Exploring Human Emotion Via Twitter

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Abstract—**Sentiment analysis or opinion mining on twitter data is an emerging topic in research. In this paper, we have described a system for emotion analysis of tweets using only the core text. Tweets are usually short, more ambiguous and contains a huge amount of noisy data, sometimes it is difficult to understand the user's opinion. The main challenge is to feature extraction for the purpose of classification and feature extraction depends on the perfection of preprocessing of a tweet. The preprocessing is the most difficult task, since it can be done in various ways and the methods or steps applied in preprocessing are not distinct. Most of the researches in this topic, have been focused on binary (positive and negative) and 3-way (positive, negative and neutral) classifications. In this paper, we have focused on emotion classification of tweets as multi-class classification. We have chosen basic human emotions (happiness, sadness, surprise, disgust) and neutral as our emotion classes. According to the experimental results, our approach improved the performance of multi-class classification of twitter data.**

Keywords—sentiment analysis; emotion analysis; twitter; tweet; feature extraction; unigram; POS tag; classification; bag of words; naive bayes

I. INTRODUCTION

We now live in a time where social media has great influence on our social life. Social Media has become an important part of our regular life and Twitter is one of the famous among them. As the growth and uses of social media are increasing rapidly so does the twitter. The number of twitter users reached an estimated 328 million in previous year, up from approximately 9 million in previous year [9]. Not only regular users but also celebrities, company representatives, politicians and even country presidents are audiences of twitter. The increasing importance of Twitter is also mentionable. Mainly Twitter doesn't support larger message but short message. Twitter message is called tweets which is 140 characters long. Though tweets are short in length but they are important and sometimes very effective for expressing emotions. In this short tweets people express positive or negative feelings on any subject they face in their daily life, post real time message on variety of topics, discuss about social phenomena.

As many customers post reaction about products, most manufacturing companies take feedbacks very seriously and analyze these whether feedbacks are positive or negative. They also make publicity for their products in twitter. Not only products, twitter is famous for political as well as social affairs. Some political parties make campaign on social media and twitter is favorite one. Therefore, microblogging website like twitter has potential sources of data that are important for sentiment analysis.

In our paper, we have applied a technique for emotion analysis of tweets using unigram model and unigram model with POS tags for feature extraction and Naïve Bayes classifier for classification of emotions. We have classified tweets into five classes (happiness, sadness, disgust, surprise and neutral) where four classes of emotion (except neutral) have been chosen according to the theories of psychologist Paul Ekman's basic human emotions [8] for our research. Most of the previous researches in this area used binary classification (positive, negative) and 3-way classification (positive, negative and neutral). Here we have tried to achieve a new aspect of multiclass classification of human emotion.

II. RELATED WORK

Different researchers have proposed different methods for sentiment analysis. Some based on lexicon features or probabilistic, some based on machine learning techniques, and some based on combined those two techniques. Some of them are explained in the following:

Agarawal et al. [1] built model for two classification tasks: a binary task of classifying sentiment into positive and negative classes and a 3-way task of classifying sentiment which are positive, negative and neutral classes. For the experiment they used three types of models: unigram model, a feature based model and a tree kernel based model. They used manually annotated twitter data where each tweet is labeled as positive, negative, neutral or junk and they eliminated tweet with junk label for experiments. For prior polarity scoring they used

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Dictionary of Affect in Language (DAL) and extended it using WordNet. They considered words with polarity less than 0.5 as negative, higher than 0.8 as positive, and rest as the neutral. Support Vector Machines (SVM) was used for all of their experiments and got averaged test results using 5-fold cross-validation.

Pak and Paroubek [2] collected a corpus of 300000 tweets from Twitter and evenly splitted these into three sets of texts: texts containing positive emotions, negative emotions and no emotions. They examined emoticons which were mainly happy emoticons and sad emoticons. They used TreeTagger for English to tag all the posts in the corpus. For training classifier, they used different models like unigrams, bigrams and trigrams models. For the purpose of filtering they removed the URL links, Twitter usernames and emoticons from twitter post. They segmented text by splitting it by space and punctuation marks, and form a bag of words and removed articles ("a", "an", "the") from the bag of words. For classification they built sentiment classifier using multinomial Naïve Bayes classifier. They also tried SVM and CRF, however the Naïve Bayes classifier yielded the best results.

Pang et al. [3] analyzed sentiment using three machine learning techniques. They considered the problem of classifying documents by overall sentiment and determined a review whether it was positive or negative. For their experiments, they wanted to work with movie reviews. They experimented with three standard classifiers: Naïve Bayes classification, Maximum Entropy classification and Support Vector Machines. This paper represented that better performance was achieved by accounting only for feature presence not feature frequency and bigram information did not improve performance beyond that of unigram presence.

Go et al. [4], in their research didn't consider neutral tweets in their training or testing data. They only used positive and negative tweets. They stripped the emoticons out from their training data because according to their research emoticons does negative impact on the accuracy of Maximum Entropy and SVM classifier, but little impact on Naïve Bayes. In feature reduction process, an equivalent class token("USERNAME") was replaced all words that start with the "@" symbol. They converted URL like http://tinyurl.com/cvvg9a to the token "URL". They tested different classifiers: key-based, Naïve Bayes, Maximum Entropy, and support vector machines They explored the usage of unigrams, bigrams, unigrams and bigrams, and parts of speech as features. They showed that unigrams and bigrams gave the best result.

Purver and Battersby [5] in their research they mainly worked on emoticons and hashtags. In their work, they classified emoticons and hashtags with six basic emotions. Classification in all experiments they used Support Vector Machines (SVM) via LIBSVM implementation with linear kernel and unigram features. In this paper three individual experiments were done. Experiment 1: Emotion detection, experiment 2: emotion discrimination and experiment 3: manual labeling. These experiments are based on both emoticons and hashtags and they got 50-80% accuracy varies from experiment to experiment. For reliable classification of these emoticons they further set up a web survey to examine. The survey was completed by 492 individuals.

III. Our Approach

Paul Ekman, an American psychologist has proposed a concept that emotions are discrete, measurable and physiologically distinct. Ekman's most remarkable research focused on the finding of certain emotions that is appeared to be universally acknowledged. His research made him conclude to classify six emotions as: happiness, sadness, surprise, anger, fear, disgust [8].

In 03 February, 2014, new research was published in the journal "Current Biology" by the scientists at the University of Glasgow and in that journal he challenged Ekman's view and had a different opinion that there were only four basic emotions. They said fear and surprise shared the "signal" of wide open eyes, while anger and disgust shared a wrinkled nose [9]. We have chosen four classes (happiness, sadness, surprise, disgust) and five classes (happiness, sadness, surprise, disgust, neutral) for our emotion classification from Paul Ekman's six basic human emotion.

A. *Proposed Framework:*

In the previous papers, most of the sentiment analysis have been done in binary classification or 3-way classification. Multiclass classification of sentiment analysis using basic human emotions are being researched now-a-days. Now here we will discuss about our framework on sentiment analysis using basic human emotions. Fig. 1 represents the steps our proposed framework for emotion analysis.

B. *Data Set*

As sentiment analysis of tweets is a very popular topic in research nowadays, there remains a lot of labeled data in online. Twitter APIs can also be used to access twitter data. Though there remain few papers on emotion analysis, but no labeled dataset of emotion analysis cannot be found in online. So we have to label the data by ourselves. The website Sentiment140 provides us with a human labeled corpus with over 1600000 tweets with three polarities (positive, negative and neutral). We have collected our tweets from this site then labeled manually.

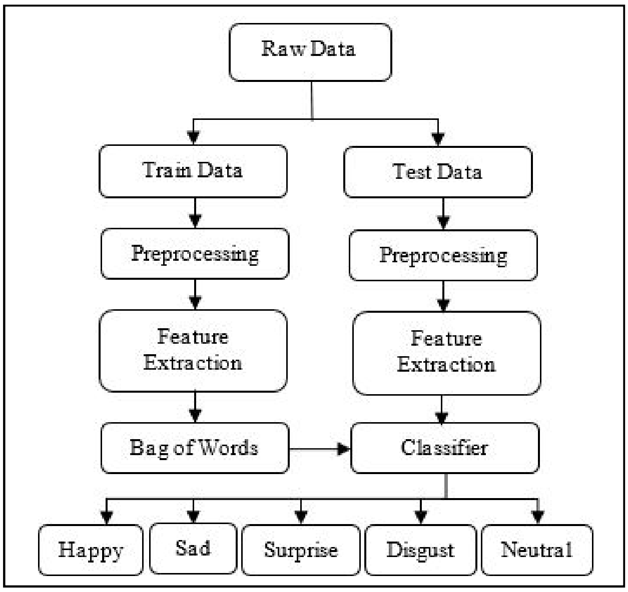

Fig. 1. Proposed Framework

We have collected 4642 tweets from the website Sentiment140. Some tweets contain only hashtags, as we want to work only with basic text, we have eliminated these tweets. Some tweets only contain symbols and some tweets contain more than one language, we have eliminated those tweets also. Then we selected total 4232 tweets form there. 1500 tweets were shared with our friends for the purpose of labeling and the rest of the tweets were labeled by us. While labeling we found some tweets that do not represent any kind of emotion, we have also eliminated these tweets. Then we have used a balanced data set of 3750 tweets (750 tweets each class from classes happy, sad, surprise, disgust, neutral as training data). From here, we have used 3500 tweets as training data and 250 tweets as test data.

C. Data Preprocessing

After getting those labeled data we have processed the data because tweets contain a lot of noisy data because of its short length. Few of the major preprocessing steps are mentioned below:

- We have created a dictionary full of acronyms and abbreviations with respect to their English expansion. Some popular acronyms that are frequently used in social media were collected [6]. Example: lol: laughing out loud; ur: your.
- In tweets there are sequence of repeated characters like “coooooool”, “wishhhhh”, “happyyyyyy”, etc. These are converted to “cool”, “wishh”, “happyy”.
- The goal of stemming and lemmatization is to identify a common base form of a word by reducing inflectional forms. We have applied stemming and lemmatization. For example, “car”, “cars”, “car’s” these all words will be reduced into “car”.
- In this step of preprocessing we have removed the punctuation marks. Because punctuation marks in a text do not represent any sentiment or emotion except “!” which represents emotion.
- A hashtag is any word or phrase immediately preceded by the “#” symbol. By clicking on the hashtag users can view other tweets containing the same keyword or topic [11]. We have seen that some researches were done using hashtag. As we have mentioned that we want to work on only text, we have removed all the hashtags from the tweets. The “@” sign is used to mention usernames in tweets [11]. Here these mentioned usernames do not represent any kind of emotions. We have removed these usernames.

We have also removed the emoticons, URLs, targets, punctuation, stop-words to simplify and make the classification more accurate.

D. Bag of Words Model

In Natural Language Processing, the Bag of Words model is a simplifying representation which is used to turn a document into an unsorted list of words, mainly used for classifying texts by getting their frequency of a word in a document [12]. We have used the frequency as a feature for training of the classifier. For a simple text document: “Busy day ahead of me”, a unigram model will parse the text into following units and store the terms frequency of each unit: [“Busy”, “day”, “ahead”, “of”, “me”].

E. Feature Extraction

For feature extraction we have used unigram model and unigram model with POS tagging. Here we have discussed about our feature extraction models.

1) Unigram: Unigram is one of the most popular feature extraction models for sentiment analysis. To find sequence of probabilities over sequence of terms we can always use the chain rule to decompose the probability of a sequence of events into the probability of each successive event conditioned on earlier events. The chain rule in general:

$$P(x_1,x_2,x_3,\ldots\ldots,x_n) = P(x_1)P(x_2|x_1)P(x_3|x_2,x_1)\ldots\ldots\ldots P(x_n|x_{n-1},\ldots\ldots x_1)$$

Unigram model is considered as the simplest form of language model as it simply doesn't consider conditioning context and determine each term independently. For such a unigram model:

$$P_{uni}(x_1,x_2,x_3,\ldots\ldots,x_n) = P(x_1)P(x_2)P(x_3)\ldots\ldots\ldots P(x_n)$$

In this model, each word hits with a probability which only depends its own so we will only have one-state finite automata as units. Many researchers showed the simplicity and effectiveness of unigram model in their sentiment analysis experiments. That's why we have used unigram model for our feature extraction.

2) Unigram with POS tag: We have processed our tweets using Natural Language Toolkit (NLTK) [10] which is popular for computational linguistic and is a suite of libraries and programs for Natural Language Processing (NLP) written in Python programming language. We have applied unigram model and using NLTK, each word is annotated with POS tag. We have chosen the words with following POS tags for our feature extraction. Example: VB, VBP, VBD, VBG, VBN, VBZ, UH, RB, RBS, RBS, JJ, JJR, JJS, NN, NNP, NNS, NNPS.

F. Classifier

We have used Multinomial Naïve Bayes for text classification which is type of Naïve Bayes classifier. Naïve Bayes is a simple model which works well to perform text classification [7]. For a document 'd' and a class 'c', Naïve Bayes classifier:

$$c_{MAP} = \arg\max_{c\in C} P(c|d) \quad (1)$$

where, MAP is "maximum a posteriori"

$$= \text{most likely class.}$$

$$= \arg\max_{c\in C} \frac{P(d|c)P(c)}{P(d)} \quad \text{[Bayes rule]}$$

$$= \arg\max_{c\in C} P(d|c)P(c)$$

because, P(d) plays no rule in selecting c (Pang et al. [3]).

$$= \arg\max_{c\in C} P(x_1, x_2, x_3, \ldots\ldots, x_n|c)P(c)$$

Document 'd' represents as features $x_1, x_2, x_3, \ldots\ldots\ldots x_n$

Assuming the feature probabilities $P(x_i|c)$ are independent given the class c,

$$P(x_1, x_2, x_3, \ldots\ldots, x_n|c) = P(x_1|c)P(x_2|c)P(x_3|c)\ldots\ldots P(x_n|c) \quad (2)$$

So,

$$C_{NB} = \arg\max_{c\in C} P(c)\prod_{x\in X} P(x|c) \quad \text{[NB=Naïve Bayes]}$$

Multinomial Naïve Bayes is a special version of Naïve Bayes that captures word frequency information in documents.

Simply using the frequencies in the data,

$$P(x_i|c_j) = \frac{\text{count}(x_i,c_j)}{\sum_{w\in V}\text{count}(x,c_j)}$$

where, v is the vocabulary.

We have also used laplace smoothing for classifying emotion accurately.

IV. EXPERIMENTAL RESULT

We have presented our results for two classification tasks:1) happy versus sad versus surprise versus disgust which is a 4-way classification and 2) happy versus sad versus surprise versus disgust versus neutral which is a 5-way classification. For each of the classification tasks we have presented our experimental results below.

A. 4-Way Classification

The performance of our two feature extraction models for 4-way classification shows in Table I.

TABLE I. ACCURACY OF 4-WAY CLASSIFICATION

Feature Extraction Model	**Accuracy**				**Average Accuracy**
	Happy	***Sad***	***Surprise***	***Disgust***	
Unigram	78%	84%	92%	70%	81%
Unigram with POS tagging	76%	80%	94%	68%	79.5%

B. 5-Way Classification

The performance of our two feature extraction models for 5-way classification shows in Table II.

TABLE II. ACCURACY OF 5-WAY CLASSIFICATION

Feature Extraction Model	**Accuracy**					**Average Accuracy**
	Happy	***Sad***	***Surprise***	***Disgust***	***Neutral***	
Unigram	70%	80%	90%	70%	20%	66%
Unigram with POS tagging	68%	76%	94%	68%	18%	64.8%

V. ANALYSIS

We have compared our result with other papers. The comparisons are given below.

Table III compares the accuracy of our system with the system of Agarwal et al. [1].

TABLE III. COMPARISON OF ACCURACY OF OUR SYSTEM AND AGARWAL ET AL. [1]

Feature Extraction	**Accuracy of our system**		**Accuracy of Agarwal et al. [1]**	
	4-way classification	***5-way classification***	***2-way classification***	***3-way classification***
Unigram	81%	66%	71.35%	56.58%

Table IV compares the accuracy of our system with the system of Go et al. [4].

TABLE IV. COMPARISON OF ACCURACY OF OUR SYSTEM AND GO ET AL. [4]

Feature Extraction	**Accuracy of our system**		**Accuracy of Go et al. [4]**
	4-way classification with Naïve Bayes	***5-way classification with Naïve Bayes***	***Binary classification with Naïve Bayes***
Unigram	81%	66%	81.3%
Unigram with POS tagging	79.5%	64.8%	79.9%

Apart from this, Agarwal et al. [1] achieved highest average accuracy of 75.39% using Unigram with Senti-features in their 2-way classification and for 3-way classification they achieved highest average accuracy of 60.83% using Kernel with Senti-features. They used SVM classifier for their experiment.

Except that, Go et al. [4] achieved highest accuracy of 83.0% using unigram with bigram and Maximum Entropy classifier. Their experiment was on binary classification: positive versus negative and they used Naïve Bayes, Maximum Entropy and SVM classifiers.

Purver and Battersby [5] achieved highest F-score of 77.5% for emoticon happy and for hashtag anger they achieved highest F-score of 65.9% while for 4-way classification and 5-way classification our achievement in highest F-score are respectively 90.4% and 83.2%.

VI. CONCLUSIONS

Now-a-days microblogging site becomes a part of our communication and social life. It has a great deal on personal, social, business and politics. So sentiment analysis of these microblogging sites have great means and researchers already have worked on sentiment analysis of these microblogging sites. We hereby have developed a system for emotion analysis with Naïve Bayes classifier for twitter data. Our prime concern is to deal with only the text portion of a text. Comparing with related papers, we can see that our results do not differ much from theirs.

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