Segmentation based Twitter Opinion Mining using Ensemble Learning

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Abstract **:** In recent years, social media has become the prime place for advertisements, activities, campaigns, protests etc. It provides a platform for the people to express their views and beliefs to the masses. The user beliefs, practices and interests are of great importance to organizations and provides insight into the minds of users. Data Mining is one such tool that enables these organizations to extract relevant information from user data, which can be analyzed to create a knowledge set and determine user opinion that allows companies to create products tailored to the user. Data Mining of Twitter and other social platforms is of a great importance because, its large user base is a goldmine of public opinions and views which if analyzed properly, can potentially be used to predict campaign results and product assessments and likeability. This project proposes a classification scheme that aims to perform Segmentation based Twitter Opinion Mining using Ensemble Learning. The proposed scheme is able to detect and filter out bots and uses text segmentation for effective text classification and part of speech tagging.**Keywords -** *machine learning, supervised learning, text analysis, sentiment analysis, natural language processing.*

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1. INTRODUCTION

Twitter is a micro blogging site that allows users to express their opinions in short public messages called tweets. As of 206, twitter has about 319 million active users and is, therefore, a hotspot of information. People express their feelings about issues, campaigns, and products, which can be used to mine the general likeability of that issue, campaign or product. An architecture for a twitter opinion miner has been proposed for implementation of an opinion miner for twitter. The aforementioned miner makes use of segmentation technique for effective part of speech tagging of sentences in natural language detection [1]. Text segmentation segments text into meaningful phrases and tag them accordingly to get an accurate measure of the degree of the meaning conveyed by that phrase. Since twitter data is multi-dimensional, one classifier is simply not enough to classify this data accurately. Therefore, the architecture uses ensemble learning to tackle this problem. Extensive pre-processing needs to be done before opinion rules are mined from the data. The pre-processors include spell checkers, bot detectors, sarcasm detectors, lemmatizers and tokenizers. The following content proposes a humble architecture for opinion mining on Twitter using ensemble learning.Liu et al. [2] define opinion as a quintuple,(e_i, a_{ij}, oo_{ijkl}, h_k, t_l), where e_i is the name of an entity, a_{ij} is an aspect of e_i, oo_{ijkl} is the orientation of the opinion about aspect a_{ij} of entity e_i, h_k is the opinion holder, and t_l is the time when the opinion is expressed by h_k. The opinion orientation oo_{ijkl} can be positive, negative or neutral, or be expressed with different strength/intensity levels. When an opinion is on the entity itself as a whole, we use the special aspect GENERAL to denote it. Mining these positive, negative or neutral opinions using natural language processing, text analysis and computational linguistics to is called opinion mining. Twitter consists of multi-dimensional data and is one of the most popular microblogging platforms. People share their opinions about products, issues, and campaigns on twitter for the masses to read. A product or a campaign can be targeted by mining people's opinions about that product or campaign which can provide an insight into the general consensus of people with respect to that product or campaign. A corpus consisting of textual tweets was created to train the classifiers to accurately classify the general emotion relating to the subject of the tweets. The corpus was then subjected to rigorous pre-processing to make it fit for mining. Then the processed corpus was subjected to three learning techniques, Naïve Bayes Classifier [11], SentiWordNet [12],[13]analysis and Emoticon analysis. The individual results of these learners were combined together to generate an opinion score which gives an idea whether a tweet is positive or negative.

2. RELATED WORKS

Extensive literature survey was conducted and the following knowledge was obtained from the conducted survey

- A twitter opinion mining framework is introduced in [3] using hybrid classification. The paper discusses various challenges offered by sentiment analysis of Twitter feeds and presents a technique for real-time text mining and sentiment analysis using three-way classification by investigating the sentiment intensity. It involves preprocessing of data using techniques such as analysis of slangs/abbreviations, lemmatization, correction and stop words removal and also testing the accuracy of sentiment identification of the proposed algorithm on 6 twitter datasets. Along with these preprocessing techniques, proposed framework contains real time access to tweets using Twitter streaming API and a three-level classification to identify the sentiment of a tweet. The first level is an emoticonclassifier which uses a sample set to identify the emoticons in a tweet and categorize it as positive or negative. The second level is a polarity classifier which uses 'bag of words' approach which is followed by a SentiWordNet Classifier. Each of these classifications assigns a score to the tweet which then determines the polarity of the tweet with respect to the topic. A tweet having a score of 0 following all 3 classification techniques is termed as neutral. A graphical representation of the results is given which compares the results on the basis of Confusion matrices, precision, accuracy, F-measure, and recall.

- Taking into account the crucial role played by media and the news in developing a personal view of an individual on any topic, [4] introduces a method of opinion mining of news headlines using SentiWordNet. It uses two algorithms to perform the task with each algorithm performing a specified function. Words are pre-processed using Python libraries and each news headline word is assigned a part-of-speech tag, which is further used to determine the sentiment of the headline. POS-Tagger is used to identify which word is which part of speech and Lemmatization is done in this algorithm itself. The second algorithm feeds the words to SentiWordNet, which further assigns a positive or negative value to each word and identifies the overall polarity of the headline in order to define its effect or opinion on a certain topic. Above listed method was applied on a set of 500 news headlines spread over a 30 day period and the average deviations per day came out to be 2.7. This illustrates the efficiency of opinion mining on offline user generated data such as newspaper headlines instead of online user generated data such as blogs, reviews, tweets etc., where most of the opinion mining research in done.

- A comparative study of existing techniques for opinion mining including machine learning and lexicon-based approaches was provided in [5] along with cross-domain and cross-lingual methods and some evaluation metrics. The research showed that the machine learning methods like SVM and Naive Bayes obtained the highest accuracy and can be regarded as baseline learning methods, while the lexicon based methods were effective in some cases of human labeled document. Among the various models studied, the bigram model provided better results compared to the unigram and trigram models and had the adaptive capacity to a variety of domains and different languages. The machine learning methods identified the given problem as a classification problem and the SVM and Naive Bayes methods were used as supervised learning methods for the study. The lexicon based approaches used dictionary-based and corpus-based methods for analysis. The overall task of sentiment analysis was decomposed into following 3 tasks, Subjectivity classification, Sentiment classification and other complementary tasks. These tasks were then done at several levels of granularity like word-level, sentence-level, document-level, and aspect-level. The dataset used for carrying out the analysis was the publicly available Twitter dataset by Stanford. A major challenge identified in this domain is the problem of sarcasm detection, i.e., a sentence that contains only positive words but expresses a negative sentiment.

- A system was proposed in [6] for recognizing and analyzing the sentiments using Support Vector Machines (SVM) for the restaurant and laptop review dataset. Another system of text classification was proposed for identification of aspect the review sentences. The restaurant reviews datasets were obtained from SemEval 2014, SemEval 2015, and SemEval 2016. The reviews were classified in various aspects such as Ambience, Food, Price etc. The overall task was divided into the following subtasks of sentiment term extraction, polarity determination, aspect term extraction and aspect term classification. The algorithm first identifies the sentiment term in the sentence and then categorizes it appropriately and then the aspect term in the sentence is identified and categorized. The experiment evaluations predict the usefulness of SVM in text classification as compared to other classification techniques. The accuracy obtained using SVM for emotion classification and aspect classification was better in most of the cases as compared to other classification techniques like KNN and Naive Bayes.

- Opinion mining extracts user opinions and reviews at three levels of document, sentence, and feature. In [7], two methods were presented for feature extraction. Those methods comprise of four stages, thecreation of lexicon to determine the orientation of user opinions; preprocessing for tokenization and syntactic dependency parsing; feature extraction using frequency-based feature extraction and grammar-based feature extraction and finally polarity determination. In the final stage, a record was created per any feature in each review, which included five characteristics including feature, polarity, date, writer and type. The polarity of the feature was determined by adding the polarity of opinion words describing the feature and considering negative-makers' role in the sentence. The dataset used was prepared from users' reviews of cell phones obtained from the digikala website and the pre-processing was performed by the Virastyar software. The results obtained of the performance of the two proposed methods showed that the dependencygrammar method fared better than thefrequency-based method in extracting features. However, it does not work properly in determining the polarity of newly extracted opinion words.

- Tang et. al [8]proposed a joint segmentation and classification framework for sentiment analysis to effectively handle inconsistent sentiment polarity between a phrase and the words it contains. A joint segmentation and classification framework (JSC) was developed which simultaneously conducts sentence segmentation and sentence level classification of sentiments. The JSC framework comprised of two models namely the Segmentation model and the Classification model. The

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01 – 09

Segmentation model consisted of two parts: segmentation candidate generation and segmentation ranking model to effectively generate segmentation candidates for each sentence using beam search with constraints on a phrase table, induced from massive corpora. The approach to identifying those phrases was based on the occurrence frequency of unigrams and bigrams in the corpora. Two kinds of features for sentence segmentation were designed, phrase-embedding feature and segmentation-specific feature and the final feature representation of each segmentation was the concatenation of these two features. Along with this, the ranking model assigned a scalar to each segmentation candidate to indicate the usefulness of the segmentation result for sentiment classification. The segmentation score was calculated using a log-linear model. For sentiment classification, a supervised learning framework was deployed from sentences with manually labeled sentiment polarity. For a test sentence, its segmentation candidates were generated and the score for each segment was calculated. The top ranked K candidates were chosen and their predicted sentiment polarity from the classifier was voted as the final result.

- A methodology was discussed in [9] that allowed utilization and interpretation of data from the popular micro blogging site Twitter to determine public opinions. The analysiswas done on tweets regarding the Apple iPhone 6 and feature specific popularities were included. The approach to finding sentiments and opinions was location-specific, i.e. the popularity of the given product was measured across several locations. Data was collected using the Twitter public API and preprocessing was done to filter out unnecessary information from the tweets. An AI tool was used to predict the gender of the user as Twitter does not ask for gender while creating a new account. Various nation-wide and city-wide metrics along with gender-separate metrics for individual cities in the USA were discussed. SentiWordNet was used to assess the sentiment present in a tweet to give it a numeric score in the range from -1 to +1. To find the trends and variations in the sentiments, various comparisons were made at different levels. Initial comparisons were done on anational level and more detailed analysis was done on cities and genders of the users. The deductions made from this were that highly negative sentiments were recorded towards the iPhone 6 screen and touch due to the bending issue which surrounded the phone during its initial release. On the other hand, high positive sentiments were observed towards the camera of the phone which was praised both by general users and reviewers alike.

3. PROBLEM STATEMENT

Upon consulting, the extensive literature on opinion mining, text classification, and machine learning, the following problems were identified

- One algorithm is simply not enough to classify and mine opinions from multidimensional twitter data.
- Social media data is prone to spelling mistakes, sarcasm and internet slang which adversely affect the quality of classification.
- The efficiency of learning algorithms is dependent on data set. There is no one algorithm, that can perform well on any data set.
- Scalability is a big issue in opinion mining. Increasing the dataset size can have an impact on the accuracy of the classifier.
- Twitter is filled with bots that exploit the machine learning algorithms to their benefit. Such bots adversely affect the accuracy of learning algorithms.

4. PROPOSED ARCHITECTURE

The opinion miner has been divided into 3 modules, Data acquisition, preprocessing and classification and evaluation. The architecture of each module is described below.

4.1 Proposed Miner Architecture

As shown in Fig. 1, live tweets were collected from Twitter streaming API according to a given input query. English language tweets were filtered out and a corpus of tweets was generated stored in JSON format. This corpus however required pre-processing for accurate mining. The tweets were subjected to Twitter Bot or Not [10] for filtering out bot accounts from the corpus. Twitter bots affect the quality of learning, and often reduce the accuracy of the learning algorithm. After filtering out the bots, URLs, usernames, and hashtags were removed. Spell check was done to correct typographical errors and misspelled words. Emoticon classifier was then used to extract emoticons from the tweets. Lemmatization [15] and stemming were done on each word of each tweet for part of speech tagging after which features were extracted for classification. Segmentation was applied on each tweet which gave the top k ranked segments. These top k segments were used as features for Naïve Bayes classifier and tweet was classified. Emoticon classifier and SentiWordNet classifier were applied to each tweet. For each tweet, scores from the three classifiers were aggregated to generate a Combined Weighted Score(CWS). The process is depicted in the algorithm below and flowchart in Fig. 2.

4.2 Algorithm for calculation of Combined Weighted Score(CWS)

Algorithm

Input: Query String

Output: Predict opinion and sentiment based on tweets.

1. Begin
2. Input a query string.
3. Retrieve data from the Twitter API based on the inputs query.
4. Filter out tweets in languages other than English.
5. Filter out tweets from bots.
6. Remove duplicate tweets.
7. Save tweets in a JSON file.
8. For each tweet,
    8.1 Procedure Pre-process(tweet)
    - Remove URL.
    - Remove username.
    - Remove hashtags.
    - Extract emoticons for emoticon classifier.
    - Replace slangs and abbreviations.
    - Apply spell Check and corrections.
    - Lemmatization.
    - Stemming and POS Tagging.
    - Extract features for classification.
    8.2 End Procedure
    8.3 Procedure Segmentation(processed tweet)
    - Generate segmentation candidates.
    - Calculate score of segmentation candidates based on segment and phrase table
    - Pick top K-ranked segments.
    8.4 End Procedure
    8.5 Procedure Classification(processed tweet)
    - Classify tweet based on Emoticon Classifier.
    - Classify tweet using Naive-Bayes Classification using segments as features.
    - Classify tweet usingSentiWordNet.
    - Combine the classification result obtained from the 3 learners.
    - Save the result of classification prediction.
9. End For
10. End

Formula for calculating the Combined Weighted Score(CWS)

$$\mathbf{CWS = 0.5*N_b + 0.3*S_w + 0.2*E_c}$$

Here,

$\mathbf{N_b}$: Naïve Bayes score of the tweets

$\mathbf{S_w}$: Score from SentiWordNet classifier

$\mathbf{E_c}$: Score from Emoticon classifier

5. EXPERIMENT SETUP

The proposed architecture was tested several times for different subsets of the corpus. The results presented in the following sections are an average of five independent runs on the dataset of 5000 samples with 90/10 splits i.e. 90% samples were used for training and 10% for testing. The process took an average time of 1012 seconds.

5.1 Segment Selection and feature Extraction

A set of bigrams and trigrams was created using brown corpus [14] which contains 3,583 and 3,585 entries respectively. Partial lists are shown in Table 1 and Table 2. Complete lists are available with the author. For each tweet, if a segment exists in these sets, only then it was selected otherwise it was rejected. The selected segments were those that had importance in sentiment analysis. Top k segments were extracted from the corpus of processed tweets and these were used as features for Naïve Bayes classification.

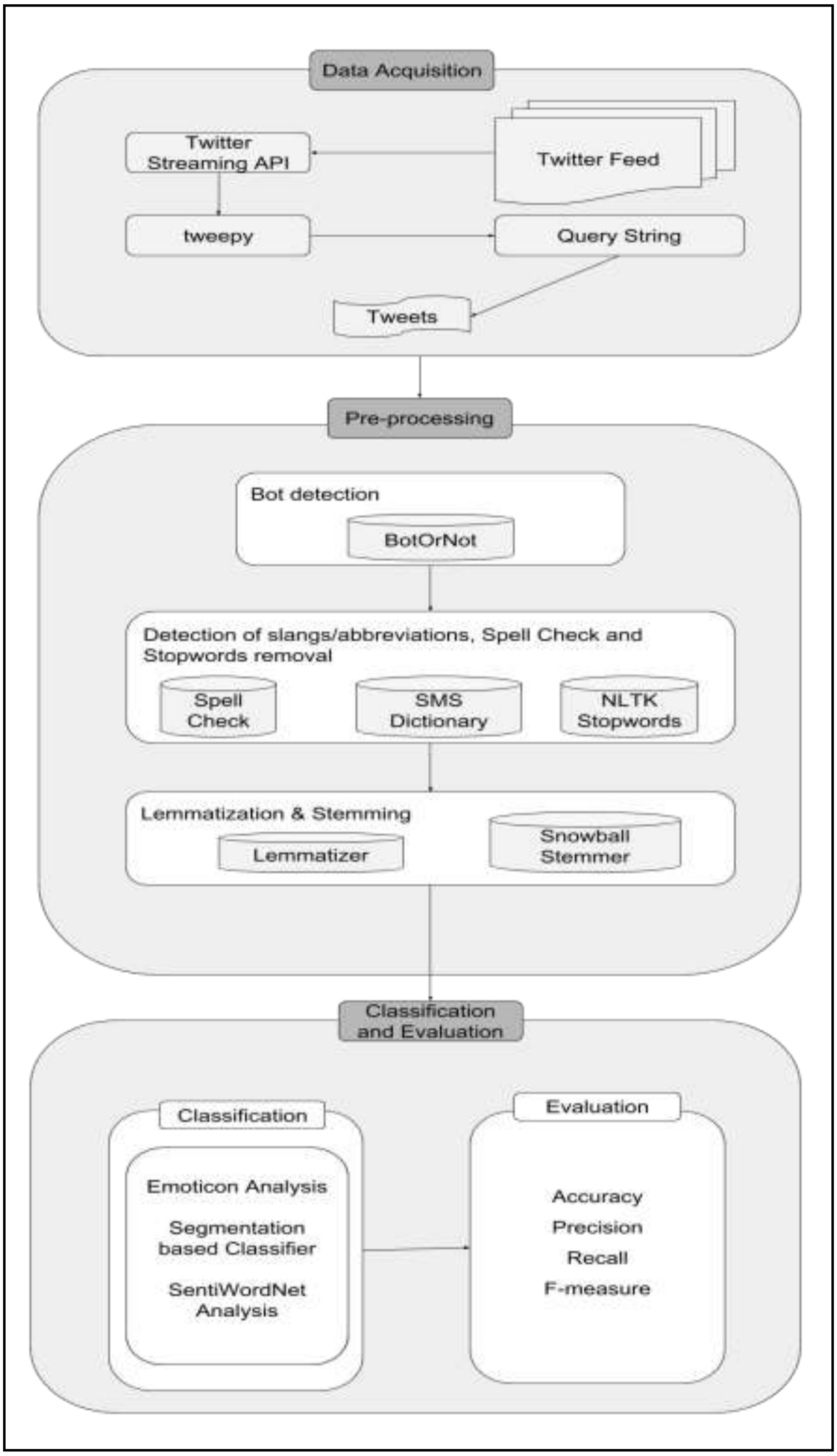

Fig. 1: Twitter Opinion Miner Architecture

Fig. 3 shows the list of top k segments extracted from the tweets according to their Naïve Bayes probability. The 1st column lists the features extracted. The second column lists the corresponding sentiment score. 0:1 being negative sentiment and 1:0 being positive sentiment. The third column is the corresponding Naïve Bayes probability of the segment. These segments are the features used by the classifier.

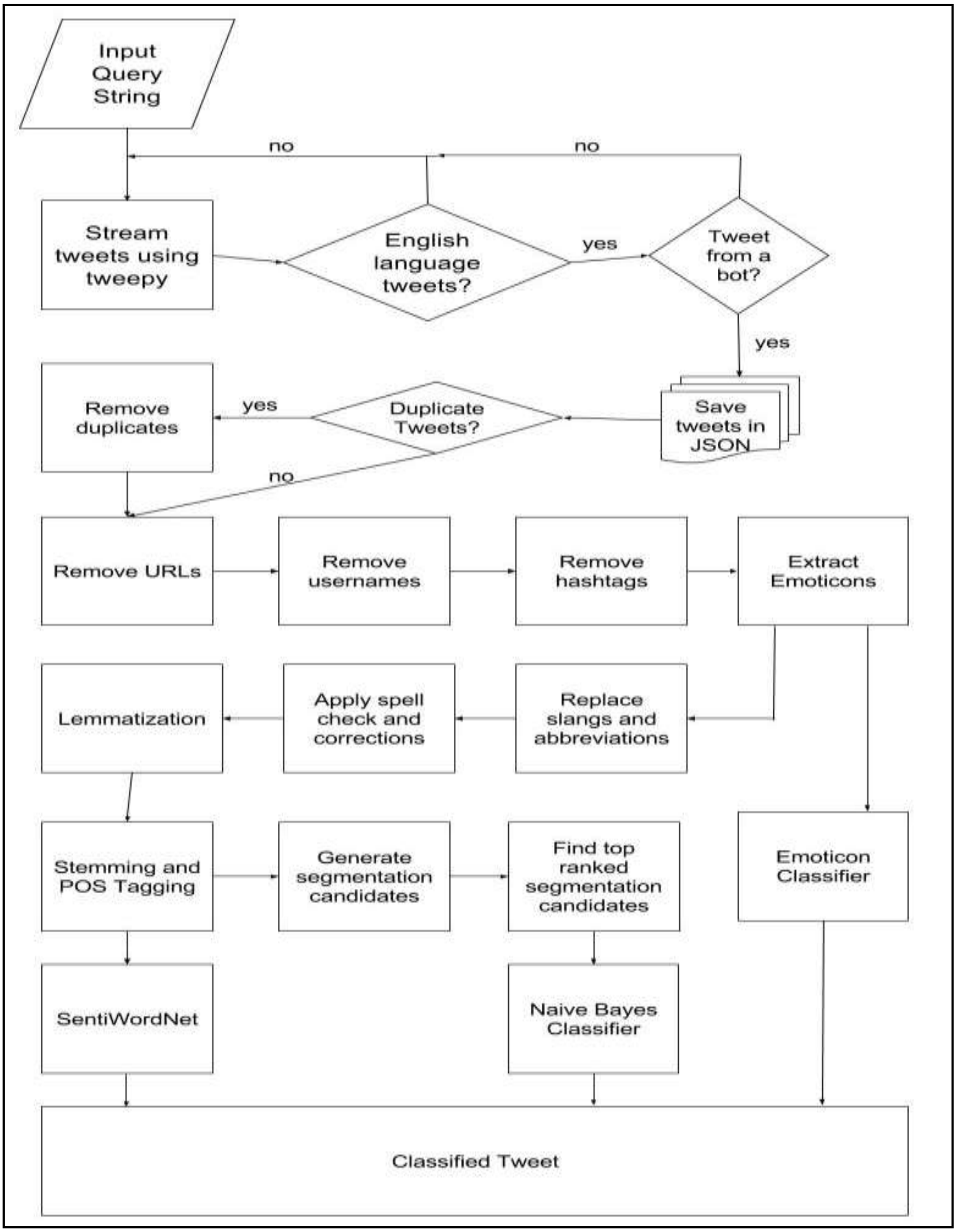

Fig. 2: Flow chart depicting Opinion Mining of Tweets

5.2 Dataset for classification

A dataset containing 1,578,627 classified tweets was used for sentiment analysis. Each row is marked 1 or 0, for positive and negative sentiment respectively. 90% of the sample size was used for training and 10% for testing. After initial filtering out, the remaining data was dumped into a JSON file for further processing and classification. Sample positive and negative tweets after processing, are depicted in Fig. 4.

Table 1: Partial list of bigrams

Bigrams
United States
New York
I don't
per cent
years ago
I think
I could
I said
AfAf
I know
I would
said I
He said
The first
could see
Rhode Island
Of course
In addition
I thought
I didn't
But I
last year
first time
It would
don't know
For example
I told

Table 2: Partial list of trigrams

Trigrams
I don't know
World War 2
United States America
New York City
Government United States
I could see
I said I
New York Times
The New York
I don't think
The United States
basic wage rate
A. Notte Jr.
Drug's chemical name
John A. Notte
New York Central
I would like
per capita income
I told I
World War 1
words electronic switches
I know I
index word electronic
index words electronic
small business concerns
word electronic switch
I don't want
result obtained item
two years ago
uniform fiscal year
Department Economic Affairs

```
Most Informative Features
             contains(sad) = True              0 : 1      =     20.7 : 1.0
         contains(excited) = True              1 : 0      =     13.2 : 1.0
           contains(enjoy) = True              1 : 0      =     12.2 : 1.0
      contains(especially) = True              1 : 0      =     10.6 : 1.0
           contains(loved) = True              1 : 0      =     10.6 : 1.0
       contains(wonderful) = True              1 : 0      =     10.6 : 1.0
        contains(remember) = True              1 : 0      =     10.6 : 1.0
             contains(bad) = True              0 : 1      =     10.0 : 1.0
             contains(thx) = True              1 : 0      =      9.0 : 1.0
   contains(getting ready) = True              1 : 0      =      9.0 : 1.0
None
training time:  1081.44099998  s
testing time:  373.823000193  s
('accuracy: ', 0.8579999999999997)
```

Fig. 3: List of most informative features

```
Positive Tweet:

Tweet: Jesus Gives Me Hope That One Day I will Rise to Heaven Too. Happy Easter
to Those Who Fears the Lord When No One Is Looking. #fyc
Processed Tweet: jesus gives hope one day rise heaven happy easter fears lord one looking

Negative Tweets:

Tweet: Feeling very #unmotivated and kinda #disappointed
Processed Tweet: feeling very unmotivated kinda disappointed
```

Fig. 4: Original and Processed tweets

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01 – 09

5.3 Emoticon Classifier

The emoticon classifier works by identifying positive and negative emoticons according to the regular expressions available in appendix A. The sentiment scores are assigned accordingly. Fig. 5 shows the output of the emoticon classifier.

```
Tweet:
Great win tonight @TheGujaratLions! Special mention to @aj191 for an amazing deb
ut and @ImRaina on playing his 150th :) #IPL
Sentiment: 1
Predction: 1

Tweet:
I miss how happy I used to be... :(
Sentiment: -1
Predction: -1
```

Fig. 5: Emoticon Classifier Output

5.4 SentiWordNet Classifier

SentiWordNet classifier uses the SentiWordNet 3 dataset for assigning sentiment score to each tweet. A positive score means a positive segment and a negative score means negative sentiment. Fig. 6 depicts scores assigned to sample tweets using the SentiWordNet classifier.

```
Tweet:
Fantastic. The real way to start a swachhagraha. Start young. All our schools sh
ould follow this example.
Sentiment: 1
Predction: 1

Tweet:
Another day another Muslim terrorist attack & people want to import these savage
s to America. #sad
Sentiment: -1
Predction: -1
```

Fig 6: SentiWordnet classifier output

5.5 Results

A comparative analysis of results of proposed miner and the miner proposed by Bashir et al. has been given in Table 3 below. The metrics precision, recall, and f-measure have been defined and compared below.

Precision is the measure of how often, a sentiment rating was correct. Mathematically, it is the ratio of true positives against all positive(true or false).

$$Precision = \frac{tpA}{tpA + fpA}$$

Recall is the ratio between correctly classified positives by the classifier and the manually classified positives(true positives + false negative). Mathematically,

$$Recall = \frac{tpA}{tpA + fnA}$$

F-measure is the harmonic mean of both precision and recall. Mathematically,

$$F - measure \ = \ 2 * \frac{precision * recall}{precision + recall}$$

Table 3: Comparison of proposed miner with existing one

Property	Proposed	Bashir et. al.
Accuracy	85.80%	85.80%
Precision	84.80%	86.00%
Recall	85.20%	82.20%
F-Measure	84.98%	84.05%

6. Comparison with Similar Opinion Miners

The proposed Opinion Miner has the following advantages over similar opinion miners.

- Scalability:The proposed miner is highly scalable and can easily handle large datasets on moderate hardware. The entire process took 1012 seconds to mine opinion from a sample of 5000 tweets.

- Bot Detection: The proposed architecture filters out posts by twitter bots from the corpus before mining. This is accomplished using the BotOrNot algorithm. The removal of these bots has increased the accuracy of the mining process.
- Contextual Spell check: The architecture employs contextual spell check that corrects the spelling of the words keeping in mind the context in which they have been used and is also able to identify popular English idioms and phrases.

7. Conclusion

The article discusses opinion mining and sentiment analysis on Twitter. It identifies some critical problems faced in opinion mining on social media like spelling mistakes and bots the affect the quality of mining. A humble architecture was proposed in section 4 that addresses these issues. Proper metrics have been collected after multiple independent runs on same and different data sets which have been tabulated in Section 5. The article provides a comparison with similar existing approaches. The proposed Miner was able to achieve 86% precision and 84% recall. The f measure was calculated to be 85.98%.

8. Future Scope

The proposed architecture only works for tweets in English language and filters out tweets in other languages. The future research will be focused on developing an architecture that can handle multiple languages. Supervised learning algorithms and SVMs can be used to further improve the accuracy.

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