A Survey on Performance Evaluation ofEmotion Recognition On Unison Model withLSSVM 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 Least Square Support Vector Machine classifier algorithm works on testing dataset with help of huge amount of training dataset. Measure the performance of POMS and Least Square Support Vector Machine classifier algorithms on Twitter API. The result shows with the help of Emoji's for emotion recognition using tweet contents.

Keywords- Emotion Recognition, Text Mining, Twitter, Recurrent Neural Networks, Convolutional Neural Networks, Unison Model, Least Square Support Vector Machine 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. 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.

III. RELATED WORK

J. Bollen, H. Mao, and X.J. Zeng investigates 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 [1].

J. Bollen, H. Mao, and A. Pepe 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 [2].

F. Godin, V. Slavkovikj, W. De Neve, B. Schrauwen, and R. Van De Walle, proposes a novel method for unsupervised and content based hashtag recommendation for tweets. This approach relies on Latent Dirichlet Allocation (LDA) to model the underlying topic assignment of language classified tweets. Advantages are: The use of a topic distribution to recommend general hashtags. Easily portable. Effective categorization and search of tweets. Disadvantages are: Need to show disambiguate tweets by using more semantic knowledge [3].

O. Irsoy and C. Cardie 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 on opinion expression extraction. Disadvantages are: RNNs do not have access to any features other than word vectors [4].

Nathan Aston, Jacob Liddle and Wei Hu* represents the implementation feature reduction we were able to make our Perceptron and Voted Perceptron algorithms more viable in a stream environment. In this 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 Pc often invalid. Conservative estimate [5].

S. M. Mohammad, X. Zhu, S. Kiritchenko, and J. Martin analyzes 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: Does not summarize tweets. It does not automatically identifying other semantic roles of emotions such as degree, reason, and empathy target [6].

S. M. Mohammad and S. Kiritchenko shows 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 [7].

X. Liu, J. Gao, X. He, L. Deng, K. Duh, and Y.-Y. Wang 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. Multi-task 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 [8].

B. Plank and D. Hovyrepresents that 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–EXTROVERT (I–E) and THINKING–FEELING (T–F), can be predicted from social media data with high reliability. The large-scale, open-vocabulary analysis of user attributes can help improve classification accuracy [9].

B. Nejat, G. Carenini, and R. Ng 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 [10].

IV. EXISTING SYSTEM

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.

V. PROPOSED SYSTEM

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 LSSVM 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.

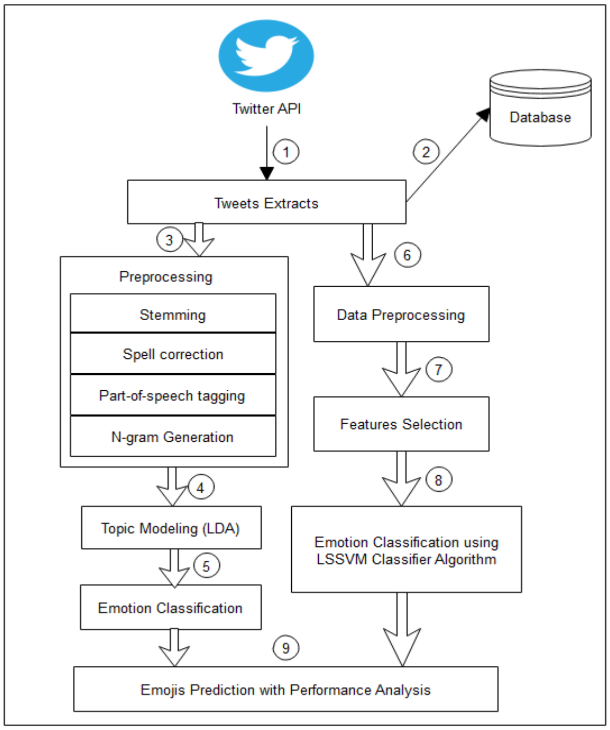

Fig. 1 System Architecture

Advantages are:

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

VI. PROPOSED ALGORITHM

A. 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

B. LS-SVM Classifier Algorithm

1. Given normalized and standardized training data $\{x_k, y_k\}_{k=1}^{N}$ with inputs $x_k \in \square^n$, outputs $y_k \in \square$ and N training data.
2. Choose a working set with size M and impose in this way a number of M support vectors (typically $M \ll N$).
3. Randomly select a support vector x^* from the working set of M support vectors.
4. Randomly select a point x^{t*} from the N training data and replace x^* by x^{t*} in the working set. If the entropy increases by taking the point x^{t*} instead of x^* then this point x^{t*} is accepted for the working set of M support vectors, otherwise the point x^{t*} is rejected (and returned to the training data pool) and the support vector x^* stays in the working set.
5. Calculate the entropy value for the present working set.
6. Stop if the change in entropy value is small or the number of iterations is exceeded; otherwise go to (3).
7. Estimate w, b in the primal space after estimating the eigenfunctions from the Nystrom approximation.

VII. 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 LSSVM classifier is used to classify emotions, which gives results as accurate and less time consumption compares to POMS.

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