PERFORMANCE ANALYSIS OF EMOTION RECOGNITION ON GAUSSION NAÏVE BAYES ALGORITHM

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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. 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

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.

Goals:

To develop a model capable of detecting emotions from the textual content and not simply find correlations between certain @mentions or links and emotions, or recommend on hashtag from the presence of the others.

Objectives:

1. To develop a single model for predicting multiple classifications at the same time.
2. Achieving highest accuracy for classifying twitter text based on their emotional states.
3. Gaussian Naïve Bayes gives more accurate results, also not requires preprocessing or tokenization.

I. EXISTING SYSTEM APPROACH

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.

A. Abbreviations and Acronyms

POMS – Profile Of Mood State
API – Application Programming Interface
LSI – Latent Semantic Indexing
LDA – Latent Diritchlet Allocation
NLP – Natural Laanguage Processing

II. SYSTEM OVERVIEW

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 containin them would represent counter-examples for their corresponding category.

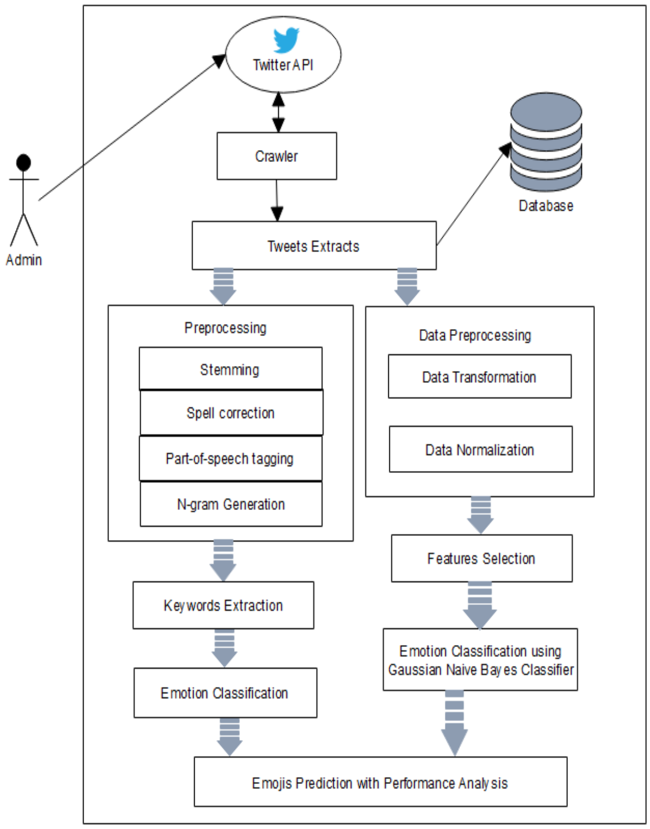

Figure 1: System Architecture

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.

A. Equation

- **Index-based Latent Semantic Analysis (ILSA) Algorithm**

Input:

Matrix U, $X = S_r^{-1}$, index I_θ, query Q and parameter k;

Output:

Top-r most similar sorted documents;

Process:

Initialize <C,S> by setting C and S as $\emptyset$;

$\bar{Q} \leftarrow XQ$;

for $t_j \in \{t_j | \bar{Q}(t_j) \neq 0\}$ **do**

for $< d_i, \mathrm{PartialSim}_\theta(d_i, t_j) > \in I_\theta(t_j)$ **do**

obtain $\mathrm{PartialSim}_\theta(d_i, t_j)$ from $< d_i, \mathrm{PartialSim}_\theta(d_i, t_j) >$;

if $d_i \in C$ **then**

$$S(d_i) \leftarrow S(d_i) + \frac{\bar{Q}(j)\text{PartialSim}_\theta(d_i, t_j)}{\sqrt{\sum_j(\bar{Q}(j))^2}};$$

else

$$S(d_i) \leftarrow \frac{\bar{Q}(j)\text{PartialSim}_\theta(d_i, t_j)}{\sqrt{\sum_j(\bar{Q}(j))^2}};$$

$C \leftarrow C \cup \{d_i\}$;

$S \leftarrow S \cup \{S(d_i)\}$;

end if

end for

end for

return GetSortedCenter($k, < C, S >$);

- **Guassion Naive Bayes:**

$$p(x = v \mid C_k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} e^{-\frac{(v-\mu_k)^2}{2\sigma_k^2}}$$

B. Preprocessing Steps

- Tweet containing @ symbol are replaced by UserId.
- Many tweet contain URL links. All URL links are replaced with URL.
- Words are repeated letters such as happyyy are common in twitter message. For instance the word ‘happyyy’ would changed into ‘happy’.
- Many tweet contain more than one hash-tag. While some may containhashtag from 2 different classes.
  For example- Got a job interview today with AT&T #nervous #excited
  #nervous from Unhappy active class
  #excited from happy active class
- Any tweet containing hash-tags from different classes are removed from training data. Tweets are removed if they contain two subjects.
- In twitter, hash-tags can be placed in the beginning middle or end of tweet.

Feature Selection

In order to train a classifier from labeled data, we represent each tweet into a vector of features. We need to capture features that describe the emotion expressed by each tweet. Feature selection plays an important part in the effective- ness of the classification process. For this study, we explore the usage of different features. We use single words, also known as unigrams as the baseline features for comparison. Other features explored included the presence of emoticons, punctuations, and negations, as elaborated below.

Unigram Features

Unigrams or single word features have been widely used to capture the sentiment or emotion of a tweet[7].Let (f1,f2,...,fm) be our predefined set of unigrams that can appear in a tweet. Each feature fi in this vector is a word from the dictionary of words in our dataset. Text messages can be classified into emotion categories based on the presence of affect words like ”annoyed”, and ”happy”. Therefore, the problem of high dimensional feature vector can be solved by identifying an appropriate emotion lexicon. We effectively design a domain-specific dictionary by using the lexicon of emotions, instead of all the words in our input dataset. As a result, our feature space does no longer include all the words in our training dataset, but instead it only contains the emotional words from the emotion lexicons. SentiwordNet contains a dictionary of several thousand words, wherein we use emotion-indicative categories such as positive emotions, negative emotions, anxiety, anger, sadness, and negation and utilize them effectively as our domain-specific dictionary.

Emotion Features

Other than unigrams, emoticons are likely to be useful features for emotion classification in text messages since they are textual portrayals of a writer’s emotion in the form of icons. These features tend to be widely used in sentiment analysis.There are many emoticons that can express happy emotion, sad emotion, annoyed emotion or sleepy emotion. For example, ”:)” and ”:-)” both express happy emotion. The full list of emoticons that we used can be found in Figure 3.

Classifier Selection

A number of statistical classification techniques have been applied to text categorization, including regression models, Bayesian classifiers, decision trees, nearest neighbor classifiers, neural networks, and support vector machines. For the task of classification we used four different classifiers including Guassion Naïve Bayes, Latent Diritchlet algorithm, Porter stemming, which have been shown to be effective in text classification work. Guassion Naïve Bayes handling real-time data with continuous distribution, Naïve Bayes classifier considers that the big data is generated through a Gaussian process with normal distribution. LDA apply on cluster and it is a topic model that generates topic based on word frequency from a set of document. Porter Stemming used POS tagger, N-gram generation, Spell correction.

C. Result

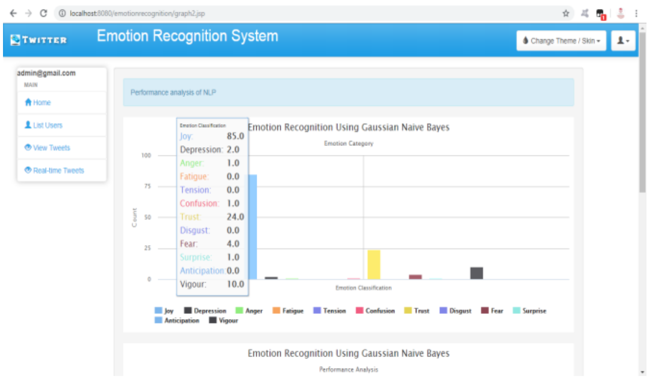

Figure 2: Emotion Recognition using Gaussian Naïve Bayes Algorithm

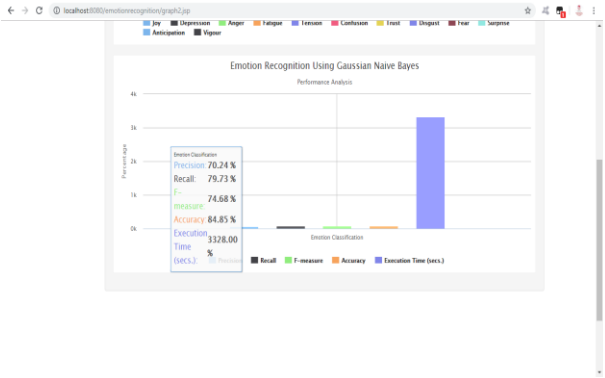

Figure 3: Graph of Emotion Recognition

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.

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