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Emotion Identification of POMS and Multinomial using Machine Learning Approach

Vinit Vijay Magre
Research Scholar, Department of Information Technology
MGM's Jawaharlal Nehru Engineering College, Aurangabad

Abstract- The analysis of social networks is a very challenging research area while a fundamental aspect concerns the detection of user communities. The existing work of emotion recognition on Twitter specifically depends on the use of lexicons and simple classifiers on bag-of words models. The vital question of our observation is whether or not we will enhance their overall performance using machine learning algorithms. The novel algorithm a Profile of Mood States (POMS) represents twelve-dimensional mood state representation using 65 adjectives with combination of Ekman's and Plutchik's emotions categories like, anger, depression, fatigue, vigour, tension, confusion, joy, disgust, fear, trust, surprise and anticipation. These emotions classify with the help of text based bag-of-words and LSI algorithms. The contribution work is to apply machine learning algorithm for emotion classification, it gives less time consumption without interfere human labeling. The Multinomial Naïve Bayes classifier works on testing dataset with help of huge amount of training dataset. Measure the performance of POMS & Multinomial Naïve Bayes algorithms on Twitter API. The result shows with the help of Emojis for emotion recognition using tweet contents.

Keywords- Emotion Recognition, Text Mining, Twitter, Recurrent Neural Networks, Convolutional Neural Networks, Multinomial Naïve Bayes Classifier

I. INTRODUCTION

Emotions can be defined as conscious affect attitudes, which constitute the display of a feeling. In recent years, a large number of studies have focused on emotion detection using opinion mining on social media. Due to some intrinsic characteristics of the texts produced on social media sites, such as the limited length and casual expression, emotion recognition on them is a challenging task. Previous studies mainly focus on lexicon-based and machine learning based methods. The performance of lexicon-based methods relies heavily on the quality of emotion lexicon and the performance of machine learning methods relies heavily on the features. Therefore, we work with three classifications that are the most popular, and have also been used before by the researchers from computational linguistics and natural language processing (NLP). Paul Ekman defined six basic emotions by studying facial expressions. Robert Plutchik extended Ekman's categorization with two additional emotions and presented his categorization in a wheel of emotions. Finally, Profile of Mood States (POMS) is a psychological instrument that defines a six-dimensional mood state representation using text mining. The novel algorithm a Profile of Mood States (POMS) generating twelve-dimensional mood state representation using 65 adjectives with combination of Ekman's and Plutchik's emotions categories like, anger, depression, fatigue, vigour, tension, confusion, joy, disgust, fear, trust, surprise and anticipation. Previous work generally studied only one emotion classification. Working with multiple classifications simultaneously not only enables performance comparisons between different emotion categorizations on the same type of data, but also allows us to develop a single model for predicting multiple classifications at the same time.

II. RELATED WORK

In [1] paper, check out whether or not public mood as measured from big-scale series of tweets published on twitter.com is correlated or even predictive of DJIA values. The consequences shows that modifications within the public temper nation can certainly be tracked from the content of large-scale Twitter feeds by way of instead simple textual content processing techniques and that such changes reply to a ramification of socio-cultural drivers in an exceptionally differentiated way. Advantages are: Increases the performance. Public temper evaluation from Twitter feeds gives an automated, fast, unfastened and massive-scale addition to this toolkit that can be optimized to degree a diffusion of dimensions of the public temper nation. Disadvantages are: It avoids geographical and cultural sampling mistakes.

The paper [2] Analyzed financial blogs and on-line news articles to expand a public mood dynamic prediction model for stock markets, referencing the perspectives of behavioral finance and the traits of online economic groups. A public mood time series prediction model is likewise provided, integrating features from social networks and behavioral finance, and uses huge information evaluation to assess emotional content material of commentary on modern inventory or economic issues to forecast changes for Taiwan stock index. Advantages are: It is convenient for feature word expansion and processing speed. More widely used. Disadvantages are: Only uses for stock prices.

In [3] paper the software of deep recurrent neural networks to the challenge of sentence-stage opinion expression extraction. DSEs (direct subjective expressions) consist of specific mentions of personal states or speech events expressing nonpublic states; and ESEs (expressive subjective expressions) encompass expressions that imply sentiment, emotion, etc., without explicitly conveying them. Advantages are: Deep RNNs outperformed previous (semi) CRF baselines; achieving new state-of-the-art results for fine-grained on opinion expression extraction. Disadvantages are: RNNs do not have access to any features other than word vectors.

In [4] paper analyze electoral tweets for extra subtly expressed facts such as sentiment (tremendous or bad), the emotion (pleasure, sadness, anger, and so forth.), the cause or reason behind the tweet (to point out a mistake, to aid, to ridicule, and so forth), and the style of the tweet (simple statement, sarcasm, hyperbole, and many others). There are sections: on annotating textual content for sentiment, emotion, fashion, and categories including cause, and on automatic classifiers for detecting those classes. Advantages are: Using a multitude of custom engineered features like those concerning emoticons, punctuation, elongated words and negation along with unigrams, bigrams and emotion lexicons features, the SVM classifier achieved a higher accuracy. Automatically classify tweets into eleven categories of emotions. Disadvantages are: Does not summarize tweets. It does not automatically identifying other semantic roles of emotions such as degree, reason, and empathy target.

In [5] paper, i) represent how large amounts of social media data can be used for large-scale open-vocabulary personality detection; ii) evaluate which features are predictive of which personality dimension; and iii) present a novel corpus of 1.2M English tweets (1,500 authors) annotated for gender and MBTI. Advantages are: The personality distinctions, namely INTROVERTEXTROVERT (IE) and THINKINGFEELING (TF), can be predicted from social media data with high reliability. The large-scale, open-vocabulary analysis of user attributes can help improve classification accuracy.

The paper [6] develops a multi-task DNN for learning delegations across multiple tasks, not only leveraging huge amounts of cross-task data, but also benefiting from a regularization effect that leads to more general representations to help tasks in new domains. A multi-task deep neural network for representation learning, in particular focusing on semantic classification (query classification) and semantic information retrieval (ranking for web search) tasks. Demonstrate strong results on query classification and web search. Advantages are: The MT-DNN strongly performs using strong baselines across all web search and query classification tasks. Multitask DNN model successfully combines tasks as disparate as classification and ranking. Disadvantages are: The query classification incorporated either as classification or ranking tasks not comprehensive exploration work.

In [7] article, show that emotion-word hashtags are good manual labels of emotions in tweets. Proposes a method to generate a large lexicon of word emotion associations from this emotion-labeled tweet corpus. This is the first lexicon with real-valued word emotion association scores. Advantages are: Using hashtagged tweets can collect large amounts of labeled data for any emotion that is used as a hashtag by tweeters. The hashtag emotion lexicon is performed significantly better than those that used the manually created WordNet affect lexicon. Automatically detects personality from text. Disadvantages are: This paper works only on given text not synonym of that text.

The paper [8] focuses on studying two fundamental NLP tasks, Discourse Parsing and Sentiment Analysis. The improvement of 3 independent recursive neural nets: for the key sub-obligations of discourse parsing, specifically structure prediction and relation prediction; the 1/3 internet for sentiment prediction. Advantages are: The latent Discourse features can help boost the performance of a neural sentiment analyzer. Pre-training and the individual models are an order of magnitude faster than the Multi-tasking model. Disadvantages are: Difficult predictions to multi-sentential text.

In [9] paper, Twitter Spam has turned into a fundamental downside nowadays. Current works have practical experience in applying machine learning procedures for Twitter spam location that construct utilization of the connected math choices of tweets. and in this manner the execution of existing machine learning based classifiers diminishes. This issue is alluded to as "Twitter Spam Drift" and the anticipated plan can find "changed". Spam tweets from unlabelled tweets and consolidate them into classifier's preparation procedure. Various examinations are performed to assess the proposed plan. The outcomes demonstrate that our proposed Lfun plan can essentially enhance the spam identification precision in certifiable situations.

The paper [10] Anomaly recognition is utilized in different applications like discovery of misrepresentation, arrange examination, observing traffic over systems, fabricating and ecological programming. The information streams which are produced are constant and changing after some time. This is the motivation behind why it turns out to be about hard to identify the exceptions in the current information which is colossal and ceaseless in nature. This method increases the speed of outlier detection by 20 times and the speed goes on increasing with the increase with the number of data attributes and input data rate.

III. OPEN ISSUES

The ability of the human face to communicate emotional states via facial expressions is well known, and past research has established the importance and universality of emotional facial expressions. However, recent evidence has revealed that facial expressions of emotion are most accurately recognized when the perceiver and expresser are from the same cultural in group. Paul Ekman explains facial expressions to define a set of six universally recognizable basic emotions: anger, disgust, fear, joy, sadness and surprise. Robert Plutchik defined a wheel-like diagram with a set of eight basic, pairwise contrasting emotions; joy –sadness, trust – disgust, fear – anger and surprise – anticipation. Consider each of these emotions as a separate category, and disregard different levels of intensities that Plutchik defines in his wheel of emotions.

Disadvantages:

A. Ekman's Facial expressions limitations:

1. Image quality

Image quality affects how well facial-recognition algorithms work. The image quality of scanning video is quite low compared with that of a digital camera.

2. Image size

When a face-detection algorithm finds a face in an image or in a still from a video capture, the relative size of that face compared with the enrolled image size affects how well the face will be recognized.

3. Face angle

The relative angle of the target's face influences the recognition score profoundly. When a face is enrolled in the recognition software, usually multiple angles are used (profile, frontal and 45-degree are common).

4. Processing and storage

Even though high-definition video is quite low in resolution when compared with digital camera images, it still occupies significant amounts of disk space. Processing every frame of video is an enormous undertaking, so usually only a fraction (10 percent to 25 percent) is actually run through a recognition system.

B. Plutchik's algorithm limitations:

1. The FPGA Kit uses hardware that is expensive. Thus, making this approach a cost ineffective technological solution.
2. Also, there is an additional dimension which involves a lot of tedious calculations.

IV. PROPOSED METHODOLOGY

Profile of Mood States is a psychological instrument for assessing the individual's mood state. It defines 65 adjectives that are rated by the subject on the five-point scale. Each adjective contributes to one of the six categories. For example, feeling annoyed will positively contribute to the anger category. The higher the score for the adjective, the more it contributes to the overall score for its category, except for relaxed and efficient whose contributions to their respective categories are negative. POMS combines these ratings into a six-dimensional mood state representation consisting of categories: anger, depression, fatigue, vigour, tension and confusion. Comparing to the original structure, we discarded the adjective blue, since it only rarely corresponds to an emotion and not a color, and word-sense disambiguation tools were unsuccessful at distinguishing between the two meanings. We also removed adjectives relaxed and efficient, which have negative contributions, since the tweets containing them would represent counter-examples for their corresponding category.

Contribution of this paper is to implement the novel algorithm a Profile of Mood States (POMS) generating twelve-dimensional mood state representation using 65 adjectives with combination of Ekman's and Plutchik's emotions categories like, anger, depression, fatigue, vigour, tension, confusion, joy, disgust, fear, trust, surprise and anticipation. The machine learning algorithm gives less time consumption without interfere human labeling. The Multinomial Naïve Bayes classifier works on testing dataset with help of huge amount of training dataset. It gives same result as POMS tagging methods. The contribution work is prediction of Emojis for emotion recognition using tweet contents.

A. Architecture

The Fig.1 shows the proposed system architecture of emotion recognition system.

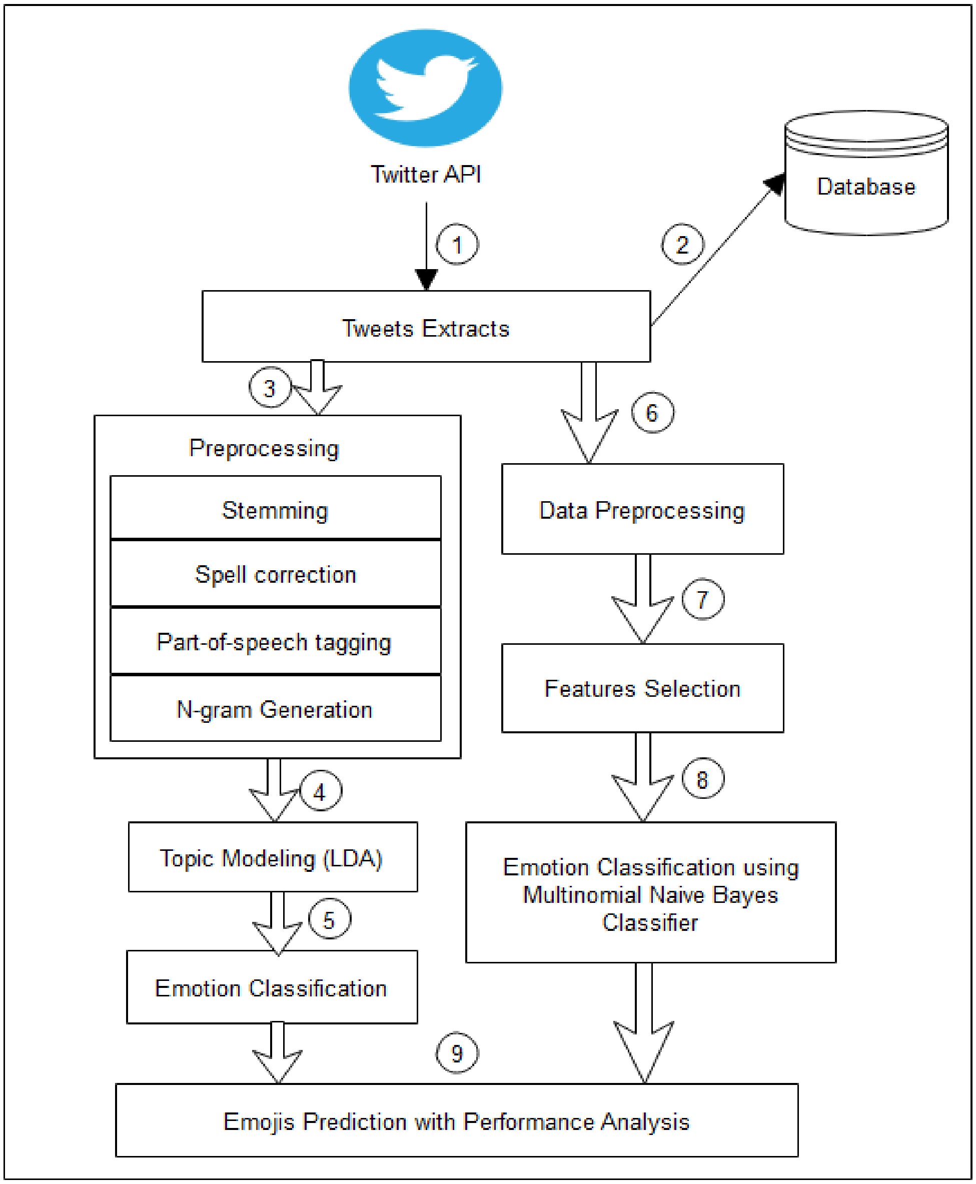

Fig. 1 Proposed System Architecture (Source: Author)

This system is working on Twitter API tweets dataset collecting at first step. There are two parts of the emotion recognition system. First, using NLP language algorithms and second one is working on machine learning classifier algorithms.

The third step is the preprocessing which includes stemming, spell correction using Porter algorithm. The NLP using Part-of-Speech tagging represents the tags of every word which is very helpful for identifying adjectives. The N-gram generation method is to design the similarity score of tweets using text clustering algorithm. The fourth step is the topic modeling using Latent Dirichlet Allocation (LDA) algorithm for extraction of topics using clustered tweets. Finally identifying the emotion of the tweets with the help of adjectives includes in emotion categories.

The sixth step is the data preprocessing which shows at machine learning algorithm preprocessing step including data transformation and normalization methods. The seventh step is to select the features which required for detection of emotion. The Multinomial Naïve Bayes classifier is an algorithm for solving the problem that arises during the training of Binarized Naïve Bayes algorithms. This is used for emotion classification system for multi-class classifier at eighth step. Finally, the ninth step is used to predict the emojis with the help of emoji dataset and analyze the performance of emotion recognition system.

B. Algorithms

1. Sentiment Analysis using Sentiwordnet Dictionary

polarizedTokensList ← newList()

while tokenizedTicket.hasNext() **do**

token←tokenizedTicket.next()

lemma←token.lemma

polarityScore←null

if DomainDictionary.contains(lemma,pos) **then**

if SentiWordNet.contains(lemma,pos) **and**

SentiWordNet.getPolarity(lemma,pos) != 0) **then**

polarityScore ← SentiWordNet.getPolarity(lemma, pos)

else

domainDicToken←DomainDictionary.getToken(lemma, pos)

if domainDicToken.PolarityOrientation == ”POSITIVE” **then**

polarityScore ← DefaultPolarity.positive

else

polarityScore ← DefaultPolarity.negative

end if

end if

polarizedTokensList.add(token, polarityScore)

end if

end while

return polarizedTokensList

2. Latent Dirichlet Allocation (LDA) Algorithm:

First and foremost, LDA provides a generative model that describes how the documents in a dataset were created. In this context, a dataset is a collection of D documents. Document is a collection of words. So our generative model describes how each document obtains its words. Initially, let's assume we know K topic distributions for our dataset, meaning K multinomial containing V elements each, where V is the number of terms in our corpus. Let βi represent the multinomial for the ith topic, where the size of βi is V: |βi|=V. Given these distributions, the LDA generative process is as follows:

Steps:

1. For each document:

(a) Randomly choose a distribution over topics (a multinomial of length K)

(b) for each word in the document:

(i) Probabilistically draw one of the K topics from the distribution over topics obtained in (a), say topic βj

(ii) Probabilistically draw one of the V words from βj

3. Multi-Nomial Naïve Bayes Classifier Algorithm

Function Train Naïve Bayes(D,C)

Returns $log\ P(c)\ and\ \log P(w|c)$

Steps:

1. For each class $c \in C$
2. Calculate $P(c)$ terms
3. N_{doc}= number of documents in D
4. N_c= number of documents from D in class c
5. $logprior[c] \leftarrow log\frac{N_c}{N_{doc}}$
6. $v \leftarrow vocabulary\ of\ D$
7. $bigdoc[c] \leftarrow append(d)$
8. For $d \in D$ with class C
9. For each word w in V
10. Calculate $P(w|c)$ terms
11. $count(w|c) \leftarrow \#\ of\ occurrences\ of\ w\ in\ bigdoc[c]$
12. $loglikelihood[w,c] \leftarrow log\frac{count(w,c)+1}{\sum_{w'\ in\ V}(count(w',c)+1}$
13. $return\ logprior, loglikelihood, V$

V. RESULT AND DISCUSSIONS

Experiments are done by a personal computer with a configuration: Intel (R) Core (TM) i3-2120 CPU @ 3.30GHz, 4GB memory, Windows 7, MySQL 5.1 backend database and Jdk 1.8. The application is web application used tool for design code in Eclipse and execute on Tomcat server. Some functions used in the algorithm are provided by list of jars like Twitter-core and Twitter-stream jars etc.

Tweets are retrieved in a streaming way, and Twitter provides the Streaming API for developers and researchers to access public tweets in real time. The aim of this paper is to bridge the gap by carrying out a performance evaluation, which was from two different aspects of NLP and machine leaning algorithms. The Unison model is the combination of Ekman's, Plutchik's and POMS emotion categories and the Multi-nomial

Naïve Bayes Classifier algorithm uses for emotion recognition performance. Finally showing the accuracy is as compared to unison model and Multi-nomial Naïve Bayes Classifier algorithm. And it gives results better than unison model within short time period.

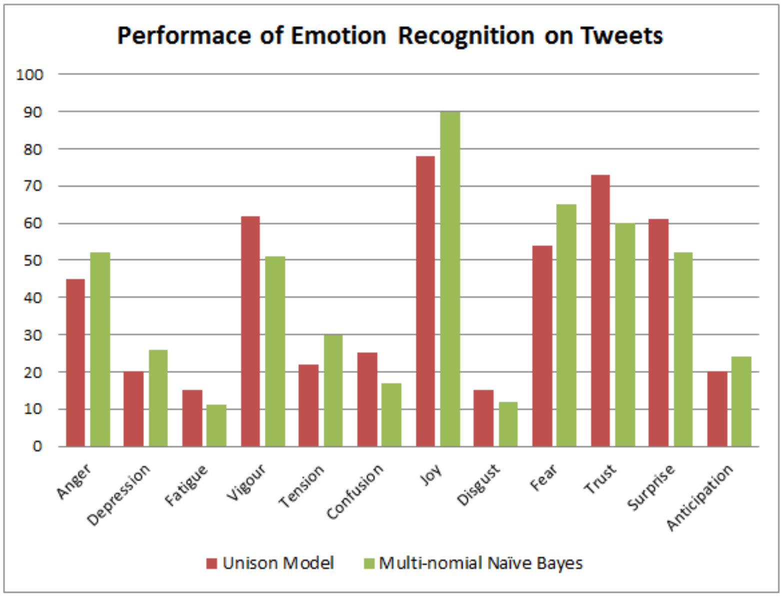

Fig. 2 Comparison of emotion identification using Unison Model versus Multi-nomial Naïve Bayes Classifier Algorithm (Source: Author)

TABLE I. Performance Analysis Between Unison Model Versus Multi-nomial Naïve Bayes Classifier

	Unison Model	**Multi-nomial Naïve Bayes**
Precision	68.45	78.70
Recall	79.44	72.64
F-Measure	72.11	84.31
Accuracy	80.29	93.26

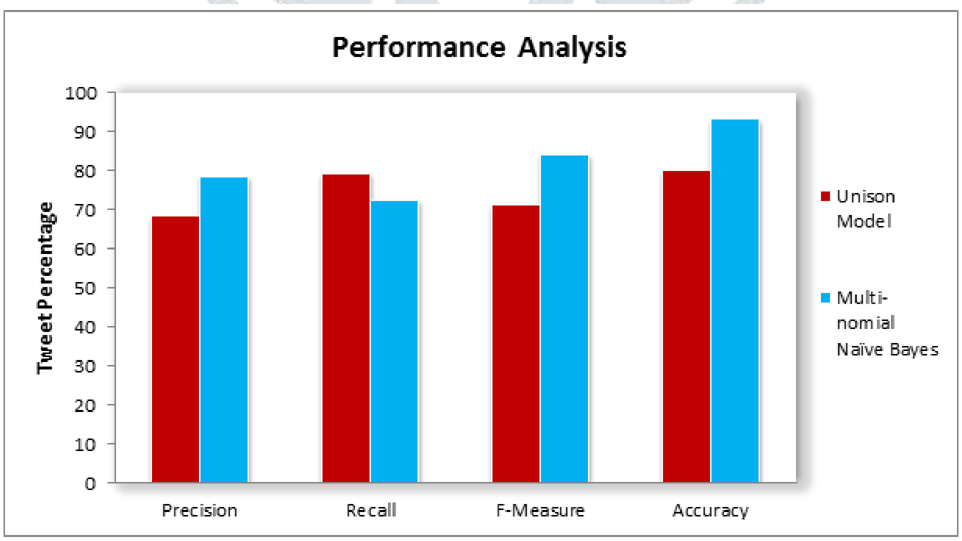

Fig. 3 Performance Analysis between existing and proposed system (Source: Author)

Fig. 2 shows the performance analysis between Unison Model and Multi-nomial Naïve Bayes classifier algorithm. The graph shows the Unison Model increases accuracy as compare to previous algorithms. But, the

Multi-nomial Naïve Bayes classifier algorithm gives better results than Unison Model. And Multi-nomial Naïve Bayes executes faster than Unison model.

VI. CONCLUSION

This project implements a novel algorithm Profile of Mood States (POMS) represents twelve-dimensional mood state representation using 65 adjectives with combination of Ekman's and Plutchik's emotions categories like, anger, depression, fatigue, vigour, tension, confusion, joy, disgust, fear, trust, surprise and anticipation. These POMS classifies the emotions with the help of bag-of-words and LSI algorithm. The machine learning Multinomial Naïve Bayes classifier is used to classify emotions, which gives results as accurate and less time consumption compares to POMS. Further work, after getting the emotion of the user, then recommending the tweet posts or motivational speech to the users when they are recognizing any negative emotion category like depression level.

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