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# User Behavior Prediction of Social Hotspots Using Interaction with Multiple Messages and Neural Networks

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Abstract: The variety of communications under social hot topics has a significant impact on user engagement behaviour in network public opinion study. This article suggests a prediction model of user participation behaviour during repeated messaging of trending social issues, taking into account interactions between numerous messages and complicated user behaviours. A multimessage interaction influence-driving method was first presented to better precisely forecast user involvement behaviour by taking into account the impact of multimessage interaction on user participation behaviour. Second, this study proposes a user participant behaviour prediction model of social hotspots based on a multimessage interaction-driving methanism and the BP neural network. This is done in light of the behavioural complexity of users participating in multimessage hotspots and the simple structure of backpropagation (BP) neural networks (which can map complex nonlinear relationships).

Keywords: Multimessage interaction, social hotspots, user behaviour, and backpropagation (BP) neural network

# I. INTRODUCTION

The ways in which people communicate and live have changed dramatically. The creation and sharing of trending topics on social media has an ongoing impact on how individuals conduct their daily lives. The user's reading and responding to messages in the network, as well as the social network's structure, encourage the spread of network themes and the transmission of information about hot subjects. Understanding user-forwarding participation behaviour is crucial for information retrieval, network monitoring of public opinion, and assessing the impact of a microblog issue. Presently, the following two methods are primarily used to forecast user behaviour in social networks. The first method examines the structural topology map that social networks employ to distribute information and forecasts the flow and spread of the information.

# II. EXISTING WORK

The user network topology and user fundamental information are taken into account in the majority of existing models when predicting user involvement behaviours, however the influence of messages spread under hot themes is ignored.

- 1) Sheikhahmadi et al. established a two-level approach that recognises and categorises user influence by taking into account user engagement.
- 2) Colombo and colleagues developed a topological map for examining how information spreads across social networks.
- 3) The majority of current studies use conventional machine learning techniques to anticipate the nonlinear relationships between the topic data input and the user participation behaviour output. By using several machine-learning techniques, Lee et al. predicted the user forwarding behaviour and the time of forwarding.

# III. PROPOSED WORK

- 1) Based on several message interactions, a model for predicting user engagement behaviour is created. The multi message interaction-driving method increases the accuracy of the prediction findings by building on the mapping correlations between the fundamental user information and participation behaviour under the conventional single message. It is more accurate to discuss the process of communication diffusion in the interim.
- 2) A multi-message interaction-based quantization approach is suggested. By quantitatively assessing the mutual influence of messages from the standpoint of subjects, this article may more precisely evaluate the multiple message selection process within the user community. The same topic's hidden influence, which affects how users participate, can be qualitatively measured in the meanwhile.



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*3)* The simulated annealing approach enhanced the performance of the BP neural network. The nonlinear relationship between the topic data input and the predicted user behaviour output is nicely matched by this strategy. Additionally, the simulated annealing approach resolves the neural network over fitting problem, substantially increasing prediction accuracy.

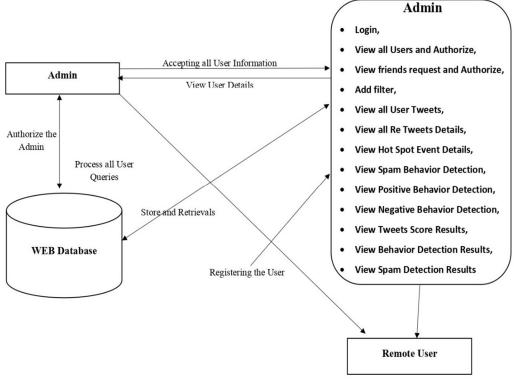


Fig. Model Diagram for Predicting User Behavior

#### IV. PREFATORY

#### A. LSTM (Long Short-Term Memory)

Recurrent neural networks include long short-term memory. The output from the previous phase is sent into the current step of an RNN as input. Hochreiter & Schmidhuber created LSTM. It addressed the issue of long-term RNN dependency, in which the RNN can predict words from current data but cannot predict words held in long-term memory. As the gap length grows, RNN's performance becomes ineffective. By default, LSTM may store information for a long time. It uses time series data for processing, forecasting, and classification.

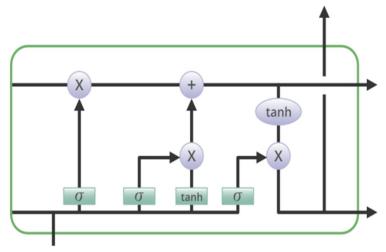


Figure: LSTM Organization



A. Tweeter's Home Page

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Cells and gates both play a role in memory modification and information retention. Three gates are present:

- Forget Gate: The forget gate eliminates information that is no longer relevant to the condition of the cell. The gate receives two inputs, x t (input at the current time) and h t1 (prior cell output), which are multiplied with weight matrices before bias is added. The output of an activation 40 function that receives the resultant is binary. If the output for a certain cell state is 0, the information for that cell is lost, however if the output is 1, the information is saved for use in the future.
- 2) Input Gate: The input gate adds useful information to the cell state. First, The sigmoid function is used to control the information, and inputs h t-1 and x t are used to filter the values that should be remembered in a manner similar to the forget gate. Then, using the tanh function, which outputs values ranging from -1 to +1, a vector is generated that contains all possible values for h t-1 and x t. To get the useful information, atlas, the vector's values and the regulated values are multiplied.
- *3) Gate at Output:* Output gates are responsible for removing pertinent information from the current cell state and presenting it as an output. The tanh function is first used to the cell to create a vector. The sigmoid function is then used to control the information, and inputs h t1 and x t are used to filter the values to be remembered. Atlast, To send the values as an output and input to the following cell, the vector's values and the controlled values are multiplied.
  - V. RESULTS
  - User Behavior Prediction of Social Hotspots Based on Multimessage Interaction and Neural Network

Backpropagation (BP) neural n	etwork, multimessage interaction,	social hotspots, user behavior
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C. Page for User Registration

#### User Behavior Prediction of Social Hotspots Based on Multimessage Interaction and Neural Network

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

Adbiya	R DETAILS HERE !!!
	h16@gmail.com
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9866095498	
India	
Telangana	
Hyderabad	
sign_up	

D. Analysis of Positive Sentiment

gative Sentiment Reviews View Neutral Sentiment Reviews View All Remote Users View All Trending Tweet Hotspot View all Rating Results View All Dislike Results View All Like Results LOGOUT  VIEW ALL POSITIVE REVIEWS	loaded Tw	reet Details Vi	iew All Tweets Recommende	d View All Tweets	Reviews V	iew All Positive Se	entiment Review
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Wive_mobiles         positive         14:08:23.918082         Purch           It is extraordinary         2022-05-12         Can	Name	Vivo_Mobiles	Review It is extraordinary mobile.	Sentiment Analysis	2022-05-1 14:08:23.	2 918082	Can Purchase

E. Analysis of Neutral Sentiment

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		VIEW ALL	L NEUTRAL REVIEWS!!!			
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	Vivo_Mobiles	Not worthy	neutral			Negative
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Adbiya Adbiya	Vivo_Mobiles Hero_Honda	Not worthy Positive Huge data can be saved	neutral neutral neutral	2022-05-12 2022-05-12	19:41:21.357621 13:47:56.650257	Negative Positive Neutral
Adbiya Adbiya Adbiya	Vivo_Mobiles Hero_Honda Sandesk HP_Laptop	Not worthy Positive Huge data can be saved	neutral neutral neutral neutral	2022-05-12 2022-05-12 2022-05-12	19:41:21.357621 13:47:56.650257 13:49:31.836202	Negative Positive Neutral Execllent



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F. Analysis of Negative Sentiment

	veet Details	View All Tweets Recommended V	iew All Tweets Rev	iews View All Positive Se	ntiment Reviews
Negative Se	ntiment Review	vs View Neutral Sentiment Review	s View All Remo	ote Users View All Trendir	ng Tweets
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#### VI. CONCLUSION

The driving mechanisms of both the user and the multimessage interaction were extracted from the user behaviour data and the basic information data of multiple messages under a hot topic being discussed on a social network, and a prediction model of the user's participation behaviour in the discussed topic was proposed. The computation findings properly depicted the impact of the trending subject on user participation behaviours and quantified the mutual effect strength between the different messages. The suggested strategy was experimentally tested using multimessage data and a popular social media topic.

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