Emotion Extraction System on real time Demonetization Tweets using Machine Learning

Sandeep Kaur¹, Pardeep Kumar²

¹Assistant Professor, Lovely Professional University, Jalandhar, Punjab, India
²Assistant Professor, Lovely Professional University, Jalandhar, Punjab, India

People usually express emotions in various forms such as speech, facial expressions and text. Analyzing human emotions in text has grabbed a lot of attention, nowadays. This research work explores ways to automatic extraction of emotions in social media text. The text under research deals with data collected from Twitter, representing data rich in affective content. Corpus is specifically prepared on Demonetization. Demonetization was one of the decisions made by the Prime Minister Narendra Modi in 2016. Nevertheless, people were not aware of this action and they expressed their views and opinions that rich in sentiments and emotive content on social media such as Twitter. Efficient machine controversial learning algorithms Naïve Bayes and Support Vector machines have been used for automatic classification of emotions. Moreover, the accuracy achieved with SVM is 90.13%, however with that of Naïve Bayes is 85.03%. Furthermore, valuable inferences have been drawn from the real time tweets of demonetization that reveal that anger, fear, surprise and sadness are mostly expressed emotions over this issue.

Index Terms—Affective computing, Emotion Analysis, Naïve Bayes, Support Vector Machines.

I. INTRODUCTION

Emotion is a key factor that influences human behavior which includes reasoning, decision making and interaction. Emotions play a vital role in everyday human-human interaction and human computer interaction (Picard et al. 1997; Minsky 2007). Extraction of emotions from text is a subfield of sentiment analysis and is referred to as Affective computing (Cambria 2016). Affective computing and Sentiment analysis aims at making decisions from opinions of people available on social media, blogs, online forums and so on. The basic task of Affective computing is to extract emotions such as happiness, sadness, surprise, love, anger and so on (Cambria 2016; Minsky 2006). However, Sentiment analysis focuses on classifying text on the basis of polarity such as positive, negative or neutral (Gezici G. et al. 2013). Social media websites such as Twitter, Facebook and Instagram act as a medium for users to express and share their perspective (Pak, A., & Paroubek, P. 2010). These are huge source of information to extract meaningful inferences from them. Due to the rise of social networking media, Affective computing and sentiment analysis recently witnessed ample amount of interest from scientific community (Hu, M., & Liu, B; 2004; R. Calvo et al 2010).

Large amount of research has been done to extract emotions using facial expressions, human gestures, pitch of voice etc. This research is part of digital image processing. However, emotion extraction from text is a challenging task in the emerging field of Affective computing. Affective computing finds applications in many fields such as extracting consumer’s emotion and behavior towards products in large and small companies, brands and business organizations (Hu, M., & Liu, B; 2004). Moreover, opinions and sentiments can be extracted from social media sites to configure political issues (Maynard, D., & Funk, A. 2011), health issues and stock market prediction (Bollen et al. 2011). Emotions extracted from product reviews can help companies to enhance and shape up the products that received negative feedback (Catal, C., & Nangir, M. 2017). It is inevitable that emotions are directly related to the state of mind of a person, therefore Affective computing can be used to detect depression (De Choudhury et al. 2013). The automated tools for detecting sentiments and emotions are useful not only for commercial purposes such as predicting attitude towards brands and products, but also beneficial for government and political parties for election prediction and liking of a particular candidate.

With the emergence of online social sites, people are able to communicate and express their reviews and opinions in real time. Therefore, social media generates huge amount of data every day that can be utilized to find hidden inferences for decision making. This paper relies on data collected from Twitter. Moreover, certain predictions have been done by extracting real time tweets on political issue (Bravo M. et al 2014; Gezici G. et al 2013).

In emotion analysis, it is important to define diligently the goals of this research paper. This paper addresses the task of analysis emotions expressed in textual data. The main task is to assign a label to tweet and the labels used in this research work are happiness, sadness, anger, disgust, surprise, fear, mixed emotion and no emotion (Ekman 1992; Aman & Szpakowicz 2007). Those are the six basic emotion categories identified by Ekman (1992), and two additional labels for the presence of more than one emotion and absence of a clearly discernible emotion. The dataset for this project is drawn from Twitter using Twitter API. Twitter reviews and opinions mostly consists of unedited narrated text to audience which makes them rich in emotion rich content. Demonetization is one of the most controversial decisions made in India in year 2016. Many people posted their opinions on Twitter that comprises certain sentiments and emotions. Therefore, the main aim is to extract different types of emotions expressed by people on this particular issue.

The techniques used in this research work are machine learning based. SVM and Naïve Bayes have been used to perform fine grained classification of emotions.
The main goal of textual affect extraction is to understand how emotions are expressed in text and how different text triggers the emotions present in it. Emotions in text are subjective expression that best describe the feelings of a person. Affect detection is a major research area in cognitive sciences. However, there are some links to affective computing as well. Affect detection is a major research area in cognitive sciences. Moreover, many researchers explored different kinds of computational techniques. In general, there are two broad categories of techniques for the task of emotion analysis: Lexicon-based approach and Machine-learning approach.  

In this paper, the ultimate goal is to train the classifier using different emoticons and enabling the system to be domain-independent for the task of sentiment analysis.  

(Davidov et al. 2010) utilized twitter hashtags and smileys to...
get rid of labor intensive task of labeling the data. Consequently, they were able to automatically identify dozens of sentiments in the Twitter dataset. Moreover, they used different feature combinations such as smileys, punctuations, words, n-grams that contribute to the task of sentiment classification.

Table 1. Emotion Extraction techniques with different domains

<table>
<thead>
<tr>
<th>Authors</th>
<th>Emotion Label</th>
<th>Domain</th>
<th>Technique Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liu et al. (2003)</td>
<td>Happy, Sad, Anger, Fear, Disgust, Surprise</td>
<td>Open Mind Common Sense</td>
<td>Used real-world knowledge for common-sense based affect recognition</td>
</tr>
<tr>
<td>Alm et al. (2005)</td>
<td>Angry, Disgusted, Fearful, Happy, Sad, Positively Surprised, Negatively Surprised</td>
<td>Children’s Fairy Tales</td>
<td>Supervised Machine Learning</td>
</tr>
<tr>
<td>Baker (2007)</td>
<td>Direct affection online, Indirect affection online, Negative emotions</td>
<td>Emails and chat of online couples</td>
<td>Use of emoticons, pseudonyms and communication patterns</td>
</tr>
<tr>
<td>Ho et al. (2012)</td>
<td>Anger, Fear, Joy and Sadness, Touching, Empathy, Boredom, Surprise and Warmness.</td>
<td>ISEAR dataset</td>
<td>High Order Hidden Markov Model</td>
</tr>
<tr>
<td>Lei et al. (2014)</td>
<td>Anger, Amusement, Sadness,</td>
<td>News articles</td>
<td>Document Selection, POS tagging and social emotion lexicon generation</td>
</tr>
<tr>
<td>Wikarsa et al. (2015)</td>
<td>Happiness, Anger, Disgust, Surprise, Fear and Sadness</td>
<td>Twitter</td>
<td>Lexicon based feature extraction</td>
</tr>
<tr>
<td>Yeole et al. (2015)</td>
<td>Happy, Sad, Anger, Fear</td>
<td>Amazon sentiment dataset</td>
<td>Naive Bayes (Supervised machine learning)</td>
</tr>
<tr>
<td>Anil Bandhakavi (2016)</td>
<td>Surprise, Fear, Sadness, Anger, Joy, Disgust</td>
<td>Text Documents</td>
<td>Knowledge based and Machine Learning</td>
</tr>
<tr>
<td>Isidoros Perikos (2016)</td>
<td>Activated-positive, activated-negative, deactivated-positive and deactivated-negative</td>
<td>News, articles and tweets</td>
<td>Knowledge based and Machine Learning</td>
</tr>
<tr>
<td>Govind Gaikwad et al. (2016)</td>
<td>Funny, Happy, Sad and Angry</td>
<td>Twitter</td>
<td>Lexicon based and Machine Learning (SVM, NB and KNN)</td>
</tr>
<tr>
<td>Lee C. et al. (2017)</td>
<td>Pride, Love and Hate</td>
<td>Social (Umbrella Movement in Hong Kong)</td>
<td>Lexicon Based Approach</td>
</tr>
</tbody>
</table>

Table 2. Contribution of different authors for Demonetization

<table>
<thead>
<tr>
<th>Author</th>
<th>Analysis Type</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggarwal et al. (2017)</td>
<td>Calculated Polarity</td>
<td>Classified tweets on the basis of polarity like positive, negative and neutral using SVM</td>
</tr>
<tr>
<td>Arun et al. (2017)</td>
<td>Positive, Negative and Neutral</td>
<td>Performed Twitter sentiment analysis using R Interface</td>
</tr>
</tbody>
</table>
II. PROPOSED METHODOLOGY

In this section, the framework for emotion analysis, annotation of the dataset and steps used in methodology is presented. Emotion analysis is a classification task in which various instances are classified according to the assigned label by the classifier. In this task, emotion labels are provided to the tweets from a group of labels. To be more precise, the task of emotion analysis is represented as:

Let \( t \) represents a tweet and \( e \) is an emotion label where \( E = (e_1, e_2, e_3, ..., e_n) \) be a set of possible emotion categories to be assigned to the instances. The goal is to assign best possible emotion label from the set 'E' to the tweet 't' where \( e \in E \). In this paper, emotion analysis has been done at the sentence level for more fine-grained classification of emotions. Machine learning algorithms such as Naïve Bayes and Support Vector Machines (SVMs) have been used for automatic classification of emotions. Moreover, prediction of real-time unlabeled tweets has also been done using emotion detector and given emotion categories to automatically classify the tweets. The framework for emotion analysis is depicted in Figure 2.

A. Methodology

Data Collection: The pre-requisite to the task of emotion extraction is appropriate data. Therefore, data for this work is collected from Twitter. Twitter being a huge source of opinions and reviews provided real-time tweets on demonetization with desired affective content (Bollen, J., Mao, H., & Pepe, A. 2011). Tweets were downloaded from Twitter by establishing connection with Twitter API through the access of four keys: Application Key, Application Secret, Access Token, and Access Token Secret. Tweets have been extracted using hashtags such as #Demonetisation, #DeMonetisation, #Currencyban and #Noteban. For training the classifier, corpus is prepared of 1000 tweets on Demonetization and is annotated with emotion labels. The performance of the classifier significantly depends on the dataset. Hence, tweets with affect related content were considered for this task of emotion recognition.

Text Preprocessing: Tweets collected from Twitter contains misspellings, slang language, hyperlinks and other noisy forms of data. In order to tackle with this problem, cleaning techniques were used to normalize the data. Pre-processing techniques such as Tokenization, Stop-words removal, stemming, lemmatization, and dimensionality reduction helped pre-process the tweets. Furthermore, weka filters such as StringToWordVector and toLowerCase were applied that significantly enhanced the classification accuracy. Text pre-processing is a significant and essential step in text mining since it helps to achieve better accuracy and performance (Bao et al. 2014).

Table 3. Emotion Categories used in Annotation

<table>
<thead>
<tr>
<th>Emotion Category</th>
<th>Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>Happiness</td>
<td>hp</td>
</tr>
<tr>
<td>Sadness</td>
<td>sd</td>
</tr>
<tr>
<td>Anger</td>
<td>ag</td>
</tr>
<tr>
<td>Disgust</td>
<td>dg</td>
</tr>
<tr>
<td>Fear</td>
<td>fr</td>
</tr>
<tr>
<td>Surprise</td>
<td>sp</td>
</tr>
<tr>
<td>Mixed Emotion</td>
<td>me</td>
</tr>
<tr>
<td>No Emotion</td>
<td>ne</td>
</tr>
</tbody>
</table>

Table 4. Example of annotated sentences with emotion labels

<table>
<thead>
<tr>
<th>Tweet</th>
<th>Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>My piece explains why #Demonetisation is a success on all fronts.</td>
<td>Happiness</td>
</tr>
<tr>
<td>Black Money,Shell Cos,Digitisation.</td>
<td></td>
</tr>
<tr>
<td>#Demonetisation..economic disaster; #GST..badly conceived, poorly</td>
<td>Sadness</td>
</tr>
<tr>
<td>implemented.</td>
<td></td>
</tr>
<tr>
<td>Got my Aadhar linked to bank accounts. This is another stupid burden</td>
<td>Disgust</td>
</tr>
<tr>
<td>on people just like #DeMonetisation .God save us.</td>
<td></td>
</tr>
<tr>
<td>Stories Planted by Jai Italy to defame our PM @narendramodi: Modi</td>
<td>Anger</td>
</tr>
<tr>
<td>Is Truly to Blame for India Economic Slowdown.</td>
<td></td>
</tr>
<tr>
<td>The economy is on a downward spiral. Many in the BJP know it but do</td>
<td>Fear</td>
</tr>
<tr>
<td>not say it out of fear.</td>
<td></td>
</tr>
<tr>
<td>What people doing with 1000 note after #DeMonetisation.</td>
<td>Surprise</td>
</tr>
<tr>
<td>Killing 1 person is a murder but killing crores of ppl in the name of</td>
<td>Mixed Emotion</td>
</tr>
<tr>
<td>development is good. @narendramodi @arunjaitley</td>
<td></td>
</tr>
<tr>
<td>#Demonetisation #GDP</td>
<td></td>
</tr>
</tbody>
</table>

Feature Selection: The unigrams and bigrams have been used to structure the feature space for this emotion analysis system. In other words, Word N grams are used ranging from \( n=1 \) to \( n=2 \). TF-IDF (Term frequency and Inverse Document Frequency) is applied to extract the features for classification (Salton, G., & Buckley, C. 1988). Term frequency denotes the relative importance of a term to a document. To be more precise, the importance of a word in a document depends on the frequency of that word. TF-IDF is used to assign weight to each term \( t \) present in a document \( d \) and is calculated by the following equation (1):

\[
tf - idf_{t,d} = tf_{t,d} \times idf_t
\]
where \( \text{id}_f \) = \( \log_2 |D| \) if \( d: t \in d \) and \( |D| \) is the total number of documents and \( d: t \in d \) is the number of documents where term \( t \) occurs.

**Classification:** Classification of tweets has been performed using two supervised classifiers. In this paper, Naïve Bayes and Support Vector Machines have been used for fine-grained classification of emotions. Ten-fold cross validation model was built to test the efficiency of the system.

1. **Naïve Bayes:** Naïve Bayes is implemented to calculate the probability of a tweet belonging to any emotion category. Therefore, for each emotion \( e \in E \), we have:

\[
P(e|t) = \frac{P(t|e)P(e)}{P(t)} = \prod_{w \in t} P(w|e)P(e)
\]

where \( w \) is the word in tweet \( t \). \( P(e) \) is the probability of tweet \( t \) belonging to emotion \( e \). \( P(w|e) \) is the probability of each word that belongs to emotion category \( e \) which yields the prediction as below:

\[
\text{value}[e] = P(e) \prod_{w \in t} P(w|e)
\]

2. **Support Vector Machines:** Support Vector Machines (SVMs) is implemented with the motive to construct a hyper-plane that separates different emotion classes with the maximum distance. In our method, each label is considered as a single class. SVM has been implemented using LibSVM, a publicly available Support Vector Machines Package.

**B. Proposed Algorithm**

**Algorithm: Emotion Extraction System**

**Input** trainset, testset  
**Output** labelset  
1: **for** each tweet \( t \in \text{testset} \) **do**  
2: **for** each emotion \( e \in E \) **do**  
3: \( \text{value}[e] = 0 \)  
4: **end for**  
5: Apply **Tokenization, Stoplists, Stemming and Lemmatization.**  
6: Convert each tweet \( t \) into feature vector \( \vec{F} \) by calculating weight \( W(w, t) \) for each word \( w \)

\[
W(w, t) = \frac{tf(w, t) \times \log(N/n_i + 0.01)}{\sqrt{\sum_{w} -[tf(w, t) \times \log(N/n_i + 0.01)]^2}}
\]

where \( tf(w, t) \) is the frequency of each word \( w \) in tweet \( t \).  
\( N \) is the total no. of tweets,  
\( n_i \) is the no. of tweets that contain word \( w \)  
7: **for** each feature vector \( \vec{F} \) **do**  
8: **for** each emotion \( e \in E \) **do**  
9: calculate probability \( p \) of \( t \in e \) using Naïve Bayes  
10: \( \text{value}[e] = p \)  
11: **end for**  
12: add each \( e \) to labelset  
13: **end for**  
14: **for** each feature vector \( \vec{F} \) **do**  
16: Classify each tweet \( t \) using Support Vector Machines such as \( H: t \rightarrow e \in E \)  
17: **end for**  
18: add each \( e \) to labelset  
19: **end for**  
20: **end for**

**IV. EVALUATION RESULTS**

In this section, the performance analysis of the proposed emotion analysis methodology has been evaluated for the Demonetization dataset. Experiments have been conducted using Netbeans. Additionally, Weka libraries are utilized for classification and evaluation purposes. Effective fine-grained emotion classification has been performed using Support Vector Machines (SVMs) and Naïve Bayes (NB). Moreover, Unigrams and Bigrams are used as features that are fed in machine learning algorithms. Moreover, a comparative performance analysis of Naïve Bayes and SVM is examined on the basis of accuracy, precision, recall, F-measure and other important parameters as shown in Table5. For evaluation purposes, ten-fold cross-validation experiments have been conducted. Dataset is randomly split in \( k \) folds and for each \( k \) fold, \( k-1 \) is used for building the model as training set. Then, to examine the effectiveness of the model, \( k^{th} \) fold is used as testing set. This procedure is repeated until all the \( k \) folds have served the dataset. The results of NB and SVM are shown in Table6 and Table7. Results are explained in terms of precision, recall and F-measure for each emotion label. Recall and precision are the measures used for determining classifier performance and are defined in terms of actual and predicted classes. The recall for a certain class is the proportion of successfully classified texts relevant to that class. A perfect recall means that every text for that class is correctly classified. It is equivalent to sensitivity.

\[
\text{Recall} = \frac{TP}{TP + FN}
\]

Precision is the measure of proportion of the classes that were classified as positive and were actually positive. It is equivalent to positive predictive value.

\[
\text{Precision} = \frac{TP}{TP + FP}
\]

F-score (also known under other names such as F-measure) is a weighted harmonic mean of precision and recall. A higher F-score indicates better joint recall and precision compared to a lower score, and therefore better performance.

\[
F \text{ measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]
The major contribution of this paper is to present that it is feasible to apply intelligent machine learning and computation techniques for the extraction of emotions in text. An automatic classification of emotions in text is presented. People expressed different emotions and sentiments on Twitter on this issue. Hence, real-time tweets were collected from Twitter for evaluation of emotions present in the opinions. Therefore, 300 tweets were collected and used for the prediction. In this case, a test data set was formed without any labels. Machine learning algorithm automatically classified tweets into emotion categories. Results show that most expressed emotions on this issue were anger, disgust and fear (Figure 5). Therefore, anger, disgust and fear being the negative emotions reveal that the impact of demonetization on Indian economy and people is negative rather than positive.

Moreover, the other main contribution of this paper is the extraction of meaningful inferences from the dataset of Demonetization. People expressed different emotions and sentiments on Twitter on this issue. Hence, real-time tweets were collected from Twitter for evaluation of emotions present in the opinions. Therefore, 300 tweets were collected and used for the prediction. In this case, a test data set was formed without any labels. Machine learning algorithm automatically classified tweets into emotion categories. Results show that most expressed emotions on this issue were anger, disgust, and fear (Figure 5). Therefore, anger, disgust, and fear being the negative emotions reveal that the impact of demonetization on Indian economy and people is negative rather than positive.

On comparing, the performance of the SVM classifier is found to be better than Naïve Bayes classifier. Accuracy achieved by SVM is 90.13%, however Naïve Bayes achieved 85.034% (Figure 3). Furthermore, precision, recall and F-measure have been calculated for each emotion label. For Naïve Bayes emotion with label ‘happiness’ achieved maximum F-measure whereas emotion labels ‘no emotion’ and ‘anger’ achieved minimum F-measure. In case of SVM, maximum of 0.962 F-measure was achieved for calculation of emotion ‘surprise’, however emotion with label ‘mixed emotion’ achieved minimum value of F-measure. Moreover, a comparative analysis of Naïve Bayes and SVM has been done on the precision parameter of each emotion label (Figure 4). For NB, precision parameter of calculation of emotion label ‘happiness’ is maximum that is 1; however it is minimum for anger. In case of SVM, precision of emotion labels ‘happiness’ and ‘no emotion’ is 1.
achieved with SVM is 90.13%. Moreover, it is inferred that precision parameter for calculation of certain emotions is more. In experiments, for SVM precision for classification of happiness and no-emotion is 1, whereas for mixed emotion is least. In case of Naïve Bayes, precision for calculation of happiness is maximum; however for anger precision is minimum. Furthermore, meaningful inferences are drawn in the domain of politics. Real time tweets were collected to predict the presence of emotions in data. It is concluded that, anger is most expressed emotions in this domain. Moreover, people expressed disgust, fear, surprise and sadness in ample amount. However, very less people expressed happiness. Therefore, the impact of demonetization is negative rather than positive.

This work can be further extended in various other domains. Moreover, emotions and other punctuation marks can be considered as features for achieving better accuracy.

REFERENCES

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