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A Sentiment Analysis Approach Based on User Ranking using Type-2 Fuzzy Logic Suitable for Online Social Networks

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Key words: Sentiment Analysis (SA), Social Network Analysis (SNA), influential users, Twitter, Fuzzy Logic (FL), Artificial Neural Networks (ANN)

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Abstract: The increasable usage of social media in expressing opinions has raised the importance of Social Network Analysis (SNA). Business owners utilize SNA to detect influence users who can motivate others to buy their products through growing positive feedback. This emphasizes the need to consider people's perspectives in the process of Sentiment Analysis (SA). Considering perspectivism while computing text polarity can help the machine to reflect the human perceived sentiment within text content. Moreover, text vagueness still distresses the accuracy of SA. In this study, a fuzzy-based SA approach for Twitter is proposed that handles perspectivism through integrating SNA with the sentiment process. SA is done using Text Blob and Fuzzy logic while SNA is done using UCINET tool and Artificial Neural Networks (ANN) to rank users. This research aims to avoid misleading sentiments, improve sentiment classification accuracy, and deal with social behaviors. After all, a more real sentiment is produced that reflects what readers have perceived. The fuzzy classification technique was adopted to deal with the vagueness of language and for fine-grained classification of Tweets into seven classes instead of the binary classification. A comparative analysis between Type-1 and Type-2 fuzzy logic is conducted to choose the technique with better performance. The proposed model is practiced on data collected from Twitter. Results show significance in the use of Type-2 fuzzy logic in terms of model accuracy with the ability to handle perspectivism.

INTRODUCTION

Online social networks like Facebook and Twitter have changed the way people communicate, interact even do shopping. Studies established that 70% of consumers trust online recommendations and would instead learn about a company from blogs than adverts. Moreover, it was found that the higher ratio of people on social networks used to read blogs than write[1, 2]. This fact shows how people influence each other on such social networks. On that point, business owners, along with researchers, turned to SNA to focus on studying users behavior. They try to find influence users to help them in promoting their products through a positive influence on their audiences[3].

Although, business owners are now aware of how people may influence each other thus texts are comprehended in different ways depending on user's influence level, they still depend on the traditional SA approaches to investigate their customer's opinions. Ignoring behavioral analysis of social media users affects SA accuracy[4]. Researchers, instead, tried to enhance the accuracy of sentiment classification through the implementation of different techniques[5, 6]. As a result, SA methods applied today are digging a gap between refining the analysis outcomes and reflecting the perspectives of readers[7]. This gap misleads decision-makers by inaccurate results due to the ignorance of perspectivism.

Text vagueness also is still considered as a problem facing the accurate classification of sentiment[8]. Most adopted techniques as shown within the last researches, restrained binary classification that is into positive or negative instead of inclusive analysis so-called fine-grained classification. The unclearness of language necessitated such inclusive analysis. Applying Fuzzy Logic (FL) technique, along with natural language processing, can fulfill this necessity. FL is not very famous in the management of vagueness generated from texts even though FL techniques can improve the process with their weight-ages and strengths which can end in a more accurate analysis[9, 10].

Type1-FL (T1-FL) is the most adopted FL in literature. However, the uncertainty associated with systems required Type2-FL which was proved to handle high levels of uncertainty and thus offers better performance model. Type2-FL (T2-FL) main feature is its ability to take into consideration the uncertainties and ambiguities of text through its membership functions with its bounded region so-called Footprint of Uncertainty (FOU). Using FOU, it is possible to capture uncertainty, minimizing consecutively its adverse effects on the control system[11].

This study is an extension to the work done in the previously published paper in IET Journal entitled "A Modified Fuzzy Sentiment Analysis Approach Based on User Ranking Suitable for Online Social Networks". In this study, T2-FL is adopted to investigate its performance on the proposed model. Moreover, results are then compared to that outputted for the use of T1-FL in the other paper.

MATERIALS AND METHODS

Literature review: Techniques of SA as shown in Fig. 1 are roughly classified as Machine Learning (ML) approach (supervised and unsupervised), Lexicon-based approach (e.g., WordNet and TextBlob) and hybrid approach (a combination between both mentioned categories)[12]. The hybrid approach has proved its effectiveness in overcoming the weaknesses of the main approaches (Lexicon and ML)[13]. In this research, the hybrid approach is embraced; demonstrating competence to enrich the efficiency of sentiment classification.

In recent researches regarding the implementation of a hybrid approach including FL, Asghar *et al*.[14] tried to analyze student's feedback and satisfaction through the adoption of T1-FL Model. An aggregated sentiment score was given to each review through the use of SentiWordNet lexicon then scores were inputted to the fuzzy module to quantify student's feedback and satisfaction. A dataset of 1415 review was used and collected from different feedback sites. The suggested model provided an accuracy of 94% which was a better performance than some state-of-art classifiers. However, the limited size of the collected dataset could severely affect the performance. Furthermore, this model failed to classify reviews when including emoticons and slang terms correctly.

Ghani *et al*.[15] also utilized an aggregated sentiment score of a set of customer's reviews collected from Amazon.com through implementing SentiWordNet and then used a T1-FL model to measure customer's loyalty to a product. The suggested model provided an accuracy of 94% that outperformed some previous works been compared to. One drawback of this model is the dependency on the small dataset size which affects the ability of model extension.

Hasan *et al*.[4] tried to analyze sentiments within political Tweets using lexicons in addition to a supervised ML algorithm rather than FL. Their work concentrated on choosing the best lexicon to be integrated with a ML algorithm, through conducting a comparison between sentiment lexicons (W-WSD, SentiWordNet and TextBlob). A calculation of sentiments from the mentioned three analyzers, was done and the outcome was examined by two supervised ML classifiers (Naive Bayes and SVM). It was found that, although the results of TextBlob alone exceeded the other lexicons, W-WSD method proved to be superior when being integrated with the ML algorithm.

Since, it was assured that hybrid methods for sentiment classification are improving accuracy, Nagarajan *et al*.[5] tried to improve accuracy. Moreover, overcome challenges affiliated with twitter data (e.g., its unstructured nature, misspells, slangs, so on). They

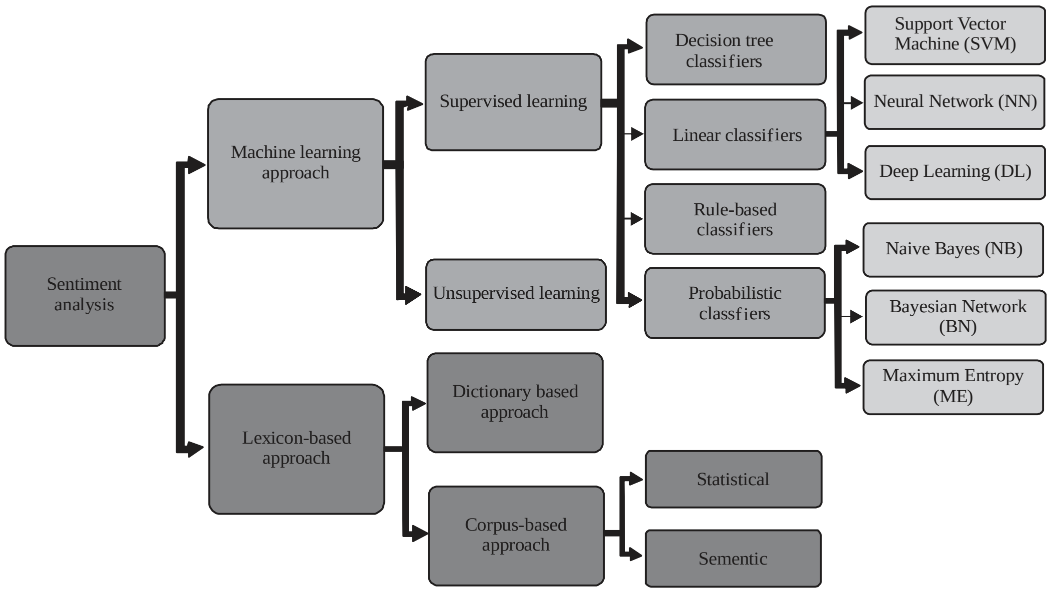

Fig. 1: Sentimental classification techniques

utilized two optimization algorithms, namely, particle swarm optimization and genetic algorithm and one ML classifier which was the decision tree in their case. The good thing is the suggested method verified to be much better in analysis when being compared to other classifiers been adopted in previous works.

Priyanka *et al*.[9] addressed the challenge of the rare implementation of FL in SA to prove the effectiveness of FL in classifying sentiments. They suggested a T1-FL model that classified online reviews into seven classes (i.e., weak positive, moderate positive, strong positive, weak negative, moderate negative and strong negative) through combining T1-FL with SentiWordNet lexicon to reach a close imitation of human behavior. An accuracy of 72-75% was the outcome of experimentation on three reviews databases with reviews of electronic devices. The superiority of this technique is evident in the fact of the absence of labeled data which is costly, time-consuming, and requires a lot of previous human work. More recent T1-FL works can be found in[16-18].

In the adoption of T2-FL for SA, it was found that T2-FL was rarely adopted in the field of SA. It was recently used by Bi *et al*.[19] to represent the results of SA. The upper membership function represented SA accuracy rate of 100% while the lower membership function was represented by the uncertain accuracy rate (the limited accuracy). Based on the constructed T2-FL sentiment numbers, a product ranking method is designed through mapping each product interval T2-FL sentiment results to the closest to either the ideal or the anti-ideal designed interval T2-FL numbers for the products (Fig. 1).

Cakmak *et al*.[20] tried to prove how feasible is the representation of Turkish emotions using FL through analyzing Turkish emotions using interval T2-FL. They conducted a survey asking people to give an interval valence, activation and dominance attributes for each emotion. A correlation detection to prove the effectiveness of the utilized T2-FL was missed. This research aimed to decrease the differences gap between human and computer in representing specific emotion.

In different circumstances, many research works have been done based on influential users and behavioral analysis. In 2010, Cha *et al*.[21] discussed the fact that some measures like in-degree alone do not show much concerning the influence of a user. They showed a detailed evaluation of three measures to represent influence intensity, namely in-degree (number of people who follow a user), reTweets and mentions (twitter's features). Their research was significant for viral marketing. In 2011, Bigonha *et al*.[22] tried to deal with the challenge of handling big data. They offered a new technique that depended on listing Twitter's most influential users to refine the data before analyzing. They listed users according to three factors: the user's place in networks-developed from Twitter connections (Network), the polarity of her opinions (Polarity) and the textual quality of her Tweets (Quality).

In 2014, Anjaria *et al*.[6] highlighted the significance of the retweeting action on Twitter based on the fact that 47% of the users prefer retweet rather than publishing a tweet. Thus, they considered retweeting original tweet without any modifications as another tweet with the same sentiment of the original one. While retweeting with modifications was considered as a new Tweet with a different sentiment.

In 2016, Neves-Silva *et al*.[23] tried to summarize sentiment into one opinion, so-called global sentiment. The global sentiment of a target indicated a weighted polarity. It included values for strength (opinions quantity throughout the sampled timeframe), intensity (posts quantity per user regarding the target), reach (representing the number of unique authors and respective followers or commenters), stability (increase or decrease of strength during the timeframe) and conflict (variance in the polarity of opinions). In 2017, Jianqiang *et al*.[3] determined influential users utilizing communications, information transition and relationships amid users in the micro-blog. They took into consideration the influence of user's Tweets by counting reTweets and replies and the influence of users in the network by calculating influence score through follower graph representation. Their method has surpassed other existing methods in accuracy, recall and F1-measure value as proved by experiments.

For analyzing social network data and getting different topology measures out of social network graphs, Hu *et al*.[24] recommended the usage of a software package known as the UCINET tool (the University of California at Irvine Network). The significance of UCINET in processing social network data was discussed by Yang *et al*.[25]. They explained that the complicated properties of social networking served as a grave barrier that prevented the development of SNA methods. Thus, an advanced mathematical theory was critical. UCINET helps in building social network models and designing social network diagrams based on information transition between individuals and the fullness information of individuals in the social network. This analysis tool provides a trusted guarantee for social networking data extraction and model.

According to Altaş *et al*.[26], ANN has newly been often used in engineering and social science as well. ANN is commonly used in case there is non-linear multi-dimensional, noisy, complicated, indefinite and missing data. Specifically, when the mathematical model and method for a problem's solution are missing. Studies made on ANN show that the network behavior is unexplainable. It is commonly approved that ANN provides a solution for a problem without providing any explanation of how or why this solution was given, something that is called "black box". This reduces the reliance on the result of the network. That is why ANN is recent and frequently used in social sciences.

Adding to recent works on SA, influential user's detection and the IET paper, this research introduces an advanced SA approach to express not only tweet's text sentiment polarity but also the real perceived sentiment in content. It integrates TextBlob and T2-FL sentiment classification technique for SA with UCINET Tool and ANN for SNA and users ranking and weighting, respectively for behavioral analysis of online social users. Moreover, the performance of using T2-FL is compared to that of the previously used T1-FL to investigate the best technique for our proposed model.

Problem definition: Within today's text processing technology, it is feasible to automatically create knowledge bases from relatively unconstrained texts such as Tweets. Ignoring perspectivism in analyzing such texts, however, results in knowledge bases that are not only very incomplete but also dramatically different form knowledge bases created by humans, based on the same texts. To achieve this, SNA could be integrated with SA to represent as close sentiment as possible to what is perceived by people on social media networks. The problems that this research is trying to solve are summarized as follows:

- Scarcity considering user's behavior and influence while computing text's polarity
- Desire to effectively calculate user's influence. (What are the influential factors to be considered?),
- Desire to integrate SNA with sentiment analysis towards polarity that represents more realistic sentiments to what others perceived
- Besides the continuous desire to enhance the accuracy of text classification results and a better handle of the high level of text vagueness and uncertainty

Proposed model: The proposed model substantially targets all previously declared problems. It integrates SNA with SA in Twitter to express not only tweet's text sentiment polarity but also the real perceived sentiment associated with the text. The contribution of the proposed model is as follows. The proposed model considers the user's influence while computing sentiment polarity scores (Fig. 2).

A hybridization technique is adopted for sentiment classification; hybrid sentiment classification methods proved its ability to improve accuracy. This is done by combining the scores from the popularly used sentiment-based lexicon TextBlob to imitate close to human behavior with fuzzy classification technique which can handle the vagueness of language. A combination between topological measures, named user's network influence (Centrality, Betweenness, and Closeness) and tweet's influence (Retweet "RT" and Replies) are adopted for SNA to obtain more accurate influential scores. Reason for that is it was found that topological measures alone fail to conclude the influence of users accurately. Moreover, these influential factors (tweet's and user's network influence) are inputted to ANN to acquire user's ranks and their corresponding weights. ANN was chosen for this mission in consequence of the complicatedness of network behavior and the fact that it is unexplainable.

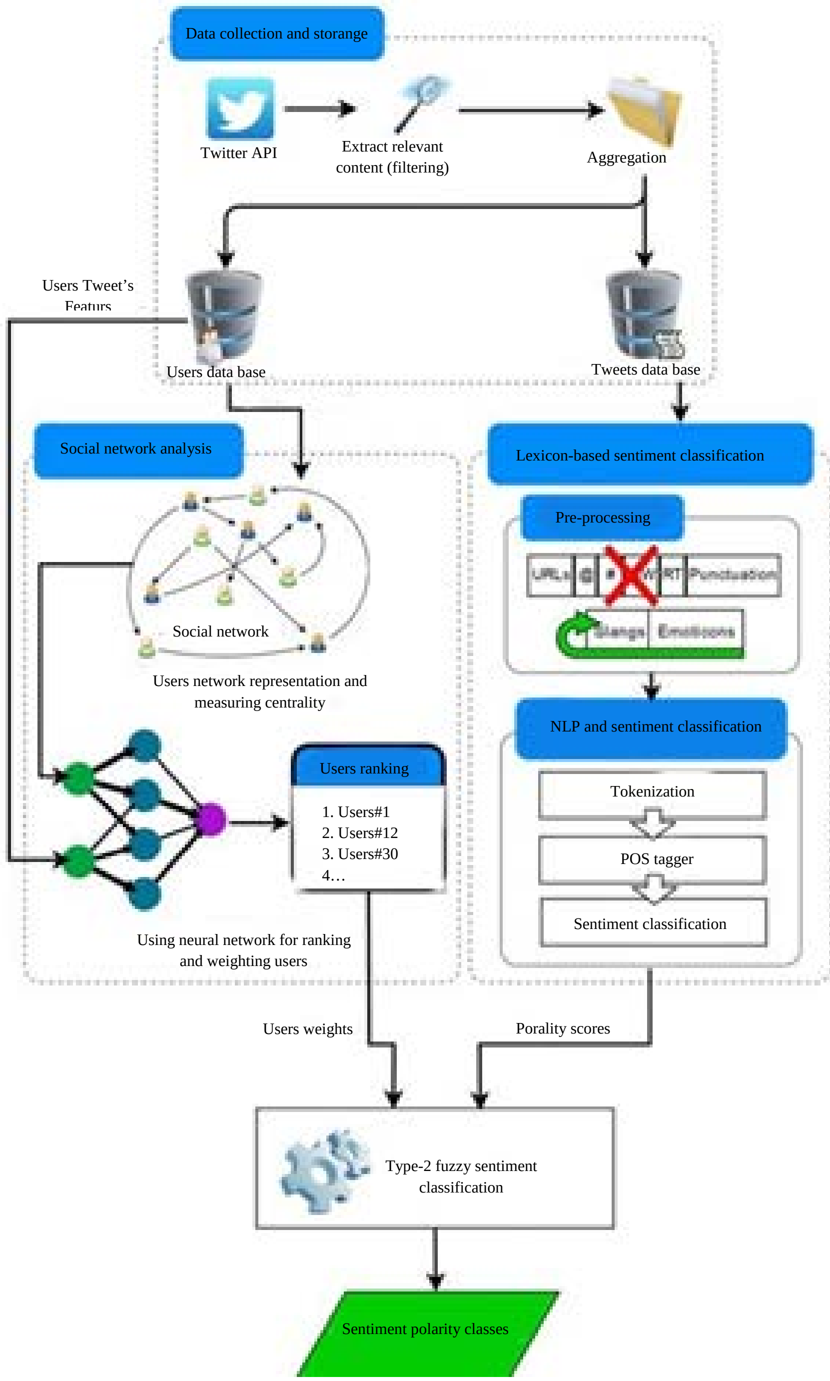

Fig. 2: The proposed fuzzy-based SA Model

ANN is wide utilized in similar situations by virtue of its "black box" feature because it is not seemingly to know the explanation for the made solutions. For integrating results from ANN (user's weights) with the text polarity score achieved from TextBlob, the fuzzy technique is adopted to deliver an inclusive classification of Tweets into seven classes (e.g., weak positive, positive, strong positive, so on). FL is performed using both of its types (T1-FL and T2-FL) and the better performance technique is chosen for our proposed model. Figure 2 presents the proposed model and its components. The phases in the proposed model are described as the following:

Data collection and storage: There is no established benchmark data for evaluating user in uence detection on Twitter. Therefore, a significant effort of this work is to build the data sets. This process is vital for experimental validation. The process of data gathering was parallel to the world's cup kick-off. World Cup 2018 has been chosen as a topic of concern to cope with the current situation besides inspecting the sentiment related to the innovative applied technology in matches (Video Assistant Referee “VAR”). For collecting the data concerning the chosen topic, Twitter API is used (twurl tool of twitter API in the form of 100 requests per time). Tweets were collected by querying the API for those Tweets holding the hashtags, e.g., #WorldCup, #World Cup, 2018, #VAR (Filtering). Tweets for different users are collected and manually aggregated daily during the period of holding the World’s Cup in Russia from 14th June, 2018 till 15th July, 2018 (Aggregation). Finally, Data is stored in a database that encompasses two portions. Portion 1 has Tweets (Tweets Database). Portion 2 has the user’s features such as followers and following lists and the features of the user’s Tweet, like retweet and reply counts (Users Database).

Lexicon-based sentiment classification: This phase gives a polarity score for each of the stored Tweets using the lexicon-based classification technique which is chosen to be TextBlob. Through this phase, two main processes are performed before applying TextBlob for sentiment classification, Preprocessing and Natural Language Processing (NLP).

TextBlob is a Python (2 and 3) library for processing textual data. It provides a simple API for diving into standard Natural Language Processing (NLP) tasks such as tokenization, part-of-speech tagging, noun phrase extraction, spelling correction, sentiment analysis, classification, translation and more[27]. TextBlob was chosen as its results verified to be comparatively higher than alternative lexicons (e.g., Senti Word Net)[4]. In consonance with this, NLP tasks additionally lexicon-based sentiment analysis are done using TextBlob.

Preprocessing: This process permits refining the accuracy of text classification. In this phase, the input is tweet’s text stored in Portion1 and output is processed and normalized Tweets where URLs, #hashtags, RT, @ handles, stop words, numbers, so on are removed while slangs, emoticons are replaced. Figure 3 shows the utilized steps of the preprocessing process. An illustration example is presented below, explaining an input tweet and its output after preprocessing is executed[27, 28]. Example:RT @wsv Dry, warm and sunny for most today.#weather Report http://bit.ly/2vcZa8w. The normalized tweet: Dry warm sunny today.

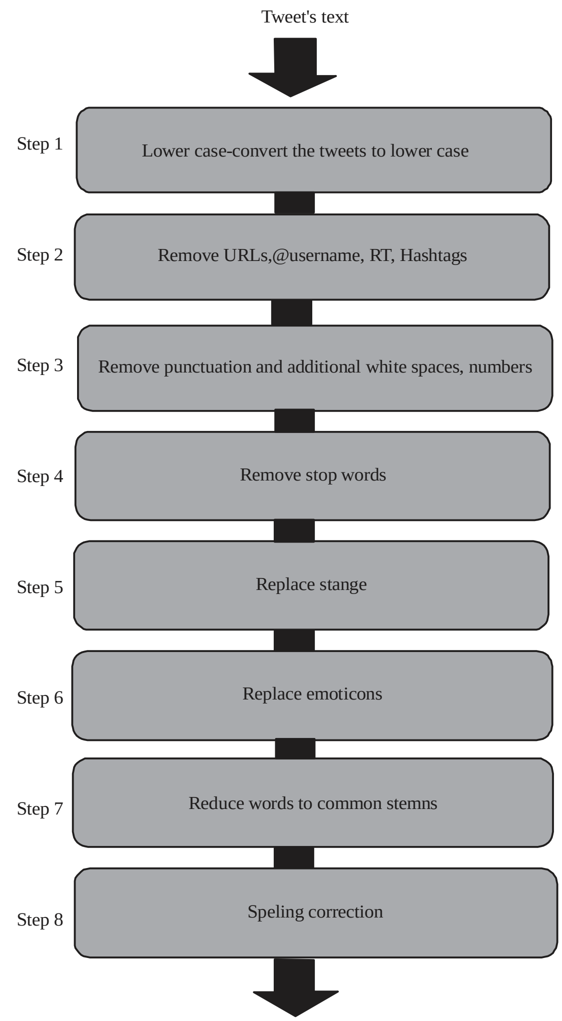

Fig. 3: Steps of pre-processing stage; process and normalization Tweets

Natural Language Processing (NLP): For NLP, two main tasks are executed as follows[9, 10, 16]. Tokenization, where the lexical analysis uses it to break the whole text into words, phrases, so on, referred to as tokens.

Part-of-Speech (POS) which allocates parts of speech to every single word (i.e., noun, Verb (VB), adjective (RB), adverbs (JJ), so on).

After performing pre-processing then NLP on Tweets, TextBlob performs sentiment classification. The sentiment function of TextBlob implements “Pattern Analyzer”-based on the pattern library-as a default sentiment classifier giving Tweets polarity scores ranged from -1 to 1. Those polarity scores corresponding to every tweet are then inputted into the fuzzy rule-based classifier to get the desired final polarity score.

Social Network Analysis (SNA) and users ranking: This phase is essential for calculating influential user’s factor which will be integrated with the text polarity score obtained from previously mentioned phases. Inputs to this phase are stored in “Users Database” (Portion2). It contains the user’s features such as Followers/ Following List for every tweet’s researchers and the features of the user’s tweet, like retweet and reply count. Three primary operations are to be performed in this phase:

Influence of tweet measurement: The features of the user’s tweet, like retweet and reply count stored in Portion 2 are used. Jianqiang *et al*.[3] explained that the in uence of a tweet is de ned as the aptitude to prompt the reader to change emotion, opinion or behavior after reading the tweet. Favorite is an indication of reader supports the opinion of the tweet. Retweeting shows evidently that a reader supports the tweet’s opinion and is eager to share with his fans and spread out the tweet. Commenting (Replying) indicates that a reader wants to discuss and disseminate further the viewpoint of tweet with his fans. A tweet is favorite, retweeted and commented more, the faster it spreads, the more chances it has to be read.

The in uence of a tweet is calculated by favoriting, retweeting and commenting behavior. sp(u) is the probability that the tweet relocated from user u to the neighbors of user u’s fans. The sp (u) can be de ned as[3]:

$$sp(u) = \sum_{t \in tweets(u)} RT(t) + Rr(t) + Fav(t) \tag{1}$$

Where, the influence of node ’s Tweets is sp (u) t is tweet, Tweets (u) is the set of user u’s original Tweets, RT (t) represents the retweet to read ratio of t which is retweet counts per tweet stored in users database, Rr(t) is the comment to read ratio of t which is replies counts per tweet also stored in users database and Fav (t) is favorite counts per tweet. If read count is zero, then Fav (t), Rr(t) Rr(t) is zero.

Influence of user network measurement: The in uence of user network is defined as the significance of the user’s position in the follower relationship network. A user’s Tweets can go viral according to his situation on the follower relationship network and his fans in uence. Using data kept in Portion2, the follower relationship is extracted to form a directed graph[3]:

$$G = (V, E) \tag{2}$$

Where, V = {u_1, u_2, u_3, ..., u_n} is the set of nodes (users) in the micro-blog networks and E = {e_1, e_2, e_3, ..., e_m} is the set of edges (relationships between users) in the microblog networks. If i is j’s follower, then there is a directed edge $\in$ from u_j to u_i.

Hanneman’s study[29] assured that node centrality could mirror an individual’s aptitude to spread information because such central nodes posse more information diffusion paths. Three indicators are used to calculate the node centrality: Degree Centrality, Betweenness Centrality and Closeness Centrality. In the follower relationship network if a user has a superior degree centrality, a higher read probability would be associated with his Tweets and there would be a higher opportunity for his TTweets to go viral. If a user’s closeness centrality is high, the user’s aptitude to control information diffusion gets stronger and the quicker a user spread information, the easier it becomes for a user to stops information from going viral. The greater a user’s betweenness centrality is the user can spread more quickly the message to the entire network through the fewer users and the faster the user spreads information.
sa (u) is de ned to measure network in uence of user the sa (u) can be defined as[3]:

$$sa(u) = C_d^-(u) + C_b(u) + C_c^-(u) \tag{3}$$

Where:
sa (u) = The influence of node’s u’s information dissemination
C_d^- = Degree centrality (out-degree) of node
u = The number of out-going edges from a node[30]

$$C_d^-(u) = \left|\vec{N}_i\right| \tag{4}$$

N = {j $\in$ V: (I, j)$\in$E} a set of neighbors of node i which i is connected to. C_b (u) is betweenness centrality of node u the number of times a certain node is in the shortest paths between nodes[33]:

$$C_b(u) = \sum_{jk} \sigma_{jk}(i) \tag{5}$$

σ_{jk} (I) is the number of the shortest paths between j and k and contain i $C_c^-(u)$ is closeness centrality (out-degree) of node u-the value that is proportional to the harmonic mean of the length of the shortest paths between the i-th node and the rest of it in a network[30]:

$$C_c^-(u) = \sum j \frac{1}{d_{ij}} \tag{6}$$

For SNA, towards calculating different centrality measures during the time that the properties of social networks are complicated and the need for being modeled in a simple mathematical theory, UCINET is used. It is the leading software package for data analysis of social networks. Using our user’s features stored in Portion2, a social network model is built. The directed

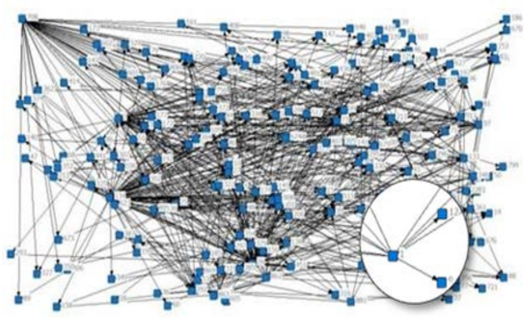

Fig. 4: Part of the communication network of our twitter users using Netdraw in UCINET

communication network of our twitter users is graphed using the NetDraw tool of UCINET for visualizing data (Fig. 4). Based on Eq. 4-6, UCINET calculates out-degree centrality, betweenness centrality and out-degree closeness centrality measures, the three indicators for user's network influence according to Eq. 3. Influence of nodes calculated using Eq. 3 in combination with the influence of node u's Tweets calculated using Eq. 1 are at that time inputted to ANN to get user's ranking value and their corresponding weights for each user in the network.

Authors ranking and weighting: Based on trial and error method, the constructed ANN is feed-forward; Single-layer ANN includes ten elements in the hidden layer. The activation function used is the sigmoid function. In the input layer of the network, we used six variables or 6 neurons in total; 3 variables as "input 1" concerning user's topologies measures (representing user's network influence)-called out-degree centrality, between ness centrality and out-degree closeness measures. Also, three other variables as "input 2" concerning tweet's features (representing tweet's influence)-called RT, Rr and Favorite counts. The output is one neuron representing user's rank value from 1-100. The ranks were inspired by Klout-a website and mobile app that apply social media logical analysis on its users to assess their online social impact. The learning technique for the constructed ANN is supervised learning and it was trained using a dataset of approximately ten thousand samples.

The ANN works with the following simple steps: the six variables of each user and his/her tweet are inputted to the constructed neural network, it then processes to reflect the input values to one value from 1-100. Finally, the produced output is the rank value that mirrors the user's influence degree based on his input variables. Users with a rank value of "1" are users with the lowest network and tweet's features measurements. Consequently, users with a rank value of "100" are with the highest tweet's and network's measurements. After obtaining rank values ranged from 1-100, normalization is processed, so that, users are having weights ranged from 0-1.

Fuzzy based sentiment classification: The output of Neural Network (User's weights) and output of TextBlob (Tweets polarities) are inputted to both T1&T2-FL sentiment classifiers. The reason is to choose the best technique that can accurately explore a new polarity level that may be a more realistic representation of how the researchers followers perceive his/her words. Steps are as follows:

Fuzzification: Crisp inputs are transformed into fuzzy inputs using suitable membership function. Input 1: user's weights crisp with a range of [0 1] and its membership function is chosen to be the trapezoidal function, inspired from[16] with three levels-Low Influence (LI), Moderate Influence (MI) and High Influence (HI).

Input 2: Tweet's polarity scores crisp range is [-1 1] and its membership function is chosen to be the triangular function, inspired from[9] with 7 levels-Strong Positive (SP), Positive (P), Weak Positive (WP), Neutral (N), Weak Negative (WN), Negative (Neg) and Strong Negative (SN).

Rule evaluation: For this work, no fuzzy rules for the same purpose are found as it was the first time to integrate human behavior with the process of SA. Thus, we designed our rules using human logic experience. The antecedent variables of the rules of our fuzzy inference system are user influence level- LI, MI or HI and tweet's polarity leve SP, P, WP, N, WN, NEG or SN. The minimum operator "AND" is used between our antecedent variables. Table 1 shows the designed rules for obtaining real-felt polarities for the collected Tweets. For example, when a celebrity (HI) tweeted a text that was assigned a NEG sentiment polarity; it is expected to be perceived as a SN text.

Defuzzification: In this stage, the most commonly used defuzzification technique, the Centre of Gravity (CoG) is used. The accumulated fuzzy rules outputs are converted to a single crisp value which represents the final polarity of a tweet. CoG is defined as:

$$z^* = \int \frac{\mu_c(z).zdz}{\mu_c(z)dz} \tag{7}$$

where, z* is the defuzzified value and μ_c (z) is the accumulated output of the list of output functions returned by the application of the implication process of each rule.

Sentiment polarity classes: The proposed algorithm considered seven polarity levels (strong positive, positive, weak positive, neutral, strong negative, Negative and weak negative) where each values range of score is

Table 1: The designed fuzzy rules

No. of rules	Rules
1, 2	IF Input1 is 'LI' and Input2 is 'SN/SP', THEN Final tweet's polarity is 'NEG/P'
3, 4	IF Input1 is 'LI' and Input2 is 'NEG/P', THEN Final tweet's polarity is 'WN/WP'
5, 6	IF Input1 is 'LI' and Input2 is 'WN/WP', THEN Final tweet's polarity is 'N'
7, 8, 9	IF Input1 is 'LI/MI/HI' and Input2 is 'N', THEN Final Tweets polarity is 'N'
10, 11	IF Input1 is 'MI' and Input2 is 'SN/SP', THEN Final Tweets polarity is 'SN/SP'
12, 13	IF Input1 is 'MI' and Input2 is 'NEG/P', THEN Final Tweets polarity is 'NEG/P'
14, 15	IF Input1 is 'MI' and Input2 is 'WN/WP', THEN Final Tweets polarity is 'WN/WP'
16, 17	IF Input1 is 'HI' and Input2 is 'SN/SP', THEN Final Tweets polarity is 'SN/SP'
18, 19	IF Input1 is 'HI' and Input2 is 'NEG/P', THEN Final Tweets polarity is 'SN/SP'
20, 21	IF Input1 is 'HI' and Input2 is 'WN/WP', THEN Final Tweets polarity is 'NEG/P'

Table 2: Seven polarity levels[28]

Scores	Polarity
>0.75	Strong positive
0.25<≤0.75	Positive
0<≤0.25	Weak positive
0	Neutral
−0.25≤< 0	Weak negative
−0.75≤< −0.25	Negative
< − 0.75	Strong negative

matched to a specific sentiment. For instance, the range [−0.25:0] is the weak negative level. Table 2 for the whole seven polarity levels documented in[27]. Where η represents the polarity scores of text.

RESULTS AND DISCUSSION

A desktop program is implemented using Python 3, integrated with MATLAB libraries to evaluate the performance of the proposed system. The used dataset consists of Tweets with their features and researchers information collected from twitter as there was no benchmark dataset available.

The first set of experiments was running to evaluate the significance of the designed fuzzy rules for both T1&T2-FL. Each rule is tested individually for each fuzzy type. For example, for rule #1: Are all the strong negative Tweets whose writers are low influencers are outputted as negative Tweets? How many outputs do not obey this rule?. Results as shown in Table 3, show that T2-FL has a higher number of significant rules with a percentage of 80.95% compared to 71% for T1-FL rules. Table 4 shows examples of the difference in some rule's significance between the T1-FL and T2-FL classifiers. Changing the membership functions of the inputs can help in eliminating the error percentage existed in some rules.

In the second experiment, the accuracy (correct instances) of the proposed lexicon-based sentiment classifier (TextBlob) and the system suggested in[4] were compared. The suggested system classifier used in[4] was a hybrid system of TextBlob with the Naïve Bayes classifier. Results under the same condition of 400 Tweets as test data showed that the proposed classifier has the highest accuracy for analyzing tweet's sentiment. It gave 340 correct instances as shown in Table 5 and an average accuracy of 85%. From the illustrated results, our system

Table 3: Results from FL comparative study

FL types	Total significance of rules (%)
T1-FL classifier	71.00
T2-FL classifier	80.95

Table 4: Changes in some rules significance between FL types

Rule	T1-FL classifier (%)	T2-FL classifier (%)
Rule #2	Significance (76)	Significance (92)
Rule #6	Significance (46.34)	Significance (76.83)
Rule #14	Significance (30)	Significance (83.33)

Table 5: Results from the comparative study

Sentiment classifier	Average accuracy (%)	Correct instances
TextBlob classifier	85.00	340/400
Hybrid classifier[4]	76.00	304/400

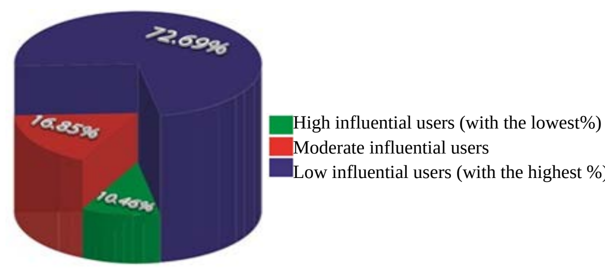

Fig. 5: Low influence, moderate influencers and high influencer's percentage existence in collected data

outperforms the other one by an average of 9%. One reason is the applied preprocessing steps. It assured the significance of text preprocessing in refining the accuracy of sentiment classification, especially when dealing with informal texts such as Tweets.

Almost all recent and previous works on sentiment analysis consider users as moderate influencers; their text's polarity calculated by sentiment analyzers is the estimated polarity for the text. The second experiment was conducted to verify that users are not only moderate influencers but also can be low and high influencers. Results from implementing user's behavior factor and ranking users using the constructed ANN are significant and support our objective. Figure 5 shows the percentages of each influence level of users exist in our collected data. Our results show that not all users are moderate influencers. Moreover, they might be low influencers with a higher percentage. These differences in user's influence are carefully handled using the designed fuzzy rules

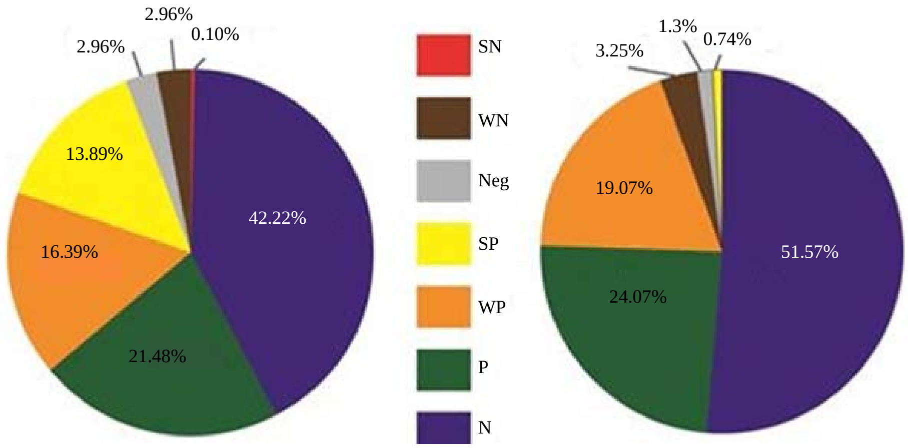

Fig. 6: Statistical representation of the sentiment polarity scores before and after implementing our model

Table 6: Sample of sentiment polarity scores before and after implementing our proposed model

Author's ID	User's influence level	Sentiment score	Author's ID
User #1	Low	0.8 (SP)	0.48 (P)
User #30	Low	-0.4 (Neg)	-0.09 (WN)
User #227	Moderate	0.5 (P)	0.50 (P)
User #401	Moderate	-0.55 (Neg)	-0.53 (Neg)
User #105	High	0.25 (WP)	0.39 (P)
User #924	High	-0.1875 (WN)	-0.27 (Neg)

Table 7: Sample of different polarity scores associated with a tweet with a polarity score of 0.8 after implementing our model

Author ID	User's rank (Obtained from ANN)	User's weight (Normalized Ranks)	Influence level	Tweet's sentiment (Obtained from textblob)	Tweet's sentiment (Using our model)
User #2	11	0.10	Low	0.8 (SP)	0.48 (P)
User #36	47	0.46	Moderate	0.3 (P)	0.26 (P)
User #284	92	0.92	High	0.8 (SP)	0.86 (SP)

within the proposed model. In general, not all users have the same impact on others. Thus, business owners and decision-makers should pay more attention to the existence of both low influential and high influential users with effective percentages that are enough to flip sentiments with some degree and causes misleading if not been taken into consideration.

The next experiment was conducted to view the difference between tweet's sentiment polarity before and after considering their researchers influential behavior on twitter. This experiment showed how incomplete and different was the sentiment associated with Tweets when applying any sentiment analysis technique (TextBlob in our case) without considering how people perceive words. Figure 6 shows a statistical summary of sentiment polarity associated with Tweets of our database in the form of pie charts. Also, Table 6 shows a sample of sentiment polarity scores before and after implementing our proposed T2-FL SA Model. This difference in polarities is consequent because of considering how others can influence people, thus perceived their words in a different way than a machine could.

The last experiment was to show how exactly user's influential degree can change the sentiment polarity of a specific text. This experiment is conducted on similar Tweets that are published by different users-like when different users retweet the same tweet written by some other user. Table 7 shows polarity scores associated with a tweet that has a sentiment polarity score of 0.8 when implementing TextBlob alone. Results show that users do have a different impact on readers causes the same text being perceived in as many different ways as their users differ.

CONCLUSION

Although, SA has many advantages for business owners and decision-makers, it also has some issues that need to be considered. Most importantly, text vagueness and the lack of considering user's influence on their audience while computing text's polarity. In this study, we proposed a new approach that tried for the first time to integrate user influence measurements with polarity scores of texts to achieve text polarities that mirrors how likely texts are perceived. It uses UCINET tool combined with ANN to rank users according to their influence level. Then, it integrates user's influence level with polarity score of user's tweet-obtained from TextBlob lexicon using FL to generate a new polarity score. This new score is from seven polarity classes to avoid text vagueness. The primary outcomes of this research work are (a) the ability to detect different levels of users' influence (b) the ability to deal with the complexity associated with social behaviors and effectively rank users using ANN (c) the ability to deal with the uncertainty and fuzziness of language using T2-FL classifier with a fine-grained sentiment classification into seven classes (d) the ability to integrate user's behavior through SNA with the process of SA for the sake of making SA process reflects the real perceived sentiment in the text's content. Consequently, this model can be considered a step forward to get sentiment scores that squarely reflect reality. The proposed model can be applied for social media monitoring, virtual and non-virtual market analysis as well as the political field.

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