Predictive Approach toward Sentiments Analysis of Twitter Feeds using Maximum Entropy Classifier Method

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***Abstract*—Twitter is most popular social networking platform where users produce and interact with messages called "tweets". This serves as a medium for users to convey their feelings and thoughts about various subject. In this paper, an attempt is presented to conduct sentiment analysis on "tweets" using Maximum Entropy classifier. Maximum Entropy Classifier model is based on the principle of Maximum Entropy. The main purpose behind it is to choose the most uniform probabilistic model that maximizes the entropy, with given constraints. It attempts to classify the polarity of the tweet where it is either positive or negative. If the tweet has both positive and negative elements, the more dominant sentiment should be picked as the final label. In general, Maximum Entropy Classifier performs better than other Classifier as presented in result.**

***Keywords*— Sentiment Analysis, Tweets, Social Networking, Naive Bayes Classifier, Maximum Entropy Classifier.**

I. Introduction

Social media, such as blogs, forums, and social network platforms (eg, Facebook, Twitter, LinkedIn, Youtube, Instagram) are quickly becoming an integral part of people's lives, the virtual spaces where daily individuals share opinions and information and maintain and/or expand their relational network [1]. The massive use of online social networks and the abundance of data collected through them has raised exponentially the attention of the scientific and business community toward them [2–4].

Sentiment analysis, which is also called opinion mining, has been one of the most active research areas in natural language processing since early 2000 [5]. The aim of sentiment analysis is to define automatic tools able to extract subjective information from texts in natural language, such as opinions and sentiments, so as to create structured and actionable knowledge to be used by either a decision support system or a decision maker.

However, sentiment analysis is often improperly used when one is referring to polarity classification, which instead is a subtask aimed at extracting positive, negative, or neutral sentiments (also called polarities) from texts. Although an opinion could also have a neutral polarity (eg, "*I don't know if I liked the movie or not. I should watch it quietly*".), most work in sentiment analysis usually assumes only positive and negative sentiments for simplicity. Depending on the field of application, several names are used for sentiment analysis (eg, opinion mining, opinion extraction, sentiment mining, subjectivity analysis, affect analysis, emotion analysis, and review mining). A taxonomy of the most popular sentiment analysis tasks is reported in Figure 1.

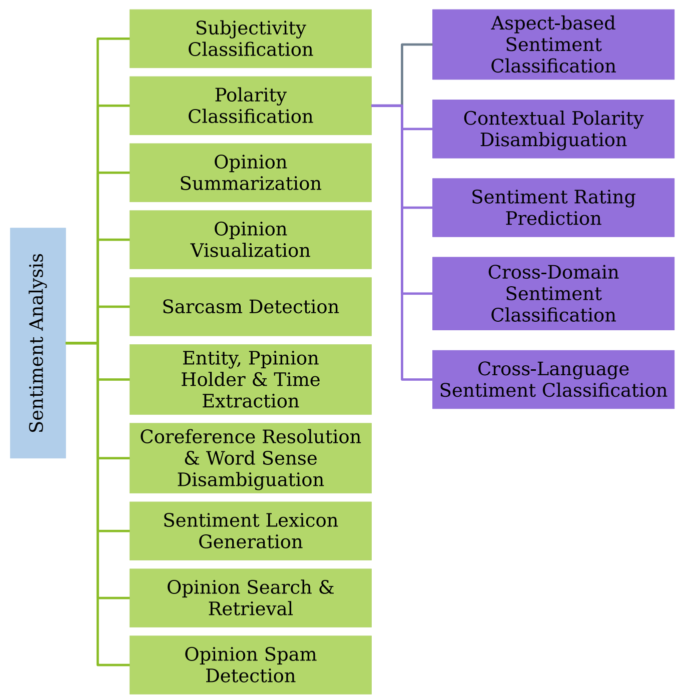

Fig. 1. Sentiment Analysis Tasks

Sentiment Analysis in Social Networks tries to overcome this limitation by

- Collecting and proposing new relevant research work from experts in the field,
- Debating the advantages and disadvantages when one is applying sentiment analysis in social networks,
- Discussing the progress of sentiment analysis in social networks and future directions.

A. Technical Aspects of Sentiment Analysis

Sentiment Analysis refers to the use of text analysis and natural language processing to identify and extract subjective information in textual contents. There are two type of user-generated content available on the web – facts and opinions. Facts are statements about topics and in the current scenario, easily collectible from the Internet using search engines that index documents based on topic keywords. Opinions are user specific statement exhibiting positive or negative sentiments about a certain topic. Generally opinions are hard to categorize using keywords. Various text analysis and machine learning techniques are used to mine opinions from a document [6]. Sentiment Analysis finds its application in a variety of domains.

- **Business:** Businesses may use sentiment analysis on blogs, review websites etc. to judge the market response of a product. This information may also be used for intelligent placement of advertisements. For example, if product "A" and "B" are competitors and an online merchant business "M" sells both, then "M" may advertise for "A" if the user displays positive sentiments towards "A", its brand or related products, or "B" if they display negative sentiments towards "A".
- **Government:** Governments and politicians can actively monitor public sentiments as a response to their current policies, speeches made during campaigns etc. This will help them make create better public awareness regarding policies and even drive campaigns intelligently.
- **Financial Markets:** Public opinion regarding companies can be used to predict performance of their stocks in the financial markets. If people have a positive opinion about a product that a company A has launched, then the share prices of A are likely to go higher and vice versa. Public opinion can be used as an additional feature in existing models that try to predict market performances based on historical data.

B. Twitter

Twitter is an online social networking and micro-blogging service that enables users to create and read short messages, called "Tweets". It is a global forum with the presence of eminent personalities from the field of entertainment, industry and politics. People tweet about their life, events and express opinion about various topics using text messages limited to 140 characters. Registered users can read and post tweets, but any unregistered users can read them. Twitter can be accessed via Web, SMS, or mobile apps. Traditionally a large volume of research in sentiment analysis and opinion mining has been directed towards larger pieces of text like movie reviews. Sentiment Analysis in micro-blogging sphere is relatively new. From the perspective of Sentiment Analysis, we discuss a few characteristics of Twitter:

- **Length of a Tweet:** The maximum length of a Twitter message is 140 characters. This means that we can practically consider a tweet to be a single sentence, void of complex grammatical constructs. This is a vast difference from traditional subjects of Sentiment Analysis, such as movie reviews.
- **Language Used:** Twitter is used via a variety of media including SMS and mobile phone apps. Because of this and the 140-character limit, language used in Tweets tend be more colloquial, and filled with slang and misspellings, as compared to other user-generated content on the web. Use of hashtags also gained popularity on Twitter and is a primary feature in any given tweet. Our analysis shows that there are approximately 1-2 hashtags per tweet.
- **Data Availability:** Another difference is the magnitude of data available. With the Twitter API, it is easy to collect millions of tweets for training. There also exist a few datasets that have automatically and manually labelled the tweets [7, 8]
- **Domain of Topics:** People often post about their likes and dislikes on social media. These are not al concentrated around one topic. This makes twitter a unique place to model a generic classifier as opposed to domain specific classifiers that could be build datasets such as movie reviews.

C. Predictive Analysis

Predictive analytics is the use of data, mathematical algorithms and machine learning to identify the likelihood of future events based on historical data [9]. The main goal of predictive analytics is to use the knowledge of what has happened to provide the best valuation of what will happen. In other words, predictive analytics can offer a complete view of what is going on and the information we need to succeed [10].

1) Predictive Analytics Process: Figure 2 represents the press involved in predictive analytics.

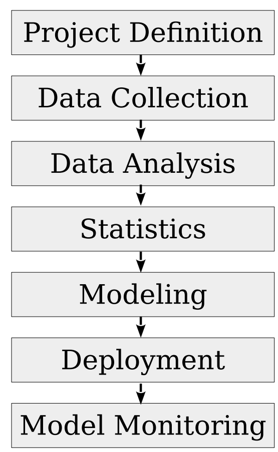

Fig. 2. Predictive Analytics Process

1) **Define Project:** Define the project outcomes, deliverable, scope of the effort, business objectives, identify the data sets that are going to be used.
2) **Data Collection:** Data mining for predictive analytics prepares data from multiple sources for analysis. This provides a complete view of customer interactions.
3) **Data Analysis:** Data Analysis is the process of inspecting, cleaning and modelling data with the objective of discovering useful information, arriving at conclusion
4) **Statistics:** Statistical Analysis enables to validate the assumptions, hypothesis and test them using standard statistical models.

5) **Modeling:** Predictive modelling provides the ability to automatically create accurate predictive models about future. There are also options to choose the best solution with multi-modal evaluation.
6) **Deployment:** Predictive model deployment provides the option to deploy the analytical results into everyday decision making process to get results, reports and output by automating the decisions based on the modelling.
7) **Model Monitoring:** Models are managed and monitored to review the model performance to ensure that it is providing the results expected.

II. Related Work

Many researcher carried out their research work in sentiments analysis using social media. Several reseacher have emphsize their attention on stastical results from social media using various sentiments analysis methods.

A. Influence Factor Based Opinion Mining of Twitter Data using Supervised Learning

Anjaria *et al.* [11] introduce the novel approach of exploiting the user influence factor in order to predict the outcome of an election result. Author also proposed a hybrid approach of extracting opinion using direct and indirect features of Twitter data based on Support Vector Machines (SVM), Naive Bayes, Maximum Entropy and Artificial Neural Networks based supervised classifiers.

On twitter, the users with more followers get to be more influential over other users due to their widespread. They also established that re-tweets and mentions have very high correlation value using Spearman's rank correlation equation [12].

$$\rho = 1 - \frac{6\sum(x_i - y_i)^2}{N^3 - N} \tag{1}$$

Social network based behavioral analysis parameters can increase the prediction accuracy along with sentiment analysis. However, presence of all the entities in unbiased and equal manner is necessary to provide accurate results. To understand the influential parameters that effect the results, semantic features are also very useful from point-view of the entity itself.

B. Analyzing Political Landscape Election in Twitter

Song *et al.* [13] employ temporal Latent Dirichlet Allocation (LDA) to analyze and validate the relationship between topics extracted from tweets and related events. They developed the term co-occurrence retrieval technique to trace chronologically co-occurring terms and thereby compensate for LDAs limitations. Finally, authors identify thematic coherence among users identified in sending receiving mentions.

Their data collection and text-mining techniques process Twitter's large stream datasets in real time. To demonstrate the usefulness of our approaches, they specifically focused on topical trend analysis and network analysis to examine presidential issues embedded in Twitter data. Figure 3 represents overall research process. This major contribution is in making it possible to mine dynamic social trends and content-based networks generated in Twitter using state-of-the-art techniques. Our empirical study also revealed some new findings on topic modeling and network analysis. Based on observations of the temporal topic modeling, they identified that Twitter is a useful medium for tracking topical trends in a timely manner. In particular, they found that controversial issues in Twitter are generated, propagated, and extinguished in a way that is similar to, but more innovative than, existing media. The mention-based network analysis indicates that Twitter users with similar political dispositions tend to communicate often with their social companions through sending/receiving mentions. So, simply focusing on the follow/following connection can mask real-world opinion behavior.

In addition, the mention-direction-based user network provides a basis for identifying a node with high betweenness centrality, in that users in Twitter are inclined to freely send/receive mentions to each other, regardless of their attitude toward a certain issue. This behavioral trait also affects the density of the user community. However, they must further analyze sentiment on tweets and sent–received mentions to properly measure connectivity among Twitter users, which could vary based on personal leanings or attitudes on particular issues. Finally, our study shows that co-occurring terms on a particular social issue can be a useful feature for content analysis. Temporal trend analysis through topic modeling, together with co-word analysis by term co-occurrence, shows the different aspects of social issues discussed in Twitter. Coupled with mention-based visualization, the resulting integrated view let us interpret the implications of social issues in an innovative manner.

C. Twitter Mining Approaches

Bing *et al.* [14] proposed a method to mine Twitter data for prediction of the movements of the stock price of a particular company through public sentiments. Authors also explain how stock price of one company to be more predictable than that of another company and they proposed to used a data mining algorithm to determine the stock price movements of 30 companies listed in NASDAQ and the New York Stock Exchange can actually be predicted by the given 15 million records of tweets (i.e., Twitter messages). They did so by extracting ambiguous textual tweet data through natural language processing (NLP) techniques to define public sentiment, then make use of a data mining technique to discover patterns between public sentiment and real stock price movements.

Go *et al.* [7] were among the first to explore sentiment analysis on Twitter. They classify Tweets for a query term into negative or positive sentiment. They collect training dataset automatically from Twitter. To collect positive and negative tweets, they query twitter for happy and sad emoticons. Happy emoticons are different versions of smiling face, like ":)", ":-)", ":)", ":D", "=)" etc. Sad emoticons include frowns, like ":(", ":-(", ": (" etc. They try various features – unigrams, bigrams and Part-of-Speech and train their classifier on various machine learning algorithms – Naive Bayes, Maximum

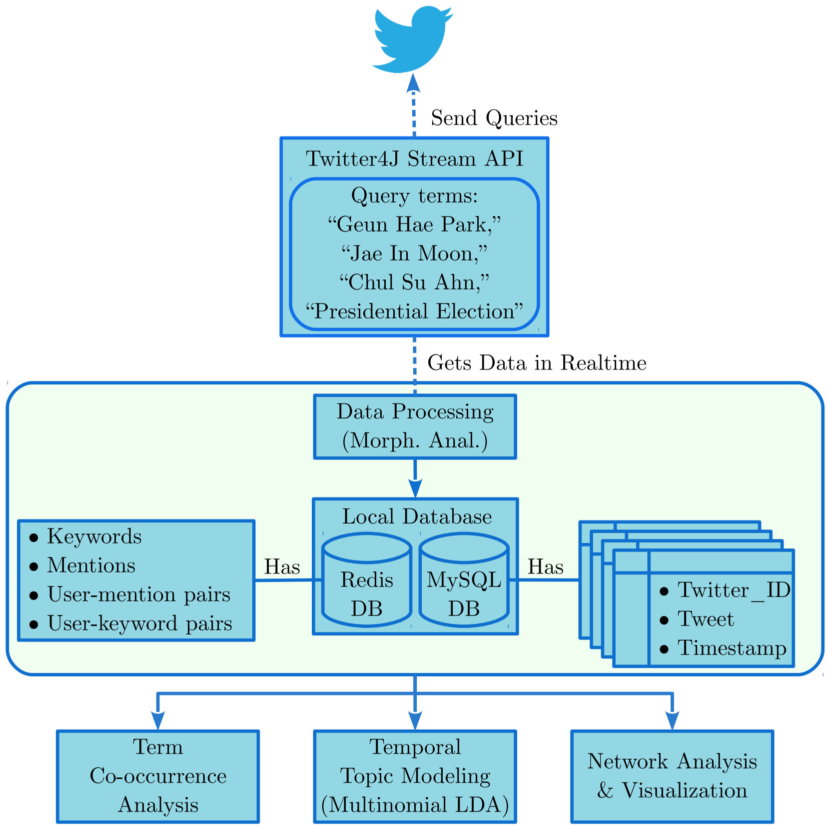

Fig. 3. Research Process – Employing The Twitter4J API

Entropy and Scalable Vector Machines and compare it against a baseline classifier by counting the number of positive and negative words from a publicly available corpus. They report that Bigrams alone and Part-of-Speech Tagging are not helpful and that Naive Bayes Classifier gives the best results.

Pak *et al.* [15] use a similar distant supervision technique to automatically collect the dataset from the web. Apart from using happy and sad emoticons for positive and negative sentiment respectively, they also query tweets from accounts of 44 newspapers, like "New York Times", "Washington Posts" etc. to collect a training set of subjective tweets. They use unigrams and filtered n-grams for their classification. They also handle negations by attaching negative cues, like "no", "not" to the words preceding and following them. They report that both bigrams and negation handling help.

Koulompis *et al.* [16] identify that use of informal and creative language make sentiment analysis of tweets a rather different task. They leverage previous work done in hashtags and sentiment analysis to build their classifier. They use Edinburgh Twitter corpus to find out most frequent hashtags. They manually classify these hashtags and use them to in turn classify the tweets. Apart from using n-grams and Part-of-Speech features, they also build a feature set from already existing MPQA subjectivity lexicon and Internet Lingo Dictionary. They report that the best results are seen with $n-$gram features with lexicon features, while using Part-of-Speech features causes a drop in accuracy.

Saif *et al.* [17] discuss a semantic based approach to identify the entity being discussed in a tweet, like a person, organization etc. They also demonstrate that removal of stop words is not a necessary step and may have undesirable effect on the classifier.

All of the aforementioned techniques rely on $n-$gram features. It is unclear that the use of Part-of-Speech tagging is useful or not. To improve accuracy, some employ different methods of feature selection or leveraging knowledge about micro-blogging. In contrast, we improve our results by using more basic techniques used in Sentiment Analysis, like stemming, two-step classification and negation detection and scope of negation.

Negation detection is a technique that has often been studied in sentiment analysis. Negation words like "not", "never", "no" etc. can drastically change the meaning of a sentence and hence the sentiment expressed in them. Due to presence of such words, the meaning of nearby words becomes opposite. Such words are said to be in the scope of negation. Many researches have worked on detecting the scope of negation.

The scope of negation of a cue can be taken from that word to the next following punctuation. Councill *et al.* [18] discuss a technique to identify negation cues and their scope in a sentence. They identify explicit negation cues in the text and for each word in the scope. Then they find its distance from the nearest negative cue on the left and right.

NaiveBays:- Naive Baysin is used by many researchers to detect the sentiments of tweet [19]. It works using probabilistic model given below

$$p(C_k \mid z_1, z_2, \ldots, z_n) \tag{2}$$

For each of k possible outcomes or classes.But if number feature is large that is value of n is large then above formula is not work well. Because probability tables become too large and infeasible to handle. Therefore Bays theorem is used, which decomposed the conditional probability as

$$p(C_k|z) = \frac{p(C_k)p(z|C_k)}{p(z)} \tag{3}$$

Where C_k is class for each of k possible outcomes. And z are the instances to be classified.

D. Sentiment Analysis of Multimodal Twitter Data

Kumar *et al.* [20] proposed a model for sentiment analysis to capture this expressiveness for text in an image, both typographic or infographic, as sentiment polarity and strength. The multimodal sentiment analysis model for Twitter offered novelty in two ways. Firstly, it was able to handle multi-modalities in tweets, that is, text and image individually and text in an image to analyze the sentiment and secondly, the textual sentiment analysis was based on a hybrid of context-aware lexicon and ensemble learning. The model will serve as a visual listening tool for enhanced social media monitoring and analytics. The performance results were motivating and improve the generic sentiment analysis task.

The primary limitation of the model is that the text recognition is restricted by the capability of the Computer Vision API. Moreover, as social media is an informal way of communication, multilinguity (code-mix and code-switch languages, for example a mix of English and Hindi, a native Indian language) is widely seen, but such content (text or text in image) could not be processed. Also, the OCR has a limited capability for handwritten text recognition and suffers from reduced accuracy with 'lack of contrast' images where the text color and the background color are almost similar. In this research, only the text and image modality type had been considered whereas other modalities such as animated GIFs and memes define an open problem within the research domain. Also, the use of word embeddings and deep learning for context-aware sentiment analysis of text can be explored.

1) Textual Sentiment Analysis: The textual sentiment analysis is a multi-step process which consists of the following:

- **Data Pre-processing:** Data pre-processing is done for cleaning and transforming the data for relevant feature extraction. The HTML entities in the tweet are decoded (Eg. &amp is changed to &), URLs were removed, expressions corresponding to retweet (RT) at the beginning of the tweet are removed, contractions present in the tweet are replaced by their extended words (Eg, BI'll is replaced with 'I will), punctuations present including hast-tag '#'etc., are removed.
- **Feature Extraction:** This step identifies the characteristics of the datasets that are specifically useful in detecting sentiments. The classical bag-of-features framework is utilized. We form a list of tweet words from the tweets in the corpus, which are tagged as a noun, verb, adjective, adverb or pronoun using the Part-of-speech (POS) tagger provided by NLTK. Now the frequency distribution of each tweet word in this list is obtained and the top 5000 most common words are considered. These words constitute the bag-of-words which are to be used as feature words to find the unigrams. Next, we form a feature vector corresponding to each tweet. The features used are:
  - Unigrams: presence/absence of feature words
  - Part-of-Speech(POS)features: count of nouns, verbs, adjectives, adverbs, interjec- tions and pronouns
  - Negation: count of occurrences of negation word 'not'
  - Count of Emoticon features: Various combinations of punctuation marks have been mapped into six classes of emoticons:-Smiley(:),:-), (:), laugh(: D, xD), love(¡3,:*), wink(;),;-D), frown(: -(,:(), and cry(:'() and their count is taken as feature
  - Count of elongated words(e.g. yummmy)
  - Count of capitalized words
  - Length of message.
- **Ensemble Learning:** An iterative learning model, gradient boosting is then used to train the textual sentiment analysis module. The gradient boosting is meta-model which consists of multiple weak models whose output is added together to get an overall prediction. The evaluated polarity is input the SentiWordNet [10] to obtain the respective sentiment score. SentiWordNet contains sentiment scores for all WordNet entries.
- **SentiCircle:** Each cleaned tweet is firstly tokenized, and each token is POS tagged using NLTK. Each token is lemmatized using WordNet Lemmatizer [15] and then stemmed to its root form using Porter Stemmer [42]. Based on the POS tag assigned to each token, it is scored using SentiWordNet. SentiWorNet offers a fixed, context-independent, word- sentiment orientations and strengths. SentiCircles considers the contextual co-occurrence patterns to capture conceptual information and update strength and polarity in sentiment lexicons accordingly.

E. Hybrid Sentiment Classification on Twitter Aspect-based Sentiment Analysis

Zainuddin *et al.* [21] proposed a new hybrid approach for a Twitter aspect-based sentiment analysis to perform finer-grained analysis. This research examined the association rule mining (ARM) that was augmented with a heuristics combination in part-of-speech (POS) patterns for detecting explicit single and multi-word aspects. The reason for this was that interrelations between a heuristic combination in POS patterns from words such as adjectives, adverbs, verbs and determiners with noun phrases are beneficial for the detection of relevant explicit aspects. Besides, the Stanford dependency parser (SDP) method, through the use of grammatical relations, is crucial in detecting implicit aspects. Our system also incorporates a rule-based with feature selection method for identifying the sentiment words. The evaluation with different classification algorithms also demonstrated that the new hybrid sentiment classification produced meaningful results with Twitter datasets, which represented different domains. The implementations showed that the new hybrid sentiment classification, that incorporated results from the aspect-based sentiment classifier method, was able to improve the performance of the existing baseline sentiment classification methods by 76.55, 71.62 and 74.24%, respectively. In a future work, we plan to conduct experiment with another social media data such as youtube and facebook by using the proposed hybrid sentiment classification approach in order to identify sentiment of people towards certain issues.

III. Proposed Method

We use different feature sets and machine learning classifiers to determine the best combination for sentiment analysis of twitter. We also experiment with various pre-processing steps like – punctuations, emoticons, twitter specific terms and stemming. We investigated the following features – unigrams, bigrams, trigrams and negation detection. We finally train our classifier using various machine-learning algorithms – Naive Bayes, Decision Trees and Maximum Entropy.

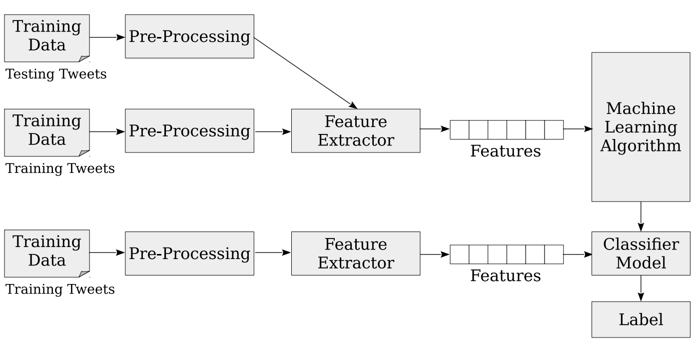

Fig. 4. Schematic Diagram of Methodology

We use a modularized approach with feature extractor and classification algorithm as two independent components. This enables us to experiment with different options for each component. Figure 4 illustrates different steps taken in the entire process.

A. Datasets

One of the major challenges in Sentiment Analysis of Twitter is to collect a labelled dataset. Researchers have made public the following datasets for training and testing classifiers.

1) Twitter Sentiment Corpus: This is a collection of 5513 tweets collected for four different topics, namely, Apple, Google, Microsoft, Twitter It is collected and hand-classified by Sanders Analytics LLC [8]. Each entry in the corpus contains, Tweet id, Topic and a Sentiment label. We use Twitter-Python library to enrich this data by downloading data like Tweet text, Creation Date, Creator etc. for every Tweet id. Each Tweet is hand classified by an American male into the following four categories. For the purpose of our experiments, we consider Irrelevant and Neutral to be the same class. Illustration of Tweets in this corpus is shown in Table I.

- **Positive:** For showing positive sentiment towards the topic.
- **Positive:** For showing no or mixed or weak sentiments towards the topic
- **Negative:** For showing negative sentiment towards the topic.
- **Irrelevant:** For non English text or off-topic comments.

TABLE I
Twitter Sentiment Corpus

Class	Count	Example
neg	529	#Skype often crashing: #microsoft, what are you doing?
neu	3770	How #Google Ventures Chooses Which Startups Get Its $200 Million http://t.co/FCWXoUd8 via @mashbusiness @mashable
pos	483	Now all @Apple has to do is get swype on the iphone and it will be crack. Iphone that is

IV. Result Analysis

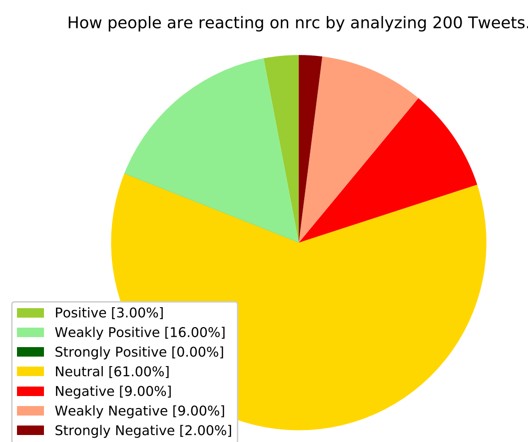

Fig. 5. Tweeter Sentiment Analysis on Keyword “NRC”

Figure 5 represents real-time tweeter sentiment analysis on the keyword “nrc”, it shows how many people are reacting on “nrc”by analyzing 200 tweets. Similarly, Figure 6 represents real-time tweeter sentiment analysis on the keyword “modi”, it shows how many people are reacting on “modi”by analyzing 200 tweets.

V. Conclusion

In this paper, the review and analysis of a sentiment classifiers are presented for twitter using labeled data sets. This report also investigate the relevance of using a double step

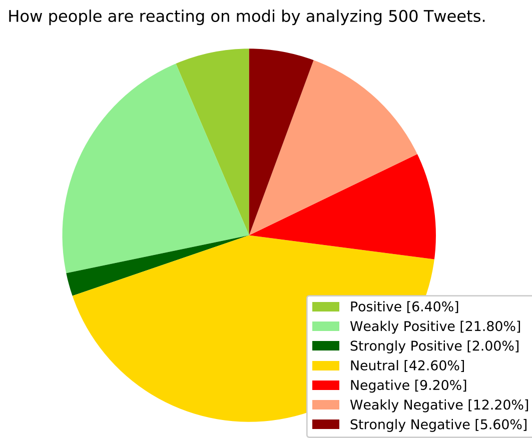

Fig. 6. Tweeter Sentiment Analysis on Keyword “MODI”

classifier and negation detection for the purpose of sentiment analysis.

Thus, it can be analyzed that both Negation Detection and higher order $n-$grams are useful for the purpose of text classification. However, if both $n-$grams and negation detection are used, the accuracy falls marginally. It is also noted that Single step classifiers out perform double step classifiers. In general, Maximum Entropy Classifier performs better than other Classifier as presented in result.

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