AUGMENTED PERSPECTIVE MINING METHODOLOGY FOR CONTROLLED SOCIAL MEDIA

K. Shantha Kumari, R. Kameswaran, S. Pravin Poul, P. Poovanna Pemmaiah

Computer Science and Engineering, Rajiv Gandhi College of Engineering and Technology Puducherry, India.
shanthajayakumar@gmail.com

K. Mahalakshmi, R. Keerthika

Information Technology, Karpagam College of Engineering Coimbatore,India mahalakshmi.k@kce.ac.in

ABSTRACT

Social media is a rich source of information which are open to anyone and can be utilized for a wide variety of application. But every information shared on this platform reflects the user's perspective. However, the truthfulness of that information on anything (event, accident, personality, product, etc.) must be verified to avoid any unwanted consequences such as rumor propaganda, character assassination, product quality evaluation etc. On specific to Twitter, users masquerading as popular personalities, post certain false information. There is a need to control such behaviour across various social media. Existing research works followed Sentiment Analysis, Opinion Mining, Intelligent technologies etc. to mine the truth from every bit of BIG DATA available at social media. This process has the probability that even false data posted by masqueraded users could be classified as truth. This requires verification from the originator [Source of information about event/personality/product etc.] of the post in an automated manner. In our work, we are proposing an augmented perspective mining algorithm that takes live streamed data from twitter and verifies its trustworthiness in an automated voting process based on Straw-poll technique. This technique uses the information from Twitter's officially verified users as training set to compare and filter the information from masqueraded users and thus improvising the performance of mining.

Index Terms—Social Media, Rumour, Big Data Analysis, Straw-Poll Voting

I. INTRODUCTION

Social media are the forms of electronic communication (such as Web sites) through which people create online communities to share information, ideas, personal messages, etc. Twitter [1] is a free social messaging service for sending and receiving short messages in real time. It's often called a social network or a microblogging service, but it's really just an instant messaging service on steroids [2]. At its core, Twitter is about sending and receiving group messages. The messages are limited to 140 characters and they are called tweets. The tweets posted by the twitter users may be mostly based on a particular event, product or any other subject. Each tweet is based on the user's perception about a particular subject. Hence every tweet has its own power over its subject. Since the user have posted a tweet it does not mean that it's completely true. Unwanted, non-verified or rumours may be spread about a particular subject. These kinds of tweets may be unhealthy to the public and may lead to chaos if strongly recognized by the public. A lot of unwanted information were spread during emergency situations and have created unnecessary issue.

Hence, the prevention of these kind of tweets stand as a key factor mostly during the time of emergency. Twitter verifies credible users who are highly recognized by the public and mentions them as verified users. Information spread by these users can be trusted and this information mostly control the current situation information passage through tweets at any particular instant of time. So, the veracity of any particular tweet can be measured by comparing them with the information passed by the verified users at that particular time period. But comparison is a tedious process for such a Big Data like tweet in a manual approach.

Hence text-classifiers can be used to classify the tweets based on their veracity level. There are already various text classifying algorithms available and each of them has its own disadvantages like text limit, precision of classification and type of classifying. We in our work have built an algorithm which processes the text using various classifiers and conducts a voting process to identify the real classification of the text.

Our classification algorithm not only classifies the text based on classifiers but also uses a dictionary approach to classify the text in case the classifiers gives a low level of accuracy over a particular classification. This classification algorithm is highly efficient for mining the opinion of the public about a particular subject at certain instance of time. Hence after calculating the veracity of each and every tweet about a particular subject the tweets which are highly true can be used to find the real opinion of the public about a particular subject.

This paper is organized as follows: Subsequent section briefs about the related works available. Section 3 described the proposed work and Section 4 details the methodology of the proposed work. The evaluation of the proposed work is discussed in Section 4. Finally, the paper concludes with pointers to further work.

RELATED WORKS

There are a large number of related studies on detection of veracity level specifically in Twitters. Many methods are mainly based on Intelligence techniques such as supervised learning. Veracity of a tweet can be determined by their content [3,4,5] or by the user who posts the [6,7,8]. The field of veracity prediction on social media is a relatively new one. There have so far been only a handful of works that address this problem. Most relevant are the works of Castillo et al., [7] and Kwon et al., [9]. These works deal with propagation of false tweets and misinformation on

Twitter. Castillo et al. study the propagation of false during real-world emergencies while Kwon et al. study the propagation of urban legends (such as bigfoot) on Twitter. The works of Castillo et al. and Kwon et al., propose a combination of linguistics and propagation features that can be used to approximate credibility of information on Twitter. However, Kwon et al.,'s work does not deal with wrong tweets surrounding real-world events and Castillo et al.'s work only approximates users' subjective perceptions of credibility on Twitter (i.e. whether users believe the tweets they are reading); they do not focus on objective credibility of messages.

Other or the previous works includes the usage of traditional methods like 'Dictionary Approach' or the well- known Classifier based approach, rather the Key technique for determining the veracity of tweets is by doing the Sentiment Analysis.

I. PROPOSED WORK

This work aims to classify the tweets posted by masqueraded users from others based on the principle of Straw-poll voting technique. The Straw-poll voting Technique [10,11,12] is explained as follows:

Originally, small informal opinion survey is carried out. Today, straw poll is generally a large-scale, scientifically determined public opinion survey based on a random sample of the population. Straw polls are commonly used to test public opinion of candidates running for office. The follo wing diagram depicts the straw poll technique.

Figure 1: Straw-Poll technique

The straw poll voting is mainly used in real life to find out the opinion or perspectives of common people for any general issue that affects their life. This referendum would help the government/private sector to know the actual feedback for any incident.

Twitter is a place where anyone can drop anything. As already stated, it is important to identify who says what? Existing mining techniques were able to find the veracity on their own methodology. There is already various text classifying algorithms available and each of them has its own merits such as accuracy level of trustworthiness of tweets and disadvantages like text limit, precision of classification and type of classifying.

The Straw-poll voting mechanism is applied to determine the veracity of the tweets as follows: If more than one classifier could reiterate similar accuracy for a common tweet, then the confidence level to stamp the tweet's veracity is higher. The following diagram depicts the veracity determination using twitter:

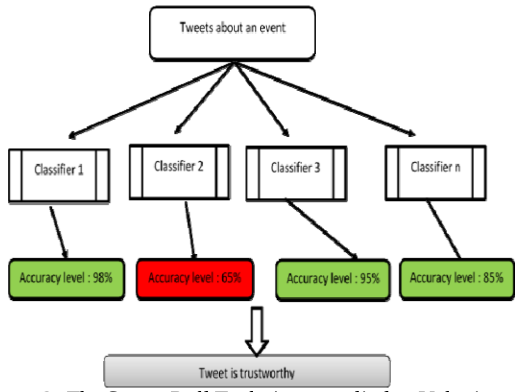

Figure 2: The Straw-Poll Technique applied to Velocity

Applying straw-poll technique definitely increases the collective probability to determine the veracity of the tweets

IV METHODOLOGY

The above explained work is implemented as follows:

a) Streaming Twitter Live Feed:

Twitter Stream APIs are available that open the door for capturing live feed from Twitter. During any sensitive issue, tweets will be flooded, which can be streamed using Public Stream API defined by Twitter Development Documentation [13] as shown in Figure 3:

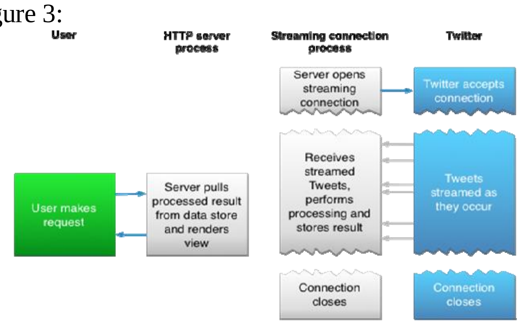

Fig 3. Public Streaming API working

b) Live Feed Storage using MongoDB [14] and Creation of Dictionary

The local database used is "MongoDB". MongoDB is an open source database that uses a docum-ent-oriented data model. MongoDB is built on an architecture of collections and documents. The tweets are stored as JavaScript Object Notation (JSON) [15] format in this Database.

JSON (JavaScript Object Notation) is a lightweight data- interchange format. It is easy for humans to read and write. It is easy for machines to parse and generate. The following diagram depicts the same:

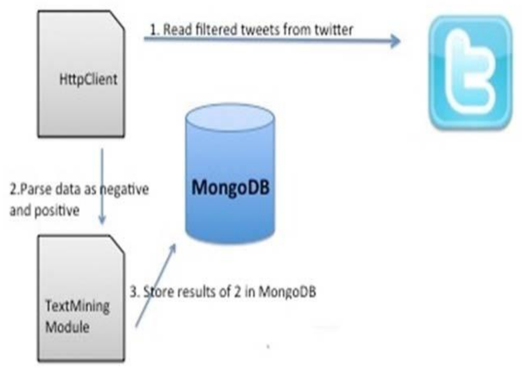

Figure 4: MongoDB-Twitter

The JSON type tweets are categorized as offline tweets which are used to classify the rest coming online tweets. Dictionary of words based on the offline tweets which are populated. The created Dictionary is so important that, it is used to compare the tweets stored in the database. Once the Dictionary is built, the stored JSON is compared and the tweets are classified

1) Classification of Tweets using Straw-Poll Algorithm: "Pycharm" [16] is an integrated development environment for python programming language, which is used to retrieve and compare the tweets with greater ease. Once the tweets are retrieved, they are classified in two-step process which is explained as follows:

a. Original Naïve Bayes Classifier [17]

The Naive Bayes Classifier is based on the bag-of-words model. With the bag-of-words model the words of the text- document are checked to appears in a positive-words-list or a negative-words-list. If the word appears in a positive-words-list the total score of the text is updated with +1 and vice versa. If at the end the total score is positive, the text is classified as positive and if it is negative, the text is classified as negative.

b. Multinomial Naive classifier [MNB classifier] [18]

The Multinomial Naive Bayes (MNB) is a probabilistic generative approach that builds a language model assuming conditional independence among the linguistic features

c. Bernoulli NB classifier [19]

An alternative to the multinomial model is the multivariate Bernoulli model or Bernoulli model, which generates an indicator for each term of the vocabulary, either 1 indicating presence of the term in the document or 0 indicating absence.

d. Logistic Regression classifier [20]

The idea of logistic regression is to make linear regression produce probabilities. It's always best to predict class probabilities instead of predicting classes

e. Linear Support vector classifier (SVC) [20]

The objective of a Linear SVC (Support Vector Classifier) is to fit to the data the user provides, returning a "best fit" hyperplane that divides, or categorizes, the tweet data. From there, after getting the hyperplane, user can then feed some ures to this classifier to see what the "predicted" class is

f. Stochastic Gradient Descent Classifier [21]

Stochastic Gradient Descent (SGD) is a simple yet very efficient approach to discriminative learning of linear classifiers under convex loss functions such as (linear) Support Vector Machines and Logistic Regression.

The straw-poll voting conducts a Referendum as its name suggest. The referendum is that all the classifiers are asked that whether the current candidate (tweet) deserves what sentiment. If the candidate gets high positive vote then the candidate is declared as a positive tweet or else if the candidate gets high negative votes it is declared as a negative tweet.

Each candidate is given as confidence level , if the confidence of the algorithm falls above 80 percentage then the Voters decision is finalized if not the candidate is sent to a re- election where this time a Dictionary classifies the candidate. Since, the dictionary approach classifies faster and with the highest accuracy ever the doubted candidate is now classified perfectly and then sent for data analysis.

2). Comparison with built-in dictionary:

The classification algorithm not only classifies the text based on the classifiers but also uses a dictionary approach to classify the text in case the classifiers gives a low level of accuracy on a selected classification. This increases efficiency of our method. The classified data is also verified from the data present at the verified users of the Twitter

V. EVALUATION

To evaluate the proposed approach tweets are extracted from twitter regarding the recent "Jallikattu" issues. The retweets were removed because those may give duplicate votes to a particular opinion. The filtered tweets are then used for classification. The tweets are classified into four categories:

Table 1: Classification of Tweets

Category	Description	Example
True Positive	The classifier is sure that the tweet is positive.	Jallikattu is good for the bulls.

The true positive and true negative classified tweets can be trusted and can be considered for data analysis. The False Positive and False Negative tweets cannot be trusted hence they are treated with well-built dictionary which classifies the tweet using the dictionary approach as sure positive and sure negative. The following figure shows the results of the 6 classifiers for the live feed regarding "jallikattu":

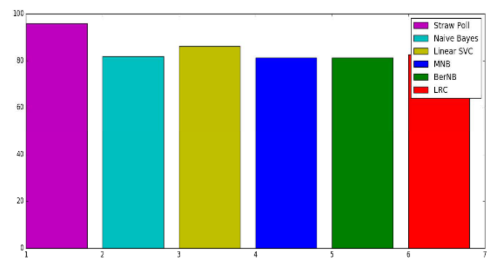

Fig4. Straw Poll Algorithm approach for "JalliKattu"

After classifying the tweets they are sent for visualisation purpose. The sentiment score of the tweets are used for visualizing the final report. The result of the report is used to show the public's opinion about a particular event or object. The visualization of the report can be done.

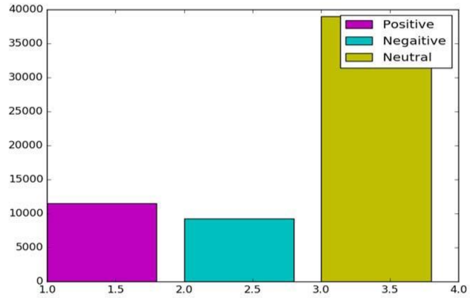

Figure 5: Data Visualization of classified data

The classifier thus designed can be used to classify any type of data. Hence to classify that whether a tweet about a particular news, object or even the tweets which were posted by the verified users of twitter about that particular event or object are used to build the training set for the classifier and then the other tweets posted by the lower level users can be used as the test set and their truthiness can be measured. It is not useful on measuring the truthiness of all the tweet hence the tweets which have reached a higher level of public views are picked and their truthiness are only measured because only those tweets are capable of spreading rumors.

Hence if those tweets are inspected and flagged the spread of unwanted information about a particular event can be prevented and data analysis on that event can be done with fully reliable information only, ultimately giving a higher-level accuracy on data analysis.

VI CONCLUSION

The classifier that has been designed can be used for any type of analysis. Since the algorithm is a combined result of several classifiers it gives a higher level of accuracy than any other approach ever designed. With the usage of this algorithm even though the classifier fails to give the perfect result, the dictionary saves the day with its sharp accuracy ultimately leading to an accuracy higher than any other approach ever designed. This technique is more efficient for keep tracking the opinion of people over a region or all over the world about a particular issue, happening or even a product and also concluding some tweets as a rumour.

REFERENCES

[1] "www.twitter.com," Online.

[2] Java, A., X. Song, T. Finin and B. Tseng, Why we twitter: understanding microblogging usage and communities, *Proceedings of the 9th Web KDD and 1st SNA-KDD 2007 workshop on Web mining and social network analysis* (2007).

[3] Ratkiewicz, J., M. Conover, M. Meiss, B. Goncalves, A. Flammini and F. Menczer, Detecting and Tracking Political abuse in social media, *Proceedings of the Fifth Annual Conference on Weblogs and Social Media (ICWSM 2011)* (2011).

[4] Q. Zhang1, S. Zhang, J. Dong, J. Xiong and X. Cheng, Automatic detection of rumor on social network, *National CCF Conference on Natural Language Processing and Chinese Computing* (2015).

[5] Takahashi, N., Y. Isaka, T. Yamamoto and T. Nakamura, Vocabulary and Grammar Differences Between Deaf and Hearing Students. *The Journal of Deaf Studies and Deaf Educatio* 22(1): 88-104 (2017).

[6] AlKhalifa H. and R. AlEidan, An experimental system for measuring the credibility. *International Journal of Web Information Systems* 7(2): 130-151 (2011).

[7] Castillo, C., M. Mendoza and B. Poblete, Information credibility on twitter, in *Proceedings of the 20th international conference on World wide web (*2011).

[8] Gupta A. and P. Kumaraguru, Credibility ranking of tweets during high impact events, *Proceedings of Workshop on Privacy and Security in Online Social Media Ser Psosm (2012).*

[9] Kwon, S., M. Cha, K. Jung, W. Chen and Y. Wang, Prominent Features of Rumor Propagation in Online Social Media, *EEE 13th International Conference on Data Mining* (2013).

[10] I. E. o. t. S. Sciences, Polling, (2008).

[11] B.P.S. Boundless, Types of Polls, 26 May (2016).

[12] T.E. The American Heritage® New Dictionary of Cultural Literacy, Straw poll, (2005).

[13] Twitter, Public Stream API, [Online]. Available: ttps://dev.twitter.com/streaming/public. [Accessed 2017].

[14] https://www.mongodb.com/,"[Online].

[15] www.json.org, [Online].

[16] https://www.jetbrains.com/pycharm/, [Online].

[17] Sentiment Analysis with the Naive Bayes Classifier, (2016). [Online].Available: http://ataspinar.com/2016/02/15/sentiment-analysis-with-the-naive-bayes-classifier/ [Accessed 2017].

[18] A. Kibriya, E. Frank, P. B. and G. Holmes, Multinomial naive bayes for text categorization revisited, *Australasian Joint Conference on Artificial Intelligence* (2004).

[19] Ismail, H., S. Harous and B. Belkhouche, Ismail, H.M., Harous, S. and Belkhouche, B., *17th International Conference on Intelligent Text Processing and Computational Linguistics-Cicling* (2016).

[20] Go, A., R. Bhayani and L. Huang, Twitter sentiment classification using distant supervision, CS224N Project Report (2009).

[21] Sharma, K. and A. Kaur, Personality prediction of Twitter users with Logistic Regression Classifier learned using Stochastic Gradient Descent. *IOSR Journal of Computer Engineering* 17(4): 39-47 (2015).