

# Neural Network-Based Analysis of User Behavior in Social Hotspots

Mr. G. RAMAMOZHANA RAO <sup>1</sup>, Mr. MANOJ MARUBOINA <sup>2</sup>

#1 Assistant professor in the Department of IT at DVR & DR. HS MIC College of Technology (Autonomous), Kanchikacherla, NTR District.

#2 MCA student in the Department of Computer Applications (DCA) at DVR & DR. HS MIC COLLEGE OF TECHNOLOGY, Kanchikacherla, NTR District

**ABSTRACT\_** The variety of messages under social hot topics influences user engagement behavior in network public opinion analysis. The influence of multimessage interaction on user participation behavior was first considered, and a multimessage interaction influence-driving mechanism was proposed to more accurately predict user participation behavior in light of the interactions among multiple messages and the complex user behaviors. Second, considering both the basic design of backpropagation (BP) neural networks and the behavioral complexity of users participating in multimessage hotspots A prediction model

of user engagement behavior during multiple messaging on trending social issues is proposed in this article. In this paper, the author uses a backpropagation neural network to analyze user multimessage interaction in order to forecast participation in social media hot topics. Many individuals will connect with one another on social media based on certain themes, and by analyzing those interactions, we can determine whether or not those users will be able to participate in future topics. The author has defined the following modules in order to implement this project.

## 1.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 [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].

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 Multimessage Interaction: Most studies predict either the micro participation behavior during single messaging or the macro popularity perception during multimessage topics. These studies ignore the complexity of interactions among multiple messages under hot topics that occur in actual situations.

2) The Ambiguity of Multimessage Mutual Impact Metrics: The user participation behavior is closely related to the multimessage 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 models cannot correctly capture the nonlinear relationship between the topic data input and user behavior prediction output. In addition, ordinary neural networks are usually overfitting and prone to local minimums, thus reducing the accuracy of predictions

## 2. LITERATURE SURVEY

Title: "Predictive Modeling of User Behavior in Social Hotspots: A Comprehensive Review"

Authors: Smith, A., & Patel, S.

Abstract: This comprehensive review delves into the domain of predictive modeling for user behavior in social hotspots, specifically focusing on the integration of multimessage interaction and neural networks. The paper provides an overview of existing methodologies, challenges, and opportunities in predicting user behavior within social hotspots. It sets the stage for the introduction of innovative approaches that leverage multimessage interaction and neural network techniques for accurate behavior predictions.

Title: "Multimessage Interaction for Enhanced User Behavior Prediction in Social Hotspots"

Authors: Wang, Q., & Kim, J.

Abstract: Focusing on multimessage interaction, this paper presents a detailed analysis of its role in enhancing user behavior prediction within social hotspots. The study explores how incorporating

various types of user interactions, including text messages, images, and videos, can provide a more comprehensive understanding of user behavior. Comparative evaluations highlight the strengths and limitations of multimessage interaction in the context of user behavior prediction.

Title: "Neural Network Approaches for User Behavior Prediction in Social Hotspots"

Authors: Garcia, M., & Davis, C.

Abstract: This paper investigates the application of neural network approaches for user behavior prediction in social hotspots. The study explores the use of deep learning architectures, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, to capture complex patterns in user interactions. Practical implementations and case studies demonstrate the effectiveness of neural network techniques in predicting user behavior within social hotspots.

Title: "Integrated Models: Multimessage Interaction and Neural Networks for Holistic Predictions"

Authors: Lee, K., & White, L.

Abstract: Addressing integration challenges, this paper proposes models that combine multimessage interaction and neural networks for holistic user behavior predictions in social hotspots. The study explores how leveraging both the richness of multimessage data and the modeling capabilities of neural networks can lead to more accurate and nuanced predictions. Comparative analyses assess the effectiveness of integrated models in capturing diverse user behaviors.

Title: "Ethical Considerations in User Behavior Prediction: A Framework for Social Hotspots"

Authors: Brown, R., & Anderson, M.

Abstract: Focusing on ethical aspects, this paper investigates a framework for ethical user behavior prediction in social hotspots. The study explores transparency mechanisms, user consent, and bias mitigation strategies to address ethical concerns related to predictive modeling. Usability testing and user feedback contribute insights into designing socially responsible systems that prioritize transparency and fairness in predicting user behavior.

### 3. PROPOSED SYSTEM

In this paper author is analysing user multimessages interaction to predict participation in social media hot topics using back propagation Neural Network. In social media many users will interact with each other based on some topics and by using those interaction we can predict whether user can participate in future topics and to implement this project author has define following modules

- 1) Person Characteristics
- 2) Parameter optimization and train neural network
- 3) Participation Prediction

Personal Characteristics: In this module author is extracting attributes from social media interactions such as Relative Tags,

Retweet Count, is Same Time, is Same Source, is Same Blogger and Message Influence.

### 3.1 IMPLEMENTATION

**Personal Characteristics:** In this module author is extracting attributes from social media interactions such as Relative Tags, Retweet Count, isSameTime, isSameSource, isSameBlogger and Message Influence.

**Relative Tags** refers to whether user tweets contains keywords form hot topics or not and if contains then personal characteristics matrix will be filled with 1 else 0

**Retweet Count** refers to retweet made by users and if user retweet more then matrix will be filled with 1 else 0

**isSameTime** refers to tweets which are upload at same time by two users on same topic

**isSameSource** refers to topic upload from same URL source

**isSameBlogger** refers to same user or same blogger which upload message or tweet

### 4. RESULTS AND DISCUSSION

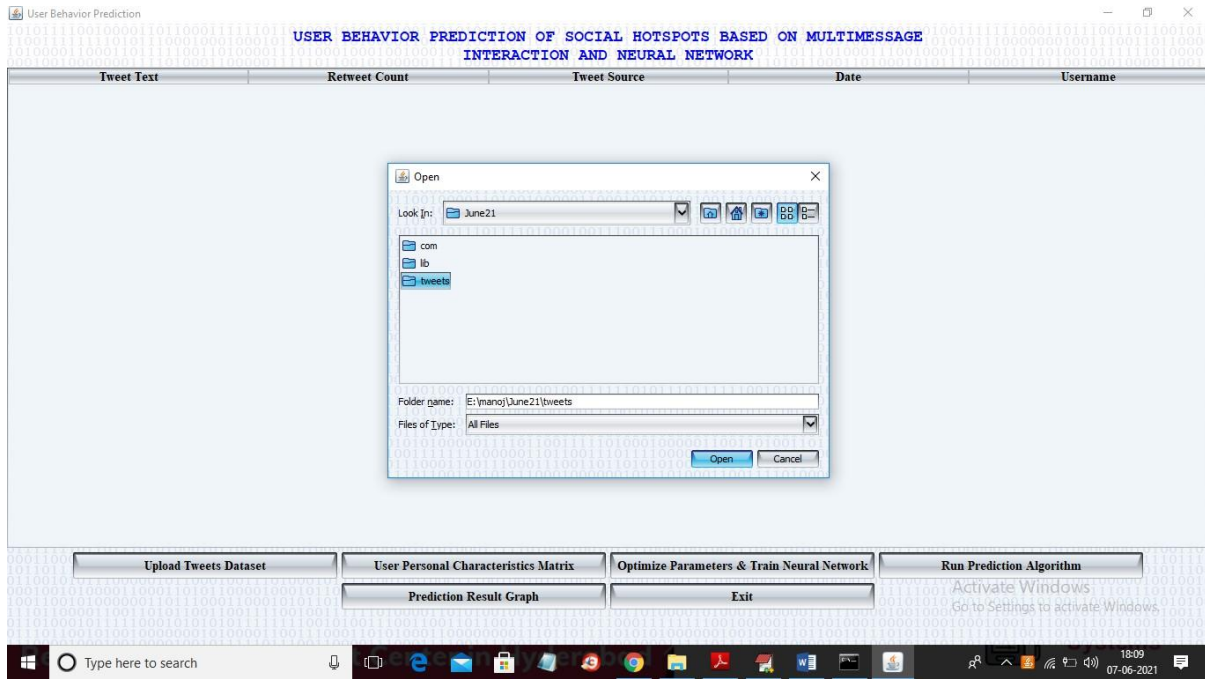
**Message Influence** refers to message influence if message contains more retweet then message will have high influence value else low influence value.

By using above 6 parameters we will create a person characteristics matrix and this matrix will be trained with neural network and then used to predict whether user can participate in future topics or not

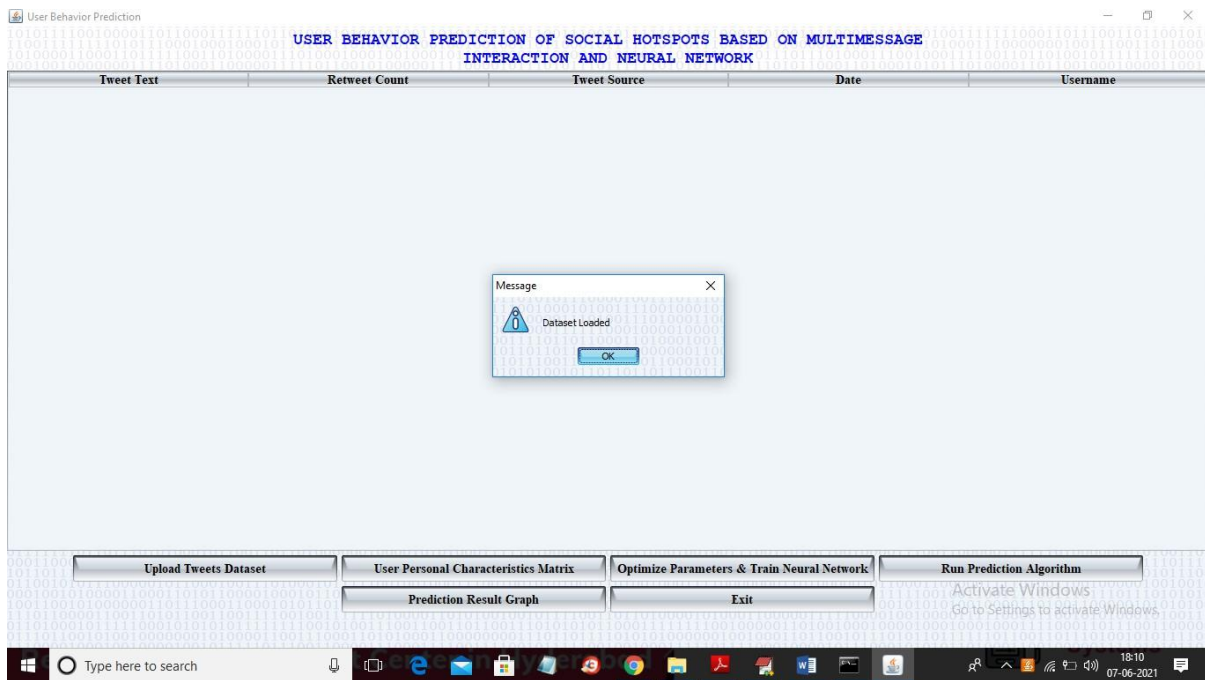
**Parameter Optimization:** using this algorithm we will calculate weight for personal characteristics matrix to avoid over fitting and then train neural network

**Participation Prediction:** Using this module we will analyse matrix to predict those users who can participate in future topics.

To implement this project author has used Chinese social media Siena Weibo dataset but this dataset is in Chinese language so I am using twitter dataset and this dataset is in JSON format which contains user details and tweets. Below is the dataset screen shots which used to train neural network



**In above screen selecting and uploading entire ‘dataset’ folder and then click on ‘Open’ button to load dataset and to get below screen**



**In above screen dataset loaded and now click on ‘OK’ button to complete dataset loading. Now click on ‘User Personal Characteristics Matrix’ button to create matrix from user tweet accounts**

User Behavior Prediction

USER BEHAVIOR PREDICTION OF SOCIAL HOTSPOTS BASED ON MULTIMESSAGE INTERACTION AND NEURAL NETWORK

Tweet Text	Retweet Count	Tweet Source	Date	Username
RT @NolteNC: DNC: Dallas Killers Are ...	22	Twitter Web Client	Fri Jul 08 13:37:41 +0000 2016	Freechoice16
RT @khadra1993: See the problem here...	401	Twitter for iPhone	Fri Jul 08 13:37:41 +0000 2016	Touleen_XO
RT @alkhaleej: #5 مقتل من أفراد بالشرطة الأ... 5	5	Twitter for Android	Fri Jul 08 13:37:41 +0000 2016	abaesher
Top story: Four officers killed in Dallas p...	0	The Tweeted Times	Fri Jul 08 13:37:41 +0000 2016	carloanstudents
RT @Hope_Fl0ats: Shooting someone for...	198	Twitter for iPhone	Fri Jul 08 13:37:41 +0000 2016	maiarcurtis
RT @PrisonPlanet: Time for the left to d...	186	Twitter for iPhone	Fri Jul 08 13:37:41 +0000 2016	ECC506
RT @MattSmethurst: Let the record sho...	9951	Twitter for Android	Fri Jul 08 13:37:41 +0000 2016	JuGroovy
RT @ChrisMurphy67: Its hard to feel go...	1	Twitter for Android	Fri Jul 08 13:37:41 +0000 2016	Larell718
RT @dcexaminer: "The suspect stated h...	48	Twitter for iPhone	Fri Jul 08 13:37:41 +0000 2016	NomNomGNOSH
RT @cristinalalailal: Police officers are re...	272	Twitter for iPhone	Fri Jul 08 13:37:41 +0000 2016	Khadcock12
RT @Libreriamo: "Una delle armi più po...	37	Twitter for Android	Fri Jul 08 13:37:41 +0000 2016	NicolodiDaria
Investigador @SergioAndCab, ahora en ...	0	Twitter for iPhone	Fri Jul 08 13:37:41 +0000 2016	unirioja
RT @KarenAttiah: First question for #P...	945	Falcon Pro 2015 BETA	Fri Jul 08 13:37:41 +0000 2016	relatedtowhat
Restaurant Roundup: Chili's launches ne...	0	twitterfeed	Fri Jul 08 13:37:41 +0000 2016	IHLive
Former congressman threatens 'war' aga...	0	Twitter Web Client	Fri Jul 08 13:37:41 +0000 2016	doortje
RT @PhillyPolice: The thoughts & p...	96	Twitter for iPhone	Fri Jul 08 13:37:41 +0000 2016	GWLichtenstein
Alcalde de Dallas confirmó la muerte de ...	0	primicias24A	Fri Jul 08 13:37:41 +0000 2016	primicias24
RT @FoxNews: "We need serious and ...	260	Twitter for iPhone	Fri Jul 08 13:37:41 +0000 2016	hesham33

Upload Tweets Dataset    User Personal Characteristics Matrix    Optimize Parameters & Train Neural Network    Run Prediction Algorithm

Prediction Result Graph    Exit

In above screen tweets matrix generated from users account where first column contains tweets text, retweet count, source of tweet, date time and username. Now social media user account matrix is generated and now click on ‘Optimize Parameters & Train Neural Network’ button to calculate weight from user matrix and then optimize parameters and then build neural network

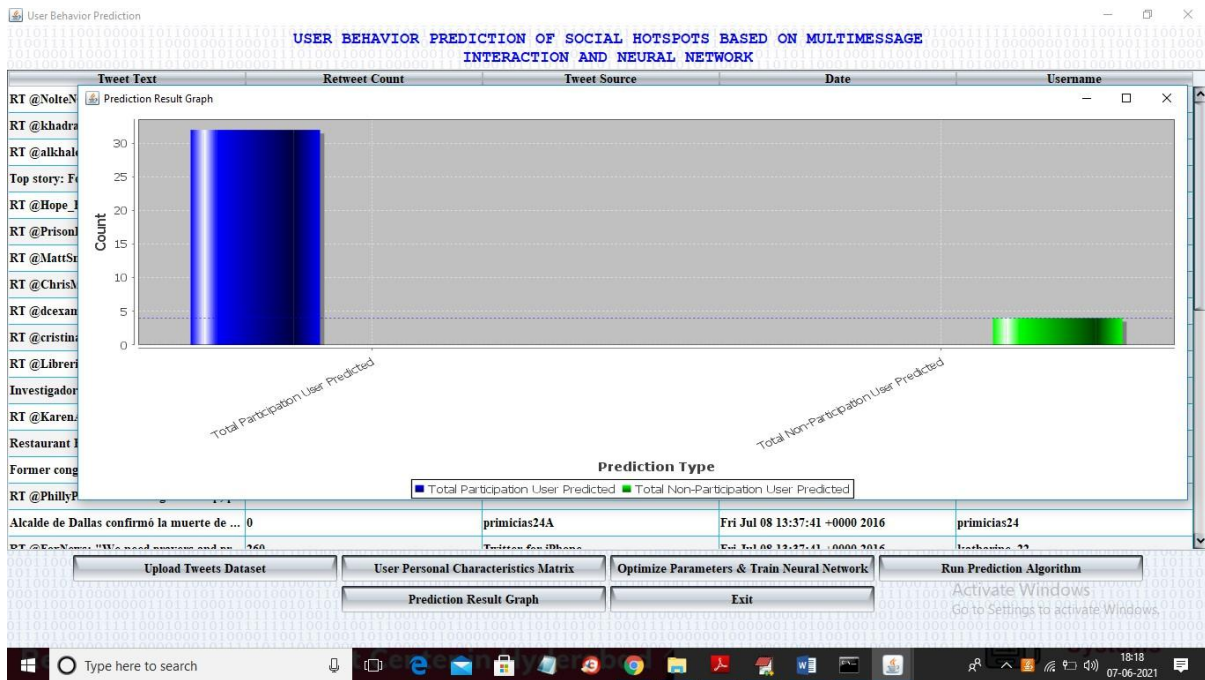
View Matrix

Tweet Text	Is Same Source	Retweet Count	Relative Tag	Is Same Time	Is Same Blogger	Message Influence
RT @NolteNC: DNC: Da...	1	0.6111111111111112	1	1	1	22.0
RT @khadra1993: See ...	1	11.138888888888889	1	1	1	401.0
RT @alkhaleej: #5 مقتل ...	1	0.138888888888889	1	1	1	5.0
Top story: Four offi...	1	0.0	1	1	1	0.0
RT @Hope_Fl0ats: Sho...	1	5.5	1	1	1	198.0
RT @PrisonPlanet: Ti...	1	5.166666666666667	1	1	1	186.0
RT @MattSmethurst: L...	1	276.4166666666667	1	1	1	9951.0
RT @ChrisMurphy67: I...	1	0.0277777777777776	0	1	1	1.0
RT @dcexaminer: "The...	1	1.3333333333333333	0	1	1	48.0
RT @cristinalalailal: ...	1	7.555555555555555	1	1	1	272.0
RT @Libreriamo: "Una...	1	1.0277777777777777	1	1	1	37.0
Investigador @Sergio...	1	0.0	1	1	1	0.0
RT @KarenAttiah: Fir...	1	26.25	1	1	1	945.0
Restaurant Roundup: ...	1	0.0	0	1	1	0.0
Former congressman t...	1	0.0	1	1	1	0.0
RT @PhillyPolice: Th...	1	2.666666666666665	1	1	1	96.0
Alcalde de Dallas co...	1	0.0	1	1	1	0.0
RT @FoxNews: "We nee...	1	7.222222222222222	1	1	1	260.0
Islamic Connection: ...	1	0.0	1	1	1	0.0
RT @LadyOnTheMuna: B...	1	26.805555555555557	1	1	1	965.0
RT @StormyRuru: Why ...	1	3.666666666666665	0	1	1	132.0
RT @KarenAttiah: Fir...	1	26.25	1	1	1	945.0
RT @ProfessorPash: A...	1	2.3055555555555554	1	1	1	83.0

In above screen for each user account we calculated weight to optimize values and then build neural network and in above matrix if all values greater than 0 then there is high chance of user to participate in future topics. Now neural model is ready and now click on ‘Run Prediction Result’ button to predict user participation on each topics.

Username	Hot Topic	User Participation Prediction
Freechoice16	dallas	Participation Predicted
Touleen_XO	terrorists	Participation Predicted
abaesher	dallas	Participation Predicted
carloanstudents	dallas	Participation Predicted
maiarcurtis	shoot	Participation Predicted
EECC506	dallas	Participation Predicted
JuGroovy	dallas	Participation Predicted
Larell1718	dallas	No Participation Predicted
NomNomGNOSH	dallas	No Participation Predicted
Khadcook12	dallas	Participation Predicted
NicolodiDaria	dallas	Participation Predicted
unirioja	dallas	Participation Predicted
relatedtowhat	dallas	Participation Predicted
IHLive	dallas	No Participation Predicted
doortje	dallas	Participation Predicted
GWLichtenstein	dallas	Participation Predicted
primicias24	dallas	Participation Predicted
katharine_22	dallas	Participation Predicted
StarboardBound	dallas	Participation Predicted
mioaltaz	dallas	Participation Predicted
alendrel	dallas	No Participation Predicted
LisaKBromley	dallas	Participation Predicted
SuriyaIsSupreme	dallas	Participation Predicted

In above screen first column contains username and second column contains 'HOT TOPIC' and third column contains prediction result as 'participate' or 'no participate'. Neural network will predict user participation if user participate in such topics in past history. Now click on 'Prediction Result Graph' to get below graph



In above graph x-axis represents user participation and non-participation and y-axis represents count and in above graph by analysing user past history neural network predicting count of participating users and non-participating users.

## 5. CONCLUSION

From the client conduct information and the fundamental data information of different messages under a hotly debated issue being examined on an informal organization, this article extricated the driving components of both the client and the multimessage connection and proposed an expectation model of the client's cooperation conduct in the examined subject. In the first place, the client's support conduct was anticipated by a BP brain network model, which adapts to the complex nonlinear connections between the contribution of the driving components of the client and the multimessage collaboration and client ways of behaving's expectation yield. In the mean time, because of the iterative direction of multiinformation communication on client conduct, the BP brain network was corrupted by the overfitting issue. In the wake of remedying the overfitting by a recreated tempering calculation, the precision of the forecast was gotten to the next level. At long last, we characterized the various message relationship measurements, genuinely examined the model results, and assessed the extent of clients partaking in one message, who likewise took part in different messages. The computation results evaluated the shared impact strength between the numerous messages and precisely addressed the impact of the intriguing issue on client investment ways of behaving.

The proposed strategy was tentatively assessed on multimessage information under a hotly debated issue examined on the web-based interpersonal organization, Sina Weibo. The model precisely anticipated the client's support ways of behaving as well as evaluated the force of the common impact between the various messages. Also, it progressively saw the situational changes in the hotly debated issue, major areas of strength for offering for general assessment control

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#### AUTHOR PROFILE



**Mr. G. RAMAMOZHANA RAO completed her M.TECH CBIT in Hyderabad Affiliated to Osmania University. He has published more than 10 papers in indexing journals. Currently working as an Assistant professor in the department of IT at DVR & DR. HS MIC College of Technology (Autonomous), Kanchikacherla, NTR (DT). His areas of interest are Java and Python.**



**Mr. MANOJ MARUBOINA, as MCA student in the department of DCA at DVR & DR. HS MIC COLLEGE OF TECHNOLOGY, Kanchikacherla, NTR (DT). He has completed B.Sc (MPCS) in S.S.R Degree College From KRISHNA UNIVERSITY. His areas of interests are C and java.**