

# PREDICTION OF USER BEHAVIOUR IN SOCIAL HOTSPOTS USING MULTI -MESSAGE INTERACTION AND NEURAL NETWORKS

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**ABSTRACT** The variety of communications under social hot themes in network public opinion analysis play a significant effect in user engagement behaviour. This paper suggests a prediction model of user participation behaviour during repeated messaging of hot social subjects while taking into account interactions between many messages and complex user behaviors. In order to better forecast user involvement behaviour, a multimessage interaction influence-driving mechanism was first presented. It takes into account how multimessage interaction affects user participation behaviour. Second, based on a multimessage interaction-driving mechanism and a BP neural network, this study proposes a user participant behaviour prediction model of social hotspots in light of the behavioral complexity of users participating in multimessage hotspots and the simple structure of BP neural networks (which can map complex nonlinear relationships). Finally, the user behaviour is iteratively guided by the multimessage interaction, which readily leads to overfitting of the BP neural network. A simulated annealing approach is used to optimize the conventional BP neural network to get around this issue and increase prediction accuracy. In evaluation studies, the model not only predicted user participation patterns in real-world scenarios including many messages, but it also quantified the relationships between various messages on trending subjects.

**INDEX TERMS:** — 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 Facebook 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.

Therefore, mastering user-forwarding participation behavior is important for evaluating the influence of a microblog topic, monitoring public opinion through networks and information retrieval. 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 and, hence, the user's participation behavior. Which users will participate in the micro blog is commonly predicted by dynamic propagation or an infectious disease model?

Such predictive models typically classify network nodes as unknowns, communicators, and immunizers. 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. Some scholars also make predictions based on the user's micro blog interest and micro blog information. 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 inputs-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.

## II LITERATURE SURVEY:

Social network user behavior analysis is abroad and popular research area, which already boasts a number of surveys, doctoral thesis, review articles, technical reports etc. An extensive survey of human activity recognition and behavior analysis developed in data drive and knowledge-based techniques has been provided. Reza Mohammedi et. al. conducted a detailed measurement study to characterize and compare the group-level behavior of users in Facebook, Twitter and Google. They basically used data mining and statistical approach to measure group level user behavior. Eduardo Serra and V. S. Subramanian provided a detailed summary of quantitative methods to predict the behavior of terrorist groups. Then they applied game theoretic method to verify the rules and predict the behavior. Die-Yong an estimated a dynamic model of user behavior in a social network site using unique data on the user's daily login activity.

There some doctoral thesis where researchers tried to characterize, recognize and predict user's behavior in social networks. David John Robinson in his doctoral thesis, proposed a novel approach to identify, extract, and analyze cyber behaviors based on a cyber user's activities. He applied Bayesian sample size estimation and behavioral state-based techniques to formulate behavior analysis. Adam Sadie in his doctoral thesis used data mining techniques to predict individual social network user behavior. Roji Bandari in his doctoral thesis, applied graph theory, language processing, and information theory to provide a top-down map of group dynamics on social news websites to study the user behavior. Xu Fei Wang in his doctoral thesis studied like-minded people in social network and their volatile behavior.

## III. 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 message propagated under hot topics. Sheikh Ahmadi and others proposed a two-level model that detects and classifies the influence of users by considering the interaction between users. Similarly, Colombo et al. established a topological map for studying information dissemination through a social network. Salehi and others extracted the attributes of a multilayer network structure for predicting the probability of microblog forwarding. Other researchers, predicted user forwarding behavior through related attributes using a machine-learning method. Janowicz 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

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

## IV. 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 singlemessage, 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 output. More over, the neural network over fitting problem is solved by the simulated annealing algorithm, and the prediction accuracy is further improved.

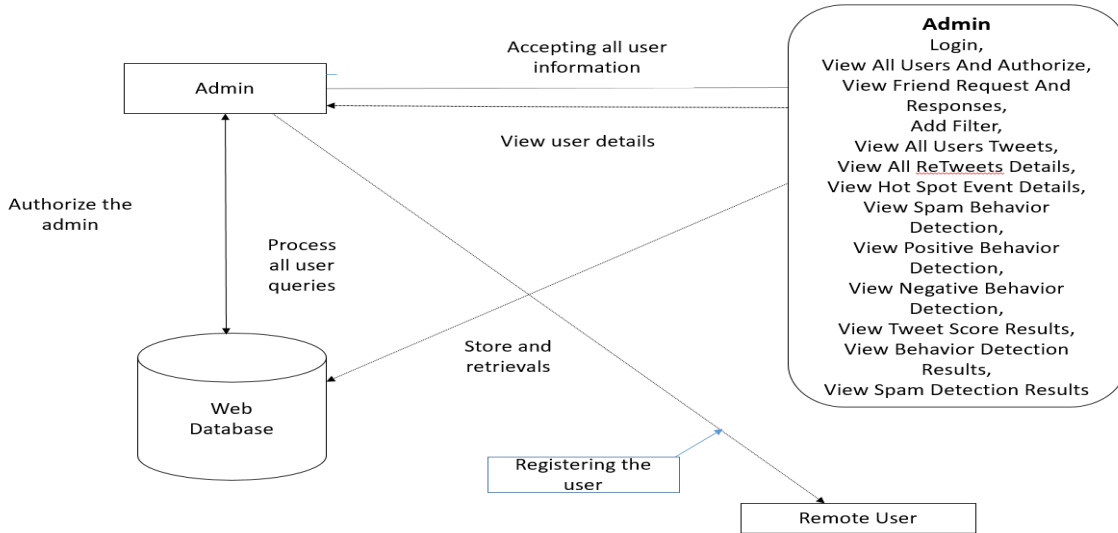


Advantages

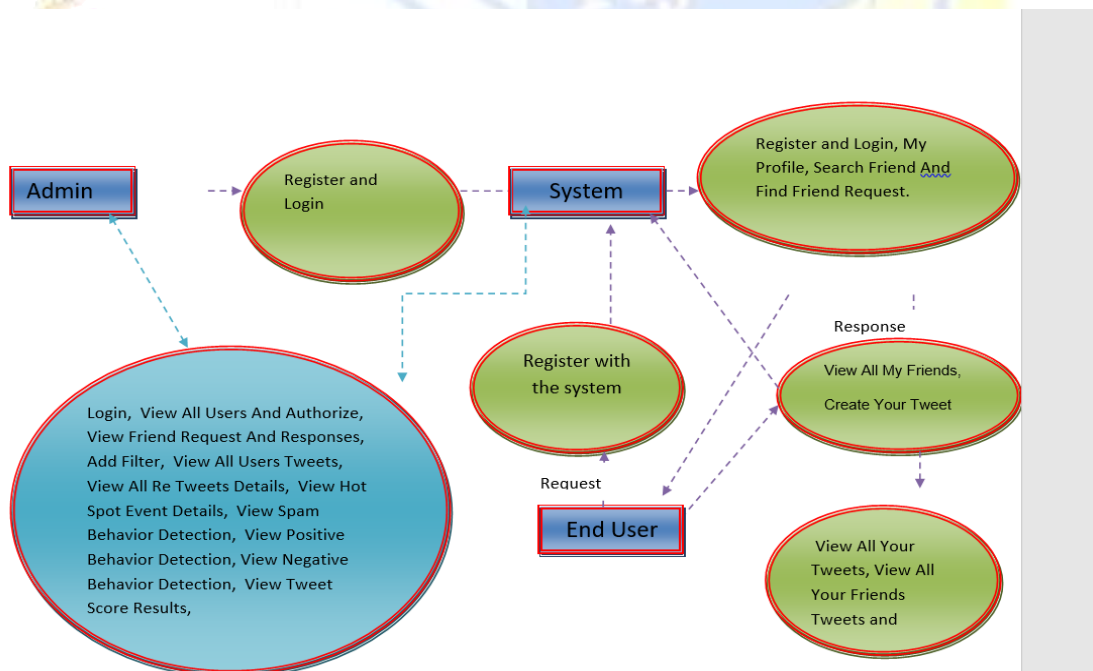
Multi message interaction mechanisms and nonlinear relationships can be handled by a back propagation (BP) neural network model. The BP neural network is a multilayer feed forward network trained by an inverse error propagation algorithm.

To The system is more effective due to presence of Driving Mechanism of User’s Personal Characteristics.

**V.SYSTEM ACHITECTURE**



**Block Diagram**



**Data Flow Diagram**

**VI. 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.

**VII. CONCLUSION:**

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. 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 behavior 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, Sine 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.

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