A Fuzzy Logic-Based Opinion Update Model for Online Social Networks with Influential Social Bots

Rashmi Ranjan Rout, Sudipta Sahana, Priyanka Parimi

Department of Computer Science and Engineering, National Institute of Technology Warangal, Telangana, India.
Email: rashrr@nitw.ac.in, sscs21223@student.nitw.ac.in, priyankap@student.nitw.ac.in

***Abstract*—Social media is a platform where people express their opinions through user-generated text. Investigating opinion changes of people based on the influence of legitimate users and bots over time is crucial. The influence of bots on opinion evolution can be different from the influence of individuals in a network since the opinion of bots does not evolve over time, irrespective of the opinion of the rest of the network. This work aims at investigating the influence of social bots on users' opinions by considering the user's bias and interactions with other users and bots over time. A fuzzy logic-based approach is designed for opinion updates, allowing for uncertainty in the opinion. By considering the tweet's sentiment, we develop a neighbor-biased-fuzzy opinion influence model and analyze the effect of bots in social media. Experiments are conducted on the Social-Honeypot Twitter dataset to evaluate the performance of the proposed approach. The change in user opinion in the presence of different bots is analyzed. Further, the shift in public opinion over time due to the influence of bots is predicted.**

***Index Terms*—Online Social Networks, Opinion, Bots, Fuzzy Logic.**

I. Introduction

In today's world, social media greatly impacts our day-to-day life. Twitter, Facebook, and Instagram are platforms where people exchange their daily opinion through user-generated text [1]. As the impact of these social media platforms plays a huge part in the formation of opinion to the evolution of opinion, many researchers have grown their interest in the area of opinion influence [2]. In social networks, people regularly interact with friends and followers and update their previous beliefs based on their interactions [3]. We also can not forget about the bots constantly trying to engage with the people. Bots are algorithmic programs that try to behave like human and often succeeds in fooling people [4]. Almost 19% of interactions on social media platforms are human-to-bots interaction [5]. Recently it has been noticed that bots-human interaction is used for the goal of opinion shaping [6], [7]. So, it has become necessary to observe the change in people's opinion in the presence of bots and how these bots influence people's opinions in a time period on specific and critical topics, such as the 2016 US presidential election.

The existing influence models, such as the Degroot and HK models, only focus on the sentiment of the users' opinion and the new coming neighbor's opinions [3]. Most existing models for opinion updating have primarily focused on utilizing neighbors' opinions, such as calculating the average opinion of neighbors or employing k-nearest neighbor classifiers to update user opinions. However, these models often overlook an important aspect such as individual biases toward specific topics. Therefore, a practical fuzzy based opinion-updating model considering the user's bias on his previous beliefs, neighbors' influence has been proposed in our work.

On the other hand, social media bots are algorithmically driven programs designed to emulate human behavior on platforms like Twitter and Facebook. One crucial distinction between legitimate users and bots is that while users tend to change their opinions over time, bots within the system typically maintain a fixed opinion without evolving [4]. By interacting with the humans, the bots influence the user opinion and govern the public towards a particular standpoint. Therefore, in this work, we analyze the bots-user influence in a given time period and how the users' opinion has evolved with the presence of bots.

To address this gap, we propose a novel approach for updating user opinions by considering the differences in opinions between the user and their neighbors. The real-world textual data is subjective, vague and imprecise [8]. To handle the uncertainty and partial truths associated with opinions, fuzzy logic is applied, allowing for more nuanced and flexible opinion updates [9] [10]. Uncertainty of opinion in fuzzy logic reflects the extent to which an opinion can be characterized as neither fully true nor fully false but rather as a gradual or fuzzy state between the two extremes. This model aims to capture the nuances and uncertainties inherent in opinions and leverage them to provide more accurate and realistic opinion updates [9]. Furthermore, it is worth noting that previous research in this domain has not extensively analyzed the influence of bots within the network, specifically concerning Twitter datasets. This study aims to fill this research gap by investigating the impact and role of bots in shaping opinions within the network. The main contributions of this paper are:

- Design a fuzzy logic based opinion update model, taking into account the bias of the users and neighbor influence.
- Analyze the influence of bots in social networks on the legitimate users and their opinions.
- Experimentation to evalute the efficacy of the proposed approach by considering the Social-Honeypot dataset.

The rest of the paper is organized as follows: A discussion on the existing literature about the opinion update models and the influence of bots on the legitimate users is presented in section II. In section III, we formally formulate the user opinion update problem in the presence of bots. The proposed fuzzy logic based opinion update model is presented in section IV. The results of the experimentation are discussed in section V and the paper is concluded in section VI.

II. Related Work

Recently, there has been a significant advancement in the development of AI-powered chatbots on various social media platforms such as Twitter, Facebook, and YouTube. These platforms have recognized chat-bots' potential in enhancing user experiences and providing assistance. Consequently, they have invested in creating their own chat-bots and allowing users to develop their own chatbots for creative purposes [11]. The use of bots in opinion manipulation is a significant challenge for social media platforms and society as a whole [11]. Studies show that only humans tend to show this follower behavior, whereas bots do not change their opinion with time [12]. Also, some bots are created to spread rumors and fake news in social media circles [11]. Stella *et al.* have analysed how bots spread negative content in social media [5]. Most of the studies examined the behavior of bots with human users and the content spread.

The study of bot activity in Ukrainian- Russian conflict showed that bots helped in spreading information as well as rumors too. And also unrelated posts spamming the content [13]. There are many methods and algorithms form which an account is a bot or not is determined like *Botornot*. *Botornot* has been trained on 1000s of instances of social bots which reflected the simple ones also and sophisticated one also with accuracy of 95% [14].

There are different frameworks to understand user behaviour in social network. Content based sequential opinion system is made on two different approaches one is on summarized sentiments and other is on collected opinion words [15]. Degroot model and Hk models k-nearest neighbour and voter model are some well known influence models which only considers the current opinion and neighbours opinion [3] [16] [17].

Most of the models have used neighbors opinion as to calculate the updated opinion like taking average of neighbours opinion or like k-nearest neighbor model where they have used k-neighbour classifier and update the opinion of user most of the models have not focused on peoples personal bias towards a specific topic. Social media bots are algorithmically-driven programs that try to mimic humans better than humans on social media platforms like Twitter, Facebook, etc. The difference between a legitimate user and a bot is that user changes its opinion with time were as the bots in system does not change opinion with time. Updating user opinion based on the difference in opinions between the user and the neighbors.Using fuzzy logic for opinion updating since it allows the result to be in partial truths and uncertainty. None of the previous work has actually analysed the influence of bots in the network on twitter dataset.

III. Problem formulation

The social network is described as a directed graph $G = (V, E)$, here V is the node set and E is the edge set. A node is represented by a user or bot in the graph and an edge between two nodes is represented by the social relationship between them. For example, in twitter, user i in V following user j in V is represented as an edge (i, j) in E. Here node, user and bot are used almost equivalent in this paper. Each user i has an initial opinion on social media network. Opinion for every user i we determine $x_i(t)$. A negative opinion is indicated by -1, positive opinion by $+1$ and neutral opinion by 0. Thus $x_i(t)$ is a real number from defined range and the vector $x(t) = (x_1(t), ...(x_n(t))$ represents the opinion profile at time t. $y_i(t)$ is positive when $x_i(t)$ is $+1$,$y_i(t)$ is negative when $x_i(t)$ is -1 and $y_i(t)$ is neutral when $x_i(t)$ is 0.

$$y_i(t) \in \{positive, nuetral, negative\} \tag{1}$$

In this system there are two types of nodes the bots and the users. So opinion of user at time $t+1$ is described as follows where δ is the change we have found

$$x_i(t+1) = f(x_i(t), \delta) \tag{2}$$

For bots opinion there will be no change in opinion with time

$$x_i(t+1) = x_i(t) \tag{3}$$

The user's connections are influencing the user through online discussions. Therefore, opinions of the users evolves in a time as they interact with their neighbors. The regular communication with neighbor for a time period with neighbours will be a included in the process . The users try to achieve a general agreement on their opinion and form a final group opinion (consensus). In this paper, we propose a model for user opinion update based on authentic features, such as the bias of the user towards his/her neighbors denoted as β and the influence power of the neighbors γ on the initial opinion of the user as x_i . Therefore, the final change in opinion of a user can be determined as a function

$$\delta = g(\beta, \gamma, x_i) \tag{4}$$

Here g is the opinion update function based on the user's repeated interactions with the neighbors.

IV. Proposed Fuzzy Logic based Opinion Update Model

We propose a model that takes users personal factors into consideration. For opinion updating model our prime factors are initial opinion, bias and neighbors influence.

A. Initial Opinion

To determine the initial opinion of each user, we utilize two factors: Bert sentiment classification and word count sentiment. These factors help us quantify the sentiment of users' opinions and assign weights to them.

For the Bert sentiment classification, we employ a model that analyzes the semantic basis of a user's tweets and provides a sentiment value. The sentiment value can be classified

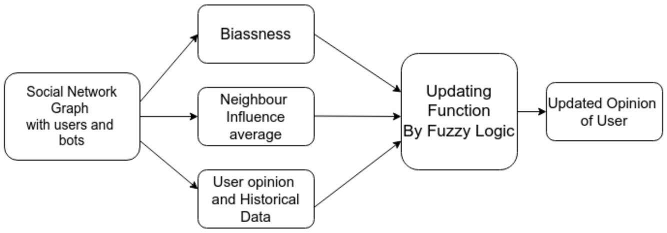

Fig. 1. Opinion Evolution Model

as positive, neutral, or negative, representing the overall sentiment of the user's expressed opinions. This sentiment value, denoted as $x_i(t)$, is a real number [15]. By applying the Bert model to each user's tweets, we obtain their respective sentiment values.

We incorporate word count sentiment analysis as another factor in determining the initial opinion. In this approach, we count the occurrences of positive and negative words within a user's initial opinion. This analysis allows us to assign weights to the sentiment expressed in their opinion. [18] The resulting score s_i reflects the overall sentiment of the user's opinion based on the prevalence of positive and negative words. we construct an opinion profile vector, denoted as $x(t) = (x_1(t), x_2(t), ..., x_n(t))$, representing the opinions of all users at a given time t. This vector captures the sentiment of each user's initial opinion.

B. Bias

Bias is generated to select the similar type of neighbor influence on a specific topic.It represents the way a person interpreted the text they assessed previously [19].This will be determined on basis of score and sentiment generated by BERT analysis. Two factors to calculate bias is sentiment and the score weights. For every opinion of user in train data we calculate mean here s_i is score and x_i is sentiment. U_{past} is user previous data on the specific topic [20] [19].

$$\mu = \sum s_i.x_i/|no.of opinions| \tag{5}$$

Calculate the standard deviation.

$$\sigma = \sqrt{\frac{\sum s_i \in U_{past}(x_i - \mu)^2}{|U_{past}|}} \tag{6}$$

Calculate bias by using mean and standard deviation.

$$\beta = \frac{1}{|U_{past}|} \sum_{d \in U_{past}} \frac{x_i - \mu}{\sigma} \tag{7}$$

C. Neighbor Influence

The selection of potential neighbors as influences is based on the differences in bias. The bias of each tweet interaction is calculated using a combination of score and sentiment. The absolute difference is calculated between the user's bias and the bias of every other neighbor's tweet interaction to identify potential influencers. This absolute difference is represented as $|\beta_1 - \beta_i|$, where β_1 is the bias of the user and β_i is the bias of the neighbor.

By computing the absolute differences for each user-neighbor pair, a set of values is obtained, denoted as $y_t = ad_1, ad_2, \ldots, ad_n$, where ad_i represents the absolute difference between the bias of the user and a specific neighbor.

The minimum value from y_t, $min(y_t)$, is filtered out, representing the neighbors with the smallest absolute difference in bias. These neighbors are identified as potential influencers. Finally, the average of y_t is calculated, providing the potential average influence γ. This average represents the sentiment of the neighbors and contributes to the determination of potential influences.

D. Fuzzy logic for the Updating Opinion

As fuzzy logic allows the result to be in partial truths and uncertainty, rather than the classic binary result that leaves us with only two options: true or false. Its use is quite popular in the field of artificial intelligence and decision-making. For conversion of input sets in fuzzy set an appropriate membership function is selected for opinion updating and i.e. triangular membership function.

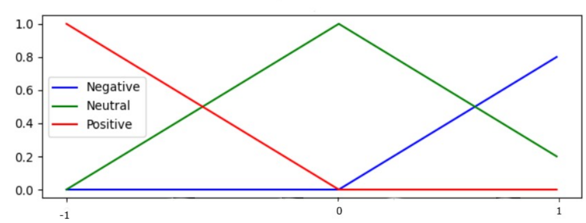

Fig. 2. Membership function for Initial Opinion

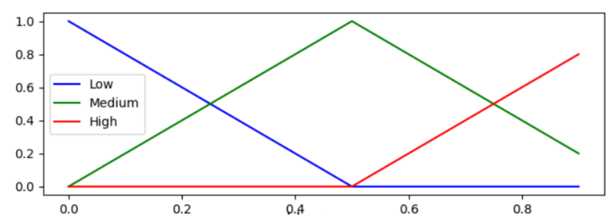

Fig. 3. Membership function for Bias and Potential Influence

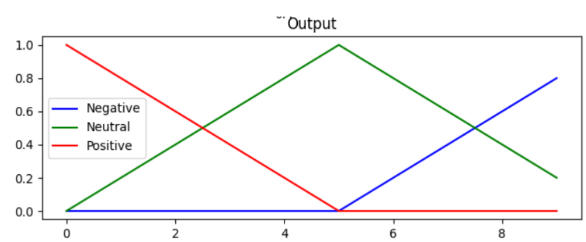

Fig. 4. Membership function for Updated Opinion

This type of function is suitable for modeling situations with a saturation point or a limit to how much a value can influence the output [9]. The fuzzy system contains three sections. Our rule set contains fuzzy *IF-THEN* rules. The Decision-making Unit performs operations with the help of rules that we have already defined. Fuzzification converts the crisp quantities into fuzzy quantities provided to the decision-making unit. Defuzzification converts the fuzzy quantities into crisp quantities, and finally, we receive our required output.

Defining linguistic values for every parameter that we are using. The labels are given for all the parameters are described in Table I. Initial opinion is classified into one of three categories: positive, neutral, or negative. This initial opinion serves as a baseline or starting point for further analysis or evaluation. The bias column indicates the degree or level of bias present in the information or viewpoint being expressed. It can be classified as high, medium, or low, depending on the extent to which the opinion is influenced by personal, cultural, or ideological biases. This column represents the average potential influence that the opinion or viewpoint may have on others or the general audience. It can be classified as high, medium, or low, based on the estimated impact or persuasive power that the expressed opinion holds.The updates opinion column indicates any changes or updates made to the initial opinion over time. It can be classified as positive, neutral, or negative, reflecting the revised stance or viewpoint after considering new information, experiences, or perspectives [21].

TABLE I
PARAMETERS FOR THE FUZZY LOGIC BASED OPINION UPDATE ALGORITHM

Parameters	Linguistic values
Initial opinion	Positive, Neutral, Negative
Biasness	High, Medium, Low
Potential influence avg	High, Medium, Low
Updates opinion	Positive, Neutral , Negative

A rule set for the decision making unit based on the linguistic labels for the parameters is defined as shown in table II. Algorithm 1 provides a systematic approach for updating opinions using fuzzy logic, enabling a more nuanced and flexible decision-making process that considers the user's initial opinion, bias, and the influence of neighbors.

TABLE II
RULE SET FOR FUZZY LOGIC

Initial	Biasness	Influence avg	Updated
Negative	Low	High	Negative
Neutral	Medium	Low	Neutral
Positive	High	Medium	Positive
Positive	High	Low	Negative
Neutral	Medium	High	Neutral
Positive	High	Medium	Positive
Negative	Medium	Medium	Negative
Neutral	High	High	Positive
Positive	Low	Low	Positive
Neutral	High	High	Positive
Negative	Low	Medium	Positive
Neutral	High	Low	Negative

The given inputs consist of the initial opinion represented as x_i, the bias as β, and the representation of potential influence average as γ (line 1). The desired output is the changed opinion, represented as δ (line 2). The ruleset mentioned above provides guidelines for determining the updated opinion based on these inputs. To convert the input sets (initial opinion, bias, and average neighbor influence) into linguistic labels, a triangular membership function is used. This function assigns a degree of membership to each linguistic label based on how well the input values fit within the defined range for each label (line 1).

Algorithm 1 Fuzzy logic based Opinion Update Algorithm

Input: x_i, β, γ
Output: δ_i
Predefined: $RULESET$
1: Conversion of input to membership values and linguistic label l using triangular membership function
2: Make a empty list ϕ
3: **for** R in $RULESET$ **do**
4: **if** $\mu(x_i), \mu(\beta), \mu(\gamma)$ fit the membership levels of R **then**
5: Determine linguistic label l from R
6: $m \leftarrow max(\mu(x_i), \mu(\beta), \mu(\gamma))$
7: Add the entry $\langle l, m \rangle$ to list ϕ
8: **end if**
9: **end for**
10: Conversion of label to updated opinion by center of gravity defuzification method δ_i
11: **return** δ_i

For each rule in the ruleset, the inputs (initial opinion, bias, and average neighbor influence) are evaluated to determine if they satisfy the conditions of the rule. If the inputs match the rule, the linguistic label of the output associated with the rule is assigned to the input set. These assigned linguistic labels are then added to an empty list, which will store the updated opinions generated by this process (line 3-9).

To convert the updated opinions from linguistic labels to a numerical value, the center of gravity defuzzification method is utilized. This method calculates the weighted average of the linguistic labels based on their degree of membership. It determines the center point of the distribution of the linguistic labels, providing a numerical value that represents the updated opinion (line 10).

In summary, this process involves converting the input sets into linguistic labels using a triangular membership function, applying the ruleset to assign linguistic labels to the inputs, and finally converting the linguistic labels back into a numerical representation using the center of gravity defuzzification method.

V. EXPERIMENTION AND RESULTS

Experiments are conducted on the Social honeypot dataset [22] and compared with other existing algorithms to evaluate the efficacy of the proposed approach. Further, we try to predict the change in user opinion due to the presence of bots in the social network.

The Social honeypot dataset [22], extracted by Lee *et al.*, is a collection of over 5,613,166 tweets over a period of about 7 months posted by 22,223 content polluters, 19,276 legitimate users and their followings. In our analysis of the social honeypot dataset, we have first performed topic classification on the random tweets. We then identified 3960 tweet IDs that had at least two different opinions on a specific topic. The proposed approach is compared with the k-nearest neighbor model of opinion update in terms of accuracy and precision. Accuracy accounts for true positives and true negatives divided by the total number of instances. Precision is the proportion of true positives to total positive instances.

In the first experiment (Exp 1), to assess the effectiveness of our bias-fuzzy model, it is compared with the k-nearest neighbor model, as shown in table III. The accuracy of our model was found to be 94.56%, while the k-nearest neighbor model achieved an accuracy of 90.33%. Our model outperformed the k-nearest neighbor approach since it incorporates the user bias and fuzzy logic. Further, the k-nearest neighbor model achieved a precision of 73.24%, whereas our bias-fuzzy model demonstrated a higher precision of 93.22%.

TABLE III
COMPARISON OF RESULTS OF OPINION UPDATE MODELS

	KNN	**Bias-fuzzy**
Exp 1: Without Bots		
Accuracy	90.33	94.56
Precision	73.24	93.22
Exp 2: With Positive Bots		
Accuracy	87.54	91.04
Precision	85.07	90.22
Exp 3: With Negative Bots		
Accuracy	90.75	96.05
Precision	87.24	89.27

In the second experiment (Exp 2), 20 positive bots (bots with positive opinion) are added to the environment and the behaviour of the models is observed. The accuracy of the proposed approach is 91.04% as compared with 87.54% from the the k-nearest neighbour model. Further, the Bias-fuzzy approach gives a precision of 90.22% which is higher than that of the KNN model.

Figure 5 shows the comparison of the number of users who have changed their opinion based on the two models. The KNN model estimates that 1223 users have changed their negative opinions to positive and 653 users have changed their opinion from positive to negative. However, the bias-fuzzy model estimates the number of users with negative-positive opinion change to be 1074, which is nearer to the ground truth 850. Further, the bias-fuzzy model estimates the number of users with positive-negative opinion change to be 821, which is closer to the ground truth 870. The opinion change in k-neighbour is much more than the original ground truth because completely dependent on neighbour to update users opinion. However, since Bias fuzzy model is based on users previous beliefs and not completely on neighbours, the number of users changing their opinion is less.

In the third experiment (Exp 3), a total of 20 negative bots (bots with negative opinion) are added to the system. The accuracy of the proposed approach is 96.05% as compared with 90.75% from the the k-nearest neighbour model. Further, the Bias-fuzzy approach gives a precision of 89.27% which is higher than that of the KNN model. Figure 6 shows the comparison of the number of users who have changed their opinion based on the two models. The KNN model estimates that 800 users have changed their negative opinions to positive and 937 users have changed their opinion from positive to negative. The bias-fuzzy model estimates the number of users with negative-positive opinion change to be 803. Also, the bias-fuzzy model estimates the number of users with positive-negative opinion change to be 914, which is closer to the ground truth 937. Therefore, the proposed Bias-fuzzy approach outperforms the KNN model.

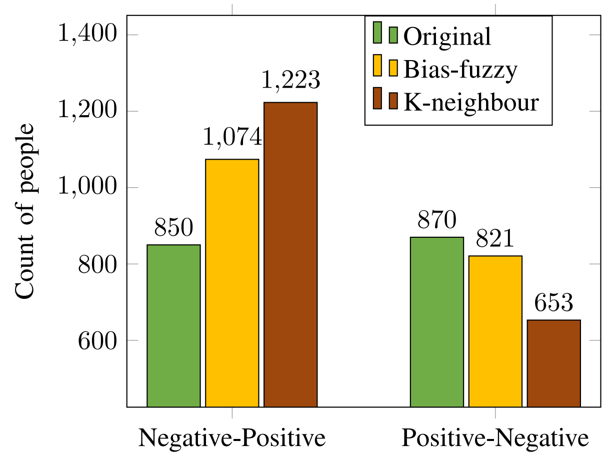

Fig. 5. Exp 2: Opinion changes in presence of Positive bots

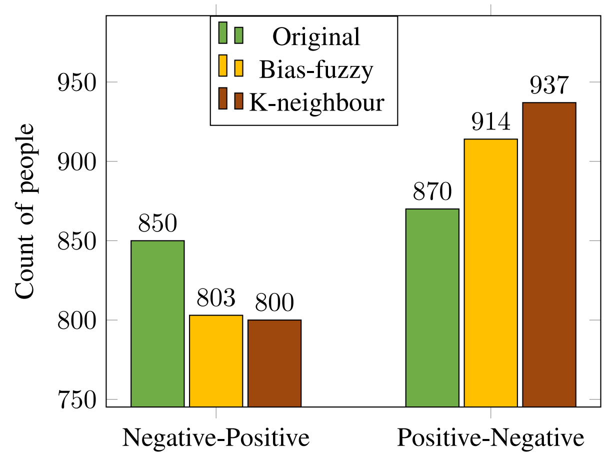

Fig. 6. Exp 3: Opinion changes in presence of Negative bots

In the forth experiment (Exp 4), we predict the number of people who change their opinion over time, with and without presence of 20 positive bots. The impact of these bots on the opinion dynamics within the system is evident from Figure 7.

Initially, there were 905 users whose the opinion shifted from negative to positive, indicating a change of perspective. Additionally, there were 929 users whose the opinion changed from positive to negative. However, after the introduction of the positive bots and the subsequent prediction of the updated opinions over time, these numbers changed. With the introduction of positive bots, the number of users with opinions changes from negative-positive has become 1074.

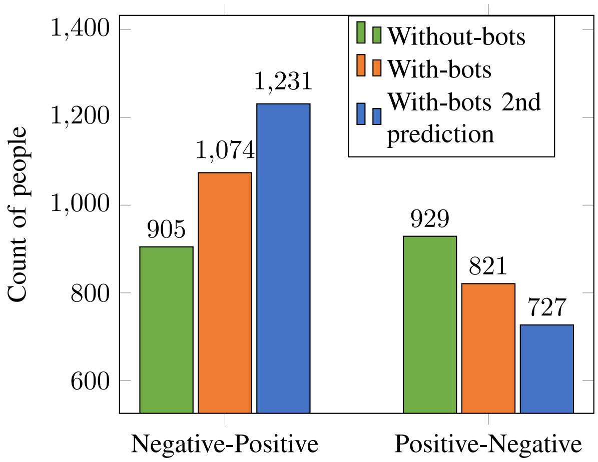

Fig. 7. Exp 4: Predicting the opinion changes in presence of Positive bots

Over time, with the second update, the number is predicted to be 1231. On the other hand, with the influence of positive bots, the number of users with opinion change from positive to negative decreased to 821 and is further predicted to drop to 727 users. This clearly illustrates the rapid and significant shifts in people's opinions in the presence of bots. It also demonstrates how easily the bots can manipulate the user opinions.

VI. Conclusion And Future Works

A fuzzy logic-based approach is presented for opinion updating. The proposed fuzzy logic-based model outperforms the k-nearest neighbor model in terms of prediction accuracy because it considers the bias of users' previous beliefs. In contrast, the k-nearest neighbor model relies solely on neighbors' opinions. By incorporating bias, our model provides more accurate results by considering individuals' own perspectives and beliefs. Our opinion-updating model, which combines bias and fuzzy logic, allows us to examine and compare opinion changes both in the presence and absence of bots within the same environment. This comparison enables us to understand the specific impact that social bots have on people's opinions. Bots maintain a fixed opinion, whereas people are susceptible to changing their beliefs over time. In future, we plan to conduct experiments on different datasets from social media and compare our model with classical and existing opinion update models. We aim to investigate opinion changes without relying on topic classification methods, exploring the broader impact of bots across various contexts.

References

[1] J. Heidemann, M. Klier, and F. Probst, "Online social networks: A survey of a global phenomenon," *Computer networks*, vol. 56, no. 18, pp. 3866–3878, 2012.

[2] R. Das, J. Kamruzzaman, and G. Karmakar, "Opinion formation in online social networks: Exploiting predisposition, interaction, and credibility," *IEEE transactions on computational social systems*, vol. 6, no. 3, pp. 554–566, 2019.

[3] Z. Wu, Q. Zhou, Y. Dong, J. Xu, A. H. Altalhi, and F. Herrera, "Mixed opinion dynamics based on degroot model and hegselmann–krause model in social networks," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 53, no. 1, pp. 296–308, 2022.

[4] A. Shukla, N. Sahasrabudhe, and S. Moharir, "Opinion dynamics in the presence of bots," in *2022 IEEE International Conference on Signal Processing and Communications (SPCOM)*. IEEE, 2022, pp. 1–5.

[5] M. Stella, E. Ferrara, and M. De Domenico, "Bots increase exposure to negative and inflammatory content in online social systems," *Proceedings of the National Academy of Sciences*, vol. 115, no. 49, pp. 12 435–12 440, 2018.

[6] E. Ferrara, O. Varol, C. Davis, F. Menczer, and A. Flammini, "The rise of social bots," *Communications of the ACM*, vol. 59, no. 7, pp. 96–104, 2016.

[7] A. Bessi and E. Ferrara, "Social bots distort the 2016 us presidential election online discussion," *First monday*, vol. 21, no. 11-7, 2016.

[8] S. Vashishtha, V. Gupta, and M. Mittal, "Sentiment analysis using fuzzy logic: A comprehensive literature review," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 13, no. 5, p. e1509, 2023.

[9] U. Ghani, I. S. Bajwa, and A. Ashfaq, "A fuzzy logic based intelligent system for measuring customer loyalty and decision making," *Symmetry*, vol. 10, no. 12, p. 761, 2018.

[10] J. Serrano-Guerrero, F. P. Romero, and J. A. Olivas, "Fuzzy logic applied to opinion mining: a review," *Knowledge-Based Systems*, vol. 222, p. 107018, 2021.

[11] A. Aldayel and W. Magdy, "Characterizing the role of bots' in polarized stance on social media," *Social Network Analysis and Mining*, vol. 12, no. 1, p. 30, 2022.

[12] O. Varol, E. Ferrara, C. Davis, F. Menczer, and A. Flammini, "Online human-bot interactions: Detection, estimation, and characterization," in *Proceedings of the international AAAI conference on web and social media*, vol. 11, no. 1, 2017, pp. 280–289.

[13] C. Chen, Z. Wang, and W. Li, "Tracking dynamics of opinion behaviors with a content-based sequential opinion influence model," *IEEE Transactions on Affective Computing*, vol. 11, no. 4, pp. 627–639, 2018.

[14] C. A. Davis, O. Varol, E. Ferrara, A. Flammini, and F. Menczer, "Botornot: A system to evaluate social bots," in *Proceedings of the 25th international conference companion on world wide web*, 2016, pp. 273–274.

[15] M. Geetha and D. K. Renuka, "Improving the performance of aspect based sentiment analysis using fine-tuned bert base uncased model," *International Journal of Intelligent Networks*, vol. 2, pp. 64–69, 2021.

[16] F. Firmansyah, W. B. Zulfikar, D. S. Maylawati, N. D. Arianti, L. Muliawaty, M. A. Septiadi, and M. A. Ramdhani, "comparing sentiment analysis of indonesian presidential election 2019 with support vector machine and k-nearest neighbor algorithm," in *2020 6th International Conference on Computing Engineering and Design (ICCED)*. IEEE, 2020, pp. 1–6.

[17] A. Sonowal, A. Idupulapati, D. Booravilli, P. Parimi, and R. R. Rout, "An improved model for dynamic opinion updates in online social networks," in *2020 IEEE 4th Conference on Information & Communication Technology (CICT)*. IEEE, 2020, pp. 1–6.

[18] E. Tankard, C. Flowers, J. Li, and D. B. Rawat, "Toward bias analysis using tweets and natural language processing," in *2021 IEEE 18th Annual Consumer Communications & Networking Conference (CCNC)*. IEEE, 2021, pp. 1–3.

[19] P. Miłkowski, M. Gruza, K. Kanclerz, P. Kazienko, D. Grimling, and J. Kocoń, "Personal bias in prediction of emotions elicited by textual opinions," in *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing: Student Research Workshop*, 2021, pp. 248–259.

[20] E. Tankard, C. Flowers, J. Li, and D. B. Rawat, "Toward bias analysis using tweets and natural language processing," in *2021 IEEE 18th Annual Consumer Communications & Networking Conference (CCNC)*. IEEE, 2021, pp. 1–3.

[21] P. Parimi and R. R. Rout, "Flacorm: fuzzy logic and ant colony optimization for rumor mitigation through stance prediction in online social networks," *Social Network Analysis and Mining*, vol. 13, no. 1, p. 22, 2023.

[22] K. Lee, B. Eoff, and J. Caverlee, "Seven months with the devils: A long-term study of content polluters on twitter," in *Proceedings of the international AAAI conference on web and social media*, vol. 5, no. 1, 2011, pp. 185–192.