

Emotion Recognition Using Twitter API and Analysis of Unison Model with Gaussian Naïve Bayes Classifier

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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 Gaussian Naïve Bayes classifier works on testing dataset with help of huge amount of training dataset. Measure the performance of POMS & Gaussian 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, Gaussian 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.

Thus refer the papers [1], [2], [3], [4], [5] and [6] and study all the details about how to work extract tweets from Twitter and sentiment analysis using deep neural network technique. The paper [1] and [6] represents recurrent neural network using NLP for sentiment analysis and emotion detection. The keywords extraction are retrieved from tweets with the help of Latent Dirichlet Allocation algorithm learned from [11] paper. Finally these keywords are remained adjectives categories using profile of mood states with the help of [1], [10] and [11].

Motivation

The system developed based on our proposed approach would be able to automatically detect

what people feel about their lives from twitter messages. For example, the system can recognize:

- percentage of people expressing higher levels of life satisfaction in one group versus another group,
- percentage of people who feel happy and cheerful,
- percentage of people who feel calm and peaceful, and
- percentage of people expressing higher levels of anxiety or depression.

II. RELATED WORK

B. Nejat, G. Carenini, and R. Ng, Exploring Joint NeuralModel for Sentence Level Discourse Parsing and Sentiment Analysis, the paper [2] focuses on studying two fundamental NLP tasks, Discourse Parsing and Sentiment Analysis. The development of three independent recursive neural nets: two for the key sub-tasks of discourse parsing, namely structure prediction and relation prediction; the third net 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.

S. M. Mohammad, X. Zhu, S. Kiritchenko, and J. Martin, Sentiment, emotion, purpose, and style in electoral tweets,. In [3] paper analyze electoral tweets for more subtly expressed information such as sentiment (positive or negative), the emotion (joy, sadness, anger, etc.), the purpose or intent behind the tweet (to point out a mistake, to support, to ridicule, etc.), and the style of the tweet (simple statement, sarcasm, hyperbole, etc.). There are two sections: on annotating text for

sentiment, emotion, style, and categories such as purpose, and on automatic classifiers for detecting these categories. 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: This does not summarize tweets. It does not automatically identify other semantic roles of emotions such as degree, reason, and empathy target.

B. Plank and D. Hovy, Personality Traits on Twitter or How to Get 1,500 Personality Tests in a Week,. In [4] paper we i) demonstrate how large amounts of social media data can be used for large-scale open-vocabulary personality detection; ii) analyze 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 INTROVERT (IE) and THINKING FEELING (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.

X. Liu, J. Gao, X. He, L. Deng, K. Duh, and Y.-Y. Wang, Representation Learning Using Multi-Task Deep Neural Networks for Semantic Classification and Information Retrieval. The paper [5] develops a multi-task DNN for learning representations across multiple tasks, not only leveraging large 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 robustly outperforms 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.

O. Irsoy and C. Cardie, Opinion Mining with Deep Recurrent Neural Networks. In [6] paper explored an application of deep recurrent neural networks to the task of sentence-level opinion expression extraction. DSEs (direct subjective expressions) consist of explicit mentions of private states or speech events expressing private states; and ESEs (expressive subjective expressions) consist of expressions that indicate 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 opinion expression extraction. Disadvantages are: RNNs do not have access to any features other than word vectors.

J. Bollen, H. Mao, and X.-J. Zeng, Twitter mood predicts the stock market,. In [7] paper, investigate whether public mood as measured from large-scale collection of tweets posted on twitter.com is correlated or even predictive of

DJIA values. The results show that changes in the public mood state can indeed be tracked from the content of large-scale Twitter feeds by means of rather simple text processing techniques and that such changes respond to a variety of socio-cultural drivers in a highly differentiated manner. Advantages are: Increases the performance. Public mood analysis from Twitter feeds offers an automatic, fast, free and large-scale addition to this toolkit that may be optimized to measure a variety of dimensions of the public mood state. Disadvantages are: It avoids geographical and cultural sampling errors.

S. M. Mohammad and S. Kiritchenko, Using Hashtag to Capture Fine Emotion Categories from Tweets. In [8] 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 detecting personality from text. Disadvantages are: This paper works only on given text not synonym of that text.

Nathan Aston, Jacob Liddle and Wei Hu*, Twitter Sentiment in Data Streams with Perceptron. The implementation feature reduction we were able to make our Perceptron and Voted Perceptron algorithms more viable in a stream environment. In

[9] paper, develop methods by which twitter sentiment can be determined both quickly and accurately on such a large scale. Advantages are: Suitable for unbalanced classes. Simple computation. Suitable for incremental learning. Disadvantages are: Independence assumption for computing P_c often invalid. Conservative estimate.

J. Bollen, H. Mao, and A. Pepe, Modeling Public Mood and Emotion: Twitter Sentiment and Socio-Economic Phenomena. The paper [10] analyzed financial blogs and online news articles to develop a public mood dynamic prediction model for stock markets, referencing the perspectives of behavioral finance and the characteristics of online financial communities. A public mood time series prediction model is also presented, integrating features from social networks and behavioral finance, and uses big data analysis to assess emotional content of commentary on current stock or financial 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.

F. Godin, V. Slavkovic, W. De Neve, B. Schrauwen, and R. Van De Walle, Using Topic Models for Twitter Hashtag Recommendation. The paper [11] analyzed financial blogs and online news articles to develop a public mood dynamic prediction model for stock markets, referencing the perspectives of behavioral finance and the characteristics of online financial communities. A public mood time series prediction model is also presented, integrating features from social networks and behavioral finance, and uses big data analysis to

assess emotional content of commentary on current stock or financial 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.

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. SYSTEM OVERVIEW

Profile of Mood States [1] 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 Gaussian 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. Also recommending the tweet posts or motivational speech to users when they are recognizing any negative emotion category.

Advantages are:

- Increases human-computer interactions
- Low-cost

- Fast emotion recognition system
- Scalable
- Comparable quality to experts

A. Architecture:

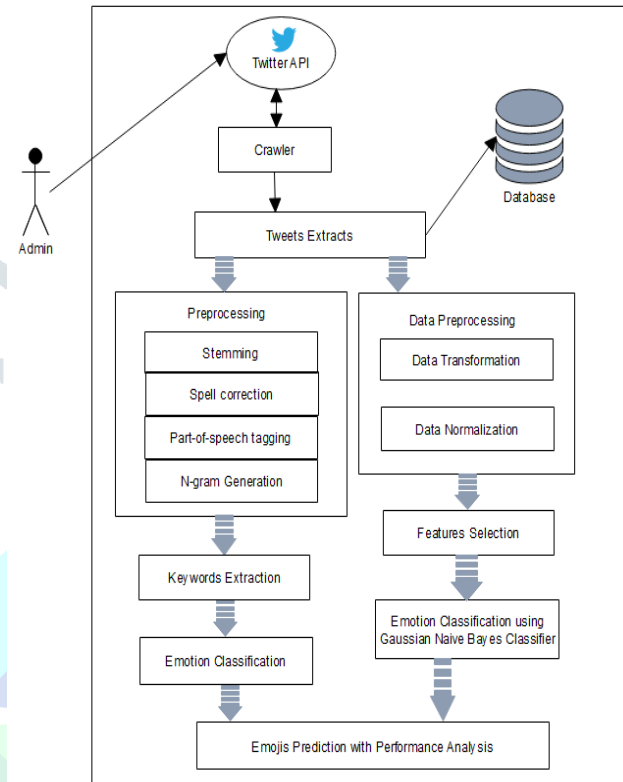


Fig. 1 System Architecture

B. Mathematical Module

- Learn a Gaussian Naive Bayes Model From Data

This is as simple as calculating the mean and standard deviation values of each input variable (x) for each class value.

$$\text{mean}(x) = 1/n * \text{sum}(x) \dots (1)$$

Where n is the number of instances and x are the values for an input variable in your training data.

We can calculate the standard deviation using the following equation:

$$\text{standard deviation}(x) = \text{sqrt}(1/n * \text{sum}(x_i - \text{mean}(x)^2)) \dots (2)$$

This is the square root of the average squared difference of each value of x from the mean value

of x , where n is the number of instances, $\text{sqrt}()$ is the square root function, $\text{sum}()$ is the sum function, x_i is a specific value of the x variable for the i 'th instance and $\text{mean}(x)$ is described above, and \wedge^2 is the square.

- **Make Predictions With a Gaussian Naive Bayes Model**

Probabilities of new x values are calculated using the Gaussian Probability Density Function (PDF).

When making predictions these parameters can be plugged into the Gaussian PDF with a new input for the variable, and in return the Gaussian PDF will provide an estimate of the probability of that new input value for that class.

$$\text{pdf}(x, \text{mean}, \text{sd}) = (1 / (\text{sqrt}(2 * \text{PI}) * \text{sd})) * \exp(-((x - \text{mean})^2 / (2 * \text{sd}^2))) \dots (3)$$

Where $\text{pdf}(x)$ is the Gaussian PDF, $\text{sqrt}()$ is the square root, mean and sd are the mean and standard deviation calculated above, PI is the numerical constant, $\text{exp}()$ is the numerical constant e or Euler's number raised to power and x is the input value for the input variable.

C. Algorithms

1. 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 multinomials containing V elements each, where V is the number of terms in our corpus. Let β_i represent the multinomial for the i th topic, where the size of β_i is V : $|\beta_i|=V$. 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 β_j

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

2. 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

3. Latent Semantic Analysis Algorithm

Step 1: Documents should be prepared in the following way:

- Exclude trivial words as well as low-frequency terms
- Conflate terms with techniques like stemming or lemmatization.

Step 2: A term-frequency matrix (A) must be created that includes the occurrences of each term in each document.

Step 3: Singular Value Decomposition (SVD):

- Extract least-square principal components for two sets of variables: set of terms and set of documents.
- SVD products include the term eigenvectors U, the document eigenvectors V, and the diagonal matrix of singular values Σ.

Step 4: From these, factor loadings can be produced for terms UΣ and documents VΣ

IV. 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 Jdk1.8. 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 learning algorithms. The Unison model is the combination of Ekman's, Plutchik's and POMS emotion categories and the Gaussian Naive Bayes Classifier algorithm uses for emotion recognition performance. Fig. 2 shows total emotion identified using unison model and fig. 3 showing the accuracy as well as execution time for performance of Unison Model.

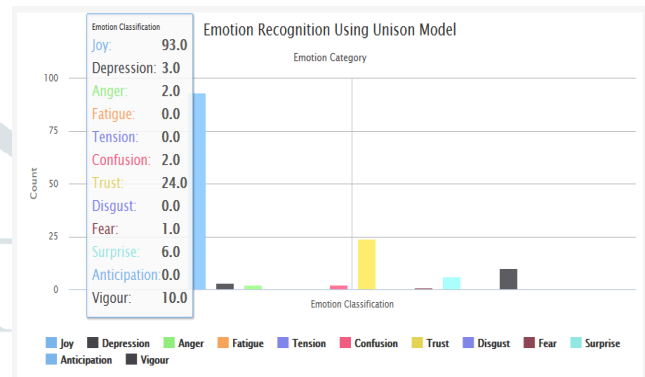


Fig. 2 Emotion detection using Unison model

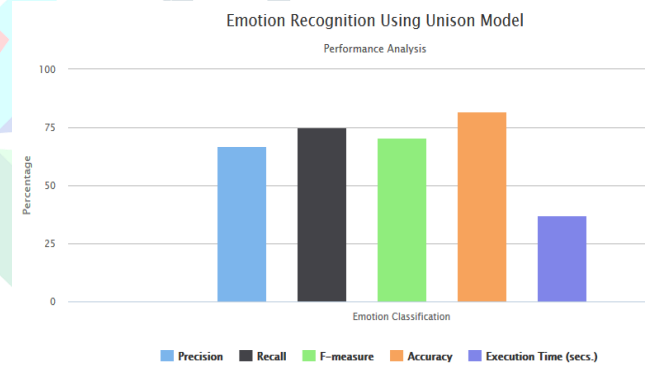


Fig. 3 Performance of emotion detection

Fig. 4 shows the emotion classification with the help of Gaussian Naive Bayes algorithm. The performance of emotion classification of Gaussian Naive Bayes algorithm shown in fig. 5.

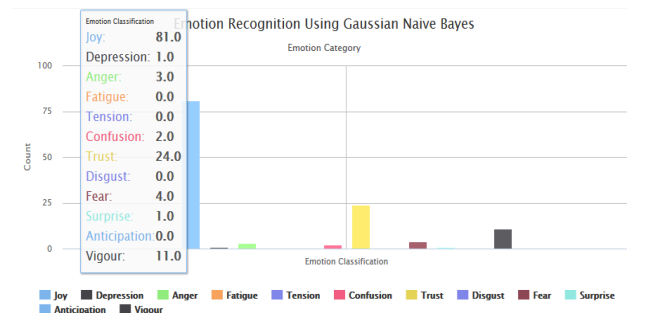


Fig. 2 Emotion recognition using Gaussian Naive Bayes Algorithm

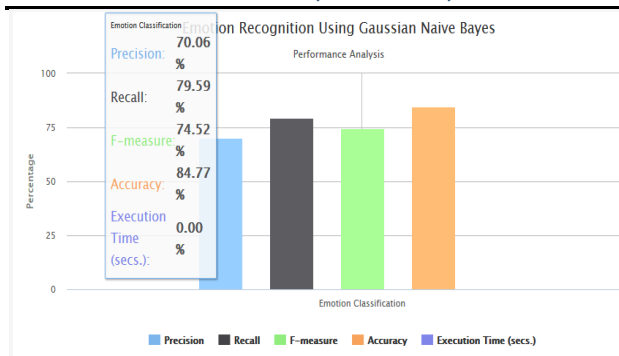


Fig. 3 Performance Analysis of Gaussian Naive Bayes Algorithm

As compared to unison model and Gaussian Naive Bayes algorithm, it gives results better than unison model within short time period.

V. 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 Gaussian Naive Bayes classifier is used to classify emotions, which gives results as accurate and less time consumption compares to POMS.

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