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Twitter Fake News Analysis using Classification Techniques

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Abstract*-Sentiment analysis is the computational study of opinions, sentiments, evaluations, attitudes, views and emotions expressed in text. It refers to a classification problem where the main focus is to predict the polarity of words and then classify them into positive or negative sentiment. Sentiment analysis over Twitter offers people a fast and effective way to measure the public's feelings towards their party and politicians. The primary issue in previous sentiment analysis techniques is the determination of the most appropriate classifier for a given classification problem. If one classifier is chosen from the available classifiers, then there is no surety in the best performance on unseen data. So, to reduce the risk of selecting an inappropriate classifier, we are combining the outputs of a set of classifiers. Thus, in this paper, we use an approach that automatically classifies the sentiment of tweets by combining machine learning classifiers with lexicon-based classifier. We physically mark a broad Twitter dataset of 100,000 tweets and perform low quality content discovery continuously dependent on the described noteworthy highlights and word level investigation. The consequences of our exploration demonstrate that our technique has a high precision of 0.9170 and a decent F1 of 0.9460 dependent on an irregular woodland classifier with continuous execution in the discovery of low-quality substance in tweets. Our work in this manner accomplishes a positive effect in improving client involvement in perusing internet-based life content.

***Keywords*-Sentiment Analysis; WordNet; SentiWordNet; Word Sense Disambiguation; Machine Learning Methods; ensemble Approach.**

I.INTRODUCTION

Currently, twitter is becoming one of the most popular micro-blogging platforms. Millions of users can share their thoughts and opinions about different events and people on the micro-blogging platform. Therefore, Twitter is considered as a rich source of information for sentiment analysis. Sentiment analysis can be considered as the use of natural language processing, text analysis and computational linguistics to identify and extract sentiment information in source materials. Generally, sentiment analysis aims to find the attitude of a writer with respect to some relevant topic or the overall contextual polarity of a document.

The main task in sentiment analysis is classifying the polarity of a given text at the document, sentence, or feature level[1] whether the expressed opinion in a document, a sentence or an feature is positive, negative, or neutral.The accuracy of a sentiment analysis is based on how well it agrees with human judgements. This can be measured by using precision and recall [2]. In this paper, we introduce an accurate sentiment classifier by combining machine learning classifiers with lexicon-based classifier for finding political sentiment and sentiment towards new released movies from real time tweets. Section 2 contains detailed study of the method. Section 3 includes implementation details and results. Section 4 is the conclusion.

II. METHODOLOGY

The system mainly deals with the tweets extraction and sentiment classification. Here we use a sentiment classifier by combining machine learning classifiers with lexicon-based classifier. The classifiers using are SentiWordNet classifier, naive bayes classifier and hidden markov model classifier. Our proposed system consists of mainly six modules.
They are

- Data acquisition
- Pre-processing
- Sentiment Classification using SentiWordNet
- Sentiment Classification using Naive Bayes
- Sentiment Classification using HMM
- Sentiment Classification using ensemble Approach.

Tweets extracted in real time manner is serve as input to pre-processing module and then they are further classified as positive, negative or neutral.

1. Data acquisition: To obtain the Twitter feeds in continuous fashion Twitter streaming API tool is used [3].

It allows real time access to publicly available data on Twitter. These tweets serve as input to pre-processing module and then they are further classified as positive, negative or neutral.

2. Pre-processing: It first identifies the presence of URL using a regular expression and removes all the URLs from the extracted tweet. Then it removes all the private usernames identified by @ user. Then it removes all the Hash tags identified by the # symbol and all the special characters. Refined tweets are then classified using classification scheme. Negation handling is one of the factors that contributed significantly to the accuracy of our classifiers. A major problem occurring during the sentiment classification is in the negation handling. Since here we use each word as feature, the word "win" in the phrase "not win" will be contributing to positive sentiment rather than negative sentiment. This will lead to the errors in classification. This type of error is due to the presence of "not" and this is not taken into account.

To solve this problem, we applied a simple algorithm for handling negations using state variables and bootstrapping. We built on the idea of using an alternate representation of negated forms [4]. This algorithm stores the negation state using a state variable. It transforms a word followed by a nt or not into "not" + word form. Whenever the negation state variable is set, the words read are treated as "not" + word. When a punctuation mark is encountered or when there is double negation, the state variable will reset. We have applied negation handling to our three classifiers separately for accurate classification.

3. Sentiment Classification using SentiWordNet: Sentiment classification is done on twitter data using SentiWordNet (SWN) and WordNet. Concept of word sense disambiguation is used for accurate classification [5]. WordNet is lexical database for the English language that groups English word into set of synonyms called synset. SentiWordNet is an extension of WordNet that assigns to each synset of WordNet three sentiment numerical scores, positivity, negativity and objectivity. WordNet lexical relations are not always a good indicator of polarity detection. Synonyms may have different polarity based on the part of speech of the word in that sentence. This can be solved by using sense-tagged word lists. For that here we introduce Sentiment Classifier using Word Sense Disambiguation which is based WordNet. SWN classifier assigns different sentiment weights to different words. It also depends on the how the word is being used in the sentence i.e. identification of "part of speech" for the word is necessary to be classified by SWN classifier.

4. Sentiment Classification using Naive Bayes: The Naive Bayes classifier is the simplest and most commonly used classifier. Naive Bayes classification model computes the posterior probability of a class, based on the distribution of the words in the document. It relies on very simple representation of document as Bag of words. The model works with the bag of words feature extraction which ignores the position of the word in the document. It uses Bayes Theorem to predict the probability that a given feature set belongs to a particular label. For twitter sentiment analysis bigrams from the twitter data are used as features on Naive Bayes. It Classifies tweets into positive and negative labels.

5. Sentiment Classification using HMM: Our sentiment tagging system makes use of the Viterbi forward backward algorithm to traverse the states: where each state represents a possible prediction of the sentiment over the context traversed by the algorithm. In the continuity sentiment tags are predicted as we move forward with the algorithm. The Viterbi algorithm is a search algorithm that avoids the polynomial expansion of a breadth first search by trimming the search tree at each level using the best" m" Maximum Likelihood Estimates (MLE) where" m" represents the number of tags of the following word.

The HMM models make use of two kinds of probabilities to keep account of the state of the sentence sentiment for the current: an emission probability keeps track of the sentiment tag given the word and its frequency of occurrence in the training data. The second probability is known as the transition probability accounts for the current state of the system given the state that the system was in previously. The advantages of this is that if there exists enough evidence to incite belief that the system is no longer analysing a positive, negative or neutral sentence, a necessary transition may be made to a better or more probable state. The decision for this transition is decided taking into context the previous state of the system, the current probability and the probability given the next word to be introduced will cause a transition. The Markov assumption takes into consideration the states preceding and succeeding the current states.

6. Sentiment Classification using Ensemble Approach: we introduce an approach that automatically classifies the sentiment of tweets by combining machine learning classifiers with lexicon-based classifier [6]. Thus, we are taking advantages of these three classifiers (SentiWordNet classifier, naive bayes classifier and hidden markov model classifier) for accurate classification of political data. Here positivity or negativity of each tweet is determined by using the majority voting principle on the result of these three classifiers. SentiWordNet classifier uses opinion lexical resource SentiWordNet and WordNet along with Word Sense Disambiguation for accurate classification of tweets which is extracted in real time manner. Thus, this classifier considers the most suitable sense of word in its context. Other two classifiers are working based on the training data. Thus, we have developed an accurate sentiment classifier for finding political sentiment from real time tweets.

III. IMPLEMENTATION RESULTS AND EVALUATION

Word Level Analysis: To accomplish a superior act through word level investigation, two exceptional components are talked about in this subsection. One is the extent of the catchphrase boycott lexicon. Generally, a bigger lexicon will expand the discovery precision however may fall into the overfitting issue. For each word safeguarded in the low-quality substance corpus, its weight decides if it very well may be included into the lexicon. Its weight is spoken to by its term recurrence in low-quality substance less its term recurrence in typical tweets. We can change the word reference estimate by setting diverse edges for weight. The other controlled factor is whether to perform stemming on the tweet writings amid the pre-processing stage.

In this subsection, we perform low-quality substance location with various word reference measure and assess the execution from the point of view of both time and discovery rate. The F1 measure results are appeared. In any case, when the word reference measure is additionally expanded, the two falls into the snare of over-fitting. No stemming performs superior to stemming when the word reference measure isn't extensive however encounters an early and extreme drop in discovery execution when lexicon estimate increments. Another preferred standpoint of no stemming is that it can spare the time cost which will generally be acquired for the additional stemming step. As indicated by our perceptions, we set the word reference size to 150 and skirt the stemming venture in the accompanying examinations.

1. Proposed before feature selection Research methodology Comparison Result Based on Accuracy

Rumor Identification Evaluation: in table 1 and figure 1 the test aftereffects of MAXENRTOPY calculation. The exactness of talk classifier utilizing the highlights of clients' practices is 0.933403. That the aftereffect of SVM calculation, the precision of gossip classifier built dependent on clients' conduct is 0.5, separately. The trial consequence of RF_Accuracy calculation. Its precision ranges to 0.662821.

Table 1 Proposed before feature selection Research methodologies Comparison Result based on accuracy.

SVM_Accuracy	MAXENT_Accuracy	RF_Accuracy
0.5	0.933403	0.662821

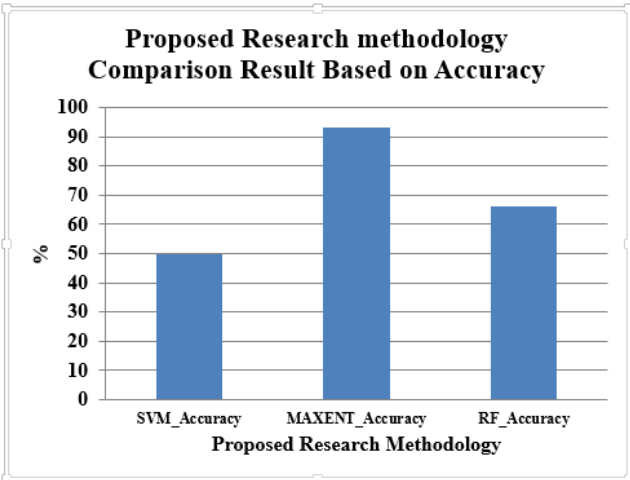

Fig.1 Proposed before feature selection Research methodologies Comparison Result based on accuracy.

2. Proposed after feature selection Research methodology Comparison Result Based on Accuracy

Rumor Identification Evaluation: in table 2, 3 and figure 2 the examination aftereffect of MAXENRTOPY calculation. The precision of talk classifier utilizing the highlights of clients' practices is 0.9373742. That the aftereffect of SVM calculation, the exactness of gossip classifier developed dependent on clients' conduct are 0.9373742, separately. The investigation consequence of RF_Accuracy calculation. Its precision scopes to 0.651818. The trial aftereffect of SVM, MAXENT, RF calculation. Its accuracy, review, and F-score reach to 91.70813, 97.7 and 94.60929.

Table 2 Proposed after feature selection Research methodologies Comparison Result based on Accuracy

SVM_Accuracy	MAXENT_Accuracy	RF_Accuracy
0.9373742	0.9373742	0.6518182

Table 3 Proposed after feature selection Research methodologies Comparison Result based on Precision, Recall, F-score.

Algorithm	Precision	Recall	F-score
Average in %	91.70813	97.7	94.60929

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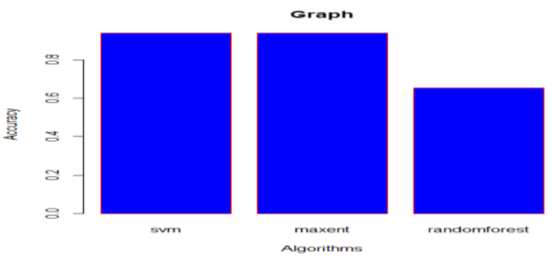

Fig.2 Proposed after feature selection Research methodologies Comparison Result based on Accuracy.

We can see that the execution of gossip classifier utilizing clients' conduct highlights is superior to anything that of benchmark approach. Contrasted and the benchmark approach, the exactness accuracy, review, and F-score of our methodology have expanded 34.21888667 %, 8.80013%, 29.566%, and 21.54929% by and large, which shows the adequacy of our strategy and the proposed highlights in bits of gossip distinguishing proof.

IV. CONCLUSION AND FUTURE WORK

1. Conclusions: In this paper, we propose an answer for location the issue of distinguishing low-quality substance on Twitter progressively. We initially infer a definition for low-quality substance as extensive measure of continued phishing, spam and low-quality notices which hamper clients from perusing typical substance and dissolve the client experience. This definition depends on the results of a study focusing on genuine clients of online informal communities and is subsequently proposed dependent on the clients' viewpoint.

It is important to recognize this low-quality substance continuously to improve client experience on OSN. We have played out a point by point investigation of 100,000 tweets and recognized various novel highlights which describe low-quality substance. We give an inside and out examination of these highlights and approve the proficiency of utilizing word level investigation for continuous low-quality substance discovery. We can see that the execution of gossip classifier utilizing clients' conduct highlights is superior to anything that of pattern approach. Contrasted and the benchmark approach, the exactness accuracy, review, and F-score of our methodology have expanded 34.21888667 %, 8.80013%, 29.566%, and 21.54929% overall, which shows the adequacy of our technique and the proposed highlights in bits of gossip distinguishing proof.

2. Future Work: It very well may be found in the overview portrayed over that 40.76% of the members trust that all the substance which they are not inspired by ought to be sifted as low-quality substance. This intriguing disclosure demonstrates the need and estimation of a substance channel for unengaged substance on online informal organizations. Along these lines later on, we intend to add more tweaked setup to the present work to execute a progressively customized substance channel not just concentrating on general low-quality substance. It is intended to consequently realize what the client isn't keen on and conceal them from the clients' timetable.

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