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 detectionusing opinion mining on social media. Due to someintrinsic 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 fundamentalNLP tasks, Discourse Parsing and Sentiment Analysis. Thedevelopment of three independent recursive neural nets: twofor the key sub-tasks of discourse parsing, namely structureprediction and relation prediction; the third net for sentimentprediction. Advantages are: The latent Discourse features canhelp boost the performance of a neural sentiment analyzer.Pre-training and the individual models are an order of magnitudefaster 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 expressedinformation such as sentiment (positive or negative), the emotion(joy, sadness, anger, etc.), the purpose or intent behindthe 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 textfor sentiment, emotion, style, and categories such as purpose,and on automatic classifiers for detecting these categories.Advantages are: Using a multitude of custom engineered featureslike those concerning emoticons, punctuation, elongatedwords and negation along with unigrams, bigrams and emotionlexicons features, the SVM classifier achieved a higheraccuracy. Automatically classify tweets into eleven categoriesof emotions. Disadvantages are: This does not summarize tweets.It does not automatically identifying other semantic roles ofemotions such as degree, reason, and empathy target.

B. Plank and D. Hovy, Personality Traits on Twitter orHow to Get 1,500 Personality Tests in a Week,. In [4]paper we i) demonstrate how large amounts of social mediadata can be used for large-scale open-vocabulary personalitydetection; ii) analyze which features are predictive of whichpersonality dimension; and iii) present a novel corpus of1.2M English tweets (1,500 authors) annotated for gender andMBTI. Advantages are: The personality distinctions, namelyINTROVERTEXTROVERT (IE) and THINKINGFEELING(TF), can be predicted from social media data with highreliability. The large-scale, open-vocabulary analysis of userattributes 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 Networksfor Semantic Classification and Information Retrieval.The paper [5] develops a multi-task DNN for learning representationsacross multiple tasks, not only leveraging largeamounts of cross-task data, but also benefiting from a regularizationeffect that leads to more general representations tohelp tasks in new domains. A multi-task deep neural networkfor representation learning, in particular focusing on semanticclassification (query classification) and semantic informationretrieval (ranking for web search) tasks. Demonstrate strongresults on query classification and web search. Advantagesare: The MT-DNN robustly outperforms strong baselinesacross all web search and query classification tasks. MultitaskDNN model successfully combines tasks as disparateas classification and ranking. Disadvantages are: The queryclassification incorporated either as classification or rankingtasks not comprehensive exploration work.

O. Irsoy and C. Cardie, Opinion Mining with Deep RecurrentNeural Networks. In [6] paper explored an applicationof deep recurrent neural networks to the task of sentence-levelopinion expression extraction. DSEs (direct subjectiveexpressions) consist of explicit mentions of private states orspeech events expressing private states; and ESEs (expressivesubjective expressions) consist of expressions that indicatesentiment, emotion, etc., without explicitly conveying them.Advantages are: Deep RNNs outperformed previous (semi)CRF baselines; achieving new state-of-the-art results for fine-grainedon opinion expression extraction. Disadvantages are:RNNs do not have access to any features other than wordvectors.

J. Bollen, H. Mao, and X.-J.Zeng, Twitter mood predicts thestock market,. In [7] paper, investigate whether public moodas measured from large-scale collection of tweets posted ontwitter.com is correlated or even predictive of DJIA values.The results show that changes in the public mood state canindeed be tracked from the content of large-scale Twitterfeeds by means of rather simple text processing techniquesand that such changes respond to a variety of socio-culturaldrivers in a highly differentiated manner. Advantages are:Increases the performance. Public mood analysis from Twitterfeeds offers an automatic, fast, free and large-scale additionto this toolkit that may be optimized to measure a variety ofdimensions of the public mood state. Disadvantages are: Itavoids geographical and cultural sampling errors.

S. M. Mohammad and S. Kiritchenko, Using Hashtagsto Capture Fine Emotion Categories from Tweets. In [8]article, show that emotion-word hashtags are good manuallabels of emotions in tweets.Proposes a method to generate alarge lexicon of word-emotion associations from this emotion-labeledtweet corpus. This is the first lexicon with realvaluedword-emotion association scores. Advantages are: Usinghashtagged tweets can collect large amounts of labeled datafor any emotion that is used as a hashtag by tweeters. Thehashtag emotion lexicon is performed significantly better thanthose that used the manually created WordNet affect lexicon.Automatically detecting personality from text. Disadvantagesare: This paper works only on given text not synonym of that
text.

Nathan Aston, Jacob LiddleandWei Hu*, Twitter Sentiment in Data Streams with Perceptron. The implementation featurereduction we were able to make our Perceptron and VotedPerceptron algorithms more viable in a stream environment.In [9] paper, develop methods by which twitter sentiment canbe determined both quickly and accurately on such a largescale. Advantages are: Suitable for unbalanced classes. Simplecomputation.Suitable for incremental learning. Disadvantagesare: Independence assumption for computing P_c often invalid.Conservative estimate.

J. Bollen, H. Mao, and A. Pepe, Modeling Public Moodand Emotion: Twitter Sentiment and Socio-Economic Phenomena.The paper [10] analyzed financial blogs and onlinenews articles to develop a public mood dynamic predictionmodel for stock markets, referencing the perspectives ofbehavioral finance and the characteristics of online financialcommunities. A public mood time series prediction modelis also presented, integrating features from social networksand behavioral finance, and uses big data analysis to assessemotional content of commentary on current stock or financialissues to forecast changes for Taiwan stock index. Advantagesare: It is convenient for feature word expansion and processingspeed. More widely used. Disadvantages are: Only uses forstock prices.

F. Godin, V. Slavkovikj, W. De Neve, B. Schrauwen,and R. Van De Walle, Using Topic Models for Twitter Hashtag Recommendation. The paper [11] analyzed financialblogs and online news articles to develop a public mooddynamic prediction model for stock markets, referencing theperspectives of behavioral finance and the characteristics ofonline financial communities. A public mood time seriesprediction model is also presented, integrating features fromsocial networks and behavioral finance, and uses big dataanalysis to assess emotional content of commentary oncurrent stock or financial issues to forecast changes forTaiwan stock index. Advantages are: It is convenient forfeature word expansion and processing speed. More widelyused. 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 65adjectives 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 postsor motivational speech to users when they are recognizing anynegative emotion category.

Advantages are:

- Increases human-computer interactions
- Low-cost
- Fast emotion recognition system
- Scalable
- Comparable quality to experts

A. Architecture:

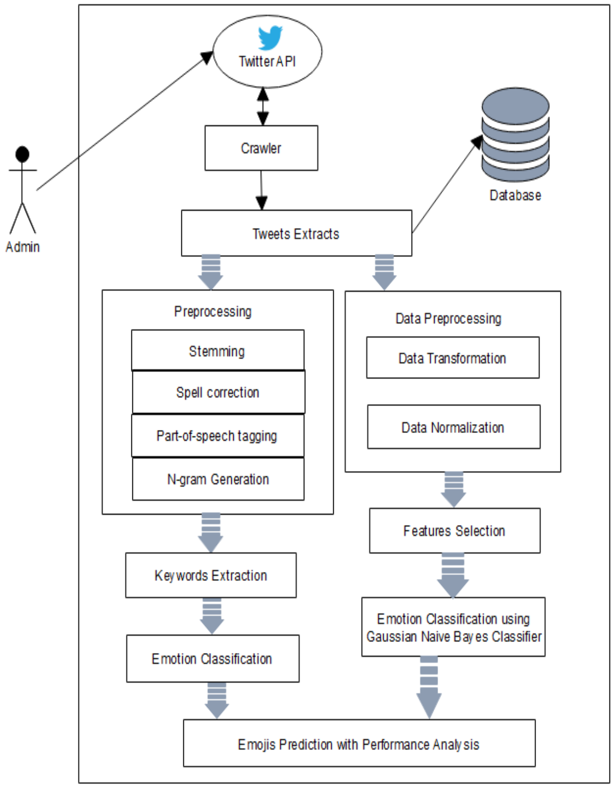

Fig.1: System Architecture

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.

mean(x) = 1/n * sum(x)….(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:

standard deviation(x) = sqrt(1/n * sum(xi-mean(x)^2))….(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, sqrt() is the square root function, sum() is the sum function, xi is a specific value of the x variable for the i'th instance and mean(x) is described above, and ^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.

pdf(x, mean, sd) = (1 / (sqrt(2 * PI) * sd)) * exp(-((x-mean^2)/(2*sd^2)))….(3)

Where pdf(x) is the Gaussian PDF, sqrt() is the square root, mean and sd are the mean and standard deviation calculated above, PI is the numerical constant, 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 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

2. Sentiment Analysis using Sentiwordnet Dictionary

polarizedTokensList ← newList()
whiletokenizedTicket.hasNext() **do**
token←tokenizedTicket.next()
lemma←token.lemma
polarityScore←null
ifDomainDictionary.contains(lemma,pos) **then**
ifSentiWordNet.contains(lemma,pos) **and**
SentiWordNet.getPolarity(lemma,pos) != 0) **then**
polarityScore ← SentiWordNet.getPolarity(lemma, pos)
else
domainDicToken←DomainDictionary.getToken(lemma, pos)
ifdomainDicToken.PolarityOrientation == "POSITIVE" **then**
polarityScore ← DefaultPolarity.positive
else
polarityScore ← DefaultPolarity.negative

end if
end if
polarizedTokensList.add(token, polarityScore)
end if
end while
returnpolarizedTokensList

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

V. RESULT AND DISCUSSIONS

Experiments are done by a personal computer with a configuration:Intel (R) Core (TM) i3-2120 CPU @ 3.30GHz, 4GBmemory, Windows 7, MySQL 5.1 backend database and Jdk1.8. The application is web application used tool for designcode in Eclipse and execute on Tomcat server. Some functionsused in the algorithm are provided by list of jars like Twitter-coreand Twitter-stream jars etc.

Tweets are retrieved in a streaming way, and Twitter providesthe Streaming API for developers and researchers toaccess public tweets in real time. The aim of this paper isto bridge the gap by carrying out a performance evaluation,which was from two different aspects of NLP and machineleaning algorithms. The Unison model is the combination ofEkman's, Plutchik's and POMS emotion categories and theGaussian Naive Bayes Classifier algorithm uses for emotionrecognition 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.

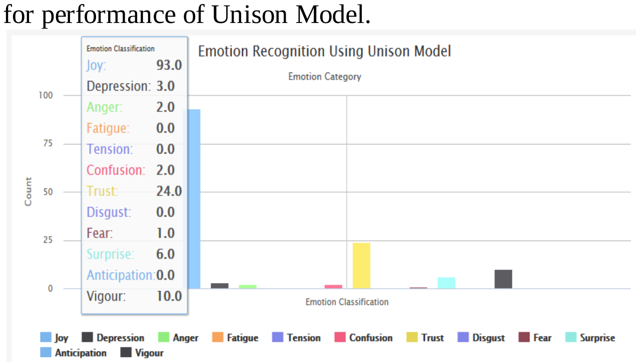

Fig.2: Emotion detection using Unison model

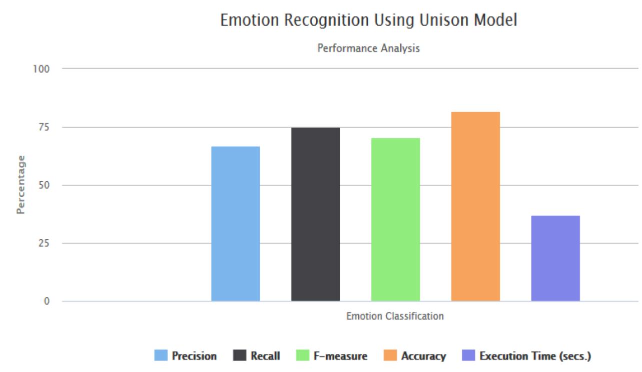

Fig.3: Performance of emotion detection

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

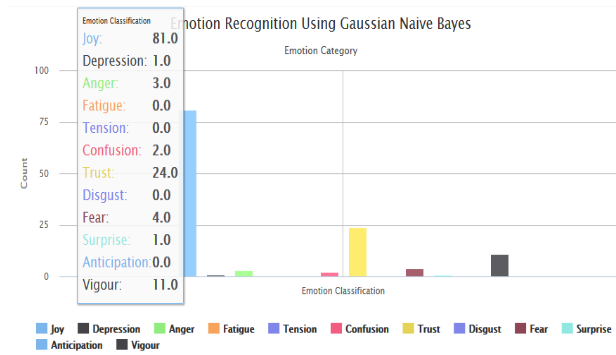

Fig.4: Emotion recognition using Gaussian Naive Bayes Algorithm

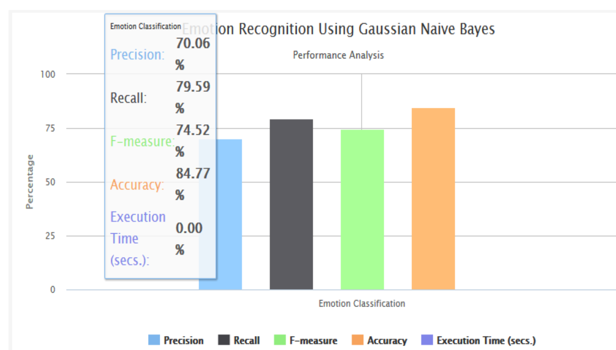

Fig.5: Performance Analysis of Gaussian Naive Bayes Algorithm

As compared to unison model and Gaussian Naive Bayesalgorithm, it gives results better than unison model withinshort time period.

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

VII. REFERENCES

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