Section V experimentally evaluates our method oon a real-world data set, and Section VI concludes this study.

II. EXISTING SYSTEM

In most current models, prediction of user participation behaviors takes into account the user network topology and user basic information while ignoring the impact of messages propagated under hot topics. Sheikhahmadi *et al.* [18] proposed a two-level model that detects and classifies the influence of users by considering the interaction between users. Similarly, Colombo *et al.* [19] established a topological map for studying information dissemination through a social network. Salehi *et al.* [20] extracted the attributes of a multilayer network structure for predicting the probability of microblog forwarding. Other researchers [21], [22] predicted user forwarding behavior through related attributes using a machine-learning method. Grabowicz *et al.* [23] predicted the user forwarding behavior by filtering the factors that are strongly related to user behaviors.

Most of the existing studies predict the nonlinear relationships between the topic data input and the user participation behavior output by traditional machine-learning methods. Lee *et al.* [24] predicted the user forwarding behavior and the time of forwarding by different machine-learning algorithms. Sankaram *et al.* [25] constructed an impact model based on a machine-learning algorithm and predicted the behavior of users and fans. Huang *et al.* [26] measured the user interest in different categories of tweets by a Bayesian model and predicted the forwarding behavior from the interest metrics. Other studies have simulated user participation in messages using infectious disease models, which cannot properly represent the nonlinearity. Huang and Su [27] analyzed the occurrence probability of user behaviors and predicted the user forwarding behavior in a susceptible-infectious-recovered (SIR) model of disease dynamics. Xiong *et al.* [28] proposed a new susceptible, contacted, infected and refractory (SCIR) model (where C denotes "Contacted") that distinguishes and predicts the user browsing behavior and forwarding behavior in detail.

Disadvantages

- In the existing work, the system does not Driving Mechanism of User's Personal Characteristics.
- This system is less performance due to lack of Parameter Optimization and Forwarding Prediction

III. PROPOSED SYSTEM

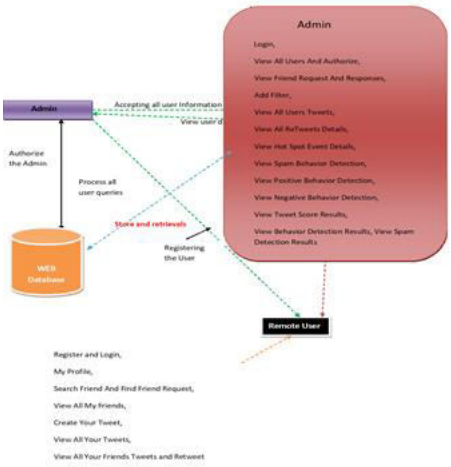
- A user participation behavior prediction model based on multi message interaction is constructed. Based on the mapping relationships between the basic user information and participation behavior under the traditional single message, the multi message interaction-driving mechanism improves the completeness of the prediction results. Meanwhile, it is more realistic to describe the process of message dissemination.
- A quantization mechanism based on multi message interaction is proposed. This article can more accurately measure the multi message selection process within the user community by quantitatively evaluating the mutual influence of messages from the perspective of topics. Meanwhile, the hidden influence under the same topic can be qualitatively measured, which leads to user's participation behavior.
- The BP neural network was improved by the simulated annealing algorithm. This method fits well with the nonlinear relationship between the topic data input and the user behavior prediction out put.More over, the neural network over fitting problem is solved by the

simulated annealing algorithm, and the prediction accuracy is further improved.

Advantages

- ❖ Multi message interaction mechanisms and nonlinear relationships can be handled by a back propagation (BP) neural network model. The BP neural network is a multilayer feed forward network trained by an inverse error propagation algorithm.
- ❖ To The system is more effective due to presence of Driving Mechanism of User's Personal Characteristics.

IV. SYSTEM ARCHITECTURE



V. MODULE IMPLEMENTATION

- **Admin**

In this module, the Admin has to login by using valid user name and password. After login successful he can perform some operations such as View All Users And Authorize,View Friend Request And Responses,Add Filter,View All Users Tweets,View All ReTweets Details,View Hot Spot Event Details,View Spam Behavior Detection,View Positive Behavior Detection,View Negative Behavior Detection,View Tweet Score Results,View Behavior Detection Results.

User

In this module, there are n numbers of users are present. User should register before performing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user can perform some operations like Search Friend And Find Friend Request,View All My Friends,Create Your Tweet,View All Your Tweets,View All Your Friends Tweets and Retweet.

VI. CONCLUSIONS

From the user behavior data and the basic information data of multiple messages under a hot topic being discussed on a social network, this article extracted the driving mechanisms of both the user and the multi message interaction and proposed a prediction model of the user's participation behavior in the discussed topic. First, the user's participation behavior was predicted by a BP neural network model, which copes with the complex nonlinear relationships between the input of the driving mechanisms of the user and the multi message interaction and user behaviors' prediction output. Meanwhile, due to the iterative guidance of multi information interaction on user behavior, the BP neural network was degraded by the over fitting problem. After correcting the over fitting by a simulated annealing algorithm, the accuracy of the prediction was improved. Finally, we defined the multiple-message correlation metrics, statistically analyzed the model outputs, and estimated the proportion of users participating in one message, who also participated in other messages. The calculation results quantified the mutual influence strength between the multiple messages and accurately represented the influence of the hot topic on user participation behaviors. The proposed method was experimentally evaluated on multi message data under a hot topic discussed on the online social network, Sina Weibo. The model not only accurately predicted the user's participation behaviors but also quantified the intensity of the mutual influence between the multiple messages. Moreover, it dynamically perceived the situational changes in the hot topic, providing strong support for public opinion control.

REFERENCES

[1] M. Takayasu, K. Sato, Y. Sano, K. Yamada, W. Miura, and H. Takayasu, "Rumor diffusion and convergence during the 3.11 earthquake: A Twitter case study," PLoS ONE, vol. 10, no. 4, Apr. 2015, Art. no. e0121443.

[2] Y. Du, Y. He, Y. Tian, Q. Chen, and L. Lin, "Microblog bursty topic detection based on user relationship," in Proc. 6th IEEE Joint Int. Inf. Technol. Artif. Intell. Conf., vol. 1, Aug. 2011, pp. 260–263.

[3] S. Gaglio, G. Lo Re, and M. Morana, "A framework for real-time Twitter data analysis," Comput. Commun., vol. 73, pp. 236–242, Jan. 2016. 4] G. Verma, A. Swami, and K. Chan, "The impact of competing zealots on opinion dynamics," Phys. A, Stat. Mech. Appl., vol. 395, pp. 310–331, Feb. 2014.

[5] L.-L. Ma, C. Ma, H.-F. Zhang, and B.-H. Wang, "Identifying influential spreaders in complex networks based on gravity formula," Phys. A, Stat. Mech. Appl., vol. 451, pp. 205–212, Jun. 2016.

[6] A. Mislove, M. Marcon, K. P. Gummadi, P. Druschel, and B. Bhattacharjee, "Measurement and analysis of online social networks," in Proc. 7th ACM SIGCOMM Conf. Internet Meas., 2007, pp. 29–42.

[7] X. Yun-Peng, L. Song-Yang, and L. Yan-Bing, "An information diffusion dynamic model based on social influence and mean-field theory," Acta Phys. Sinica, vol. 66, no. 3, 2017.

[8] Q. Su, J. Huang, and X. Zhao, "An information propagation model considering incomplete reading behavior in microblog," Phys. A, Stat. Mech. Appl., vol. 419, pp. 55–63, Feb. 2015.

[9] L.-L. Xia, G.-P. Jiang, B. Song, and Y.-R. Song, "Rumor spreading model considering hesitating mechanism in complex social networks,"Phys. A, Stat. Mech. Appl., vol. 437, pp. 295–303, Nov. 2015.

[10] R. Jie, J. Qiao, G. Xu, and Y. Meng, "A study on the interaction between two rumors in homogeneous complex networks under symmetric conditions," Phys. A, Stat. Mech. Appl., vol. 454, pp. 129–142, Jul. 2016.

[11] R.-Y. Tian, X.-F. Zhang, and Y.-J. Liu, "SSIC model: A multi-layer model for intervention of online rumors spreading," Phys. A, Stat. Mech. Appl., vol. 427, pp. 181–191, Jun. 2015.

[12] L. Zhang, Z. Qi, L. Guo, and L. Xu, "Research on online social network information diffusion detection node selection algorithm based on the random walk model," J. Comput. Theor. Nanosci., vol. 13, no. 1, pp. 971–981, Jan. 2016.

[13] J. Golbeck, C. Robles, M. Edmondson, and K. Turner, "Predicting personality from twitter," in Proc. IEEE 3rd Int. Conf. Privacy, Secur.,Risk Trust, IEEE 3rd Int. Conf. Social Comput., Oct. 2011, pp. 149–156.

[14] G. Shen, W. Yang, W. Wang, and M. Yu, "Burst topic detection oriented large-scale microblogs streams," J. Comput. Res. Develop., vol. 52, no. 2, pp. 512–521, 2015.