ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 7, Issue 3, March 2019

A Survey on Emotion Recognition on Twitter

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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 deep learning algorithms. After that, we take the advantage of hashtags to create three huge emotion categorized datasets corresponding to classifications of various emotions. We then compare the overall performance of several phrase and character-based recurrent and convolutional neural networks with the performance on bag-of-words and latent semantic indexing models. Additionally, inspect the transferability of the final hidden state representations among various classifications of emotions, and whether or not it is possible to build a unison model for predicting all of them using a shared representation. The contribution work is to apply machine learning algorithm for emotion classification, it gives less time consumption without interfere human labeling. We show that recurrent neural networks, especially character-based approaches can increase over bag-of-words and latent semantic indexing models. While the transfer capabilities of these models are poor, the novel proposed training searching produces a unison model with overall performance comparable to that of the three single models.

KEYWORDS: Emotion Recognition, Text Mining, Twitter, Recurrent Neural Networks, Convolutional Neural Networks, K-NN 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. 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.

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

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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 colour, 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.

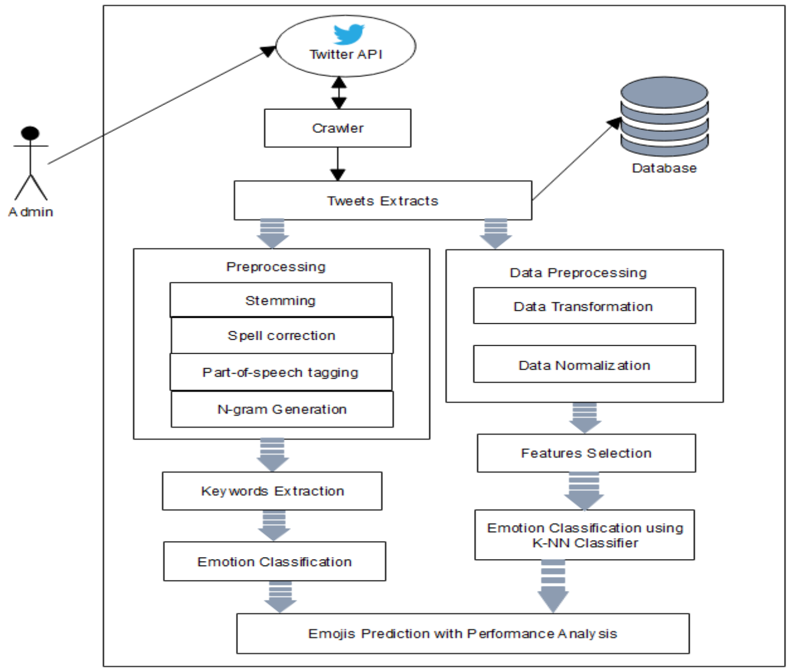

Fig. 1 System Architecture

Contribution of this paper is to implement machine learning algorithm gives less time consumption without interfere human labeling. The k-NN 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.

Advantages:

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

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II. RESULTS

Sr. No.	Author, Title and Journal Name	Advantages	Disadvantage	Refer Points	Proposed System Compare
1	B. Nejat, G. Carenini, and R. Ng, "Exploring Joint Neural Model for Sentence Level Discourse Parsing and Sentiment Analysis," Proc. of the SIGDIAL 2017 Conf., no. August, pp. 289–298, 2017.	1. The latent Discourse features can help boost the performance of a neural sentiment analyzer. 2. Pre-training and the individual models are an order of magnitude faster than the Multi-tasking model.	1. Difficult predictions to multi-sentential text. 2. The resulting accuracy is 45.7	This paper 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.	1. Efficient predictions to multi-sentential text.
2	S. M. Mohammad, X. Zhu, S. Kiritchenko, and J. Martin, "Sentiment, emotion, purpose, and style in electoral tweets," Information Processing and Management, vol. 51, no. 4, pp. 480–499, 2015.	1.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. 2. To automatically classify tweets into eleven categories of emotions	1. Does not summarize tweets. 2. Does not automatically identifying other semantic roles of emotions such as degree, reason, and empathy target 3. The resulting accuracy is 69.80	In this 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.	1. Profile of Mood States (POMS) generating twelve-dimensional mood state representation using 65 adjectives with combination of emotions categories like, anger, depression, fatigue, vigour, tension, confusion, joy, disgust, fear, trust, surprise and anticipation etc.
3	B. Plank and D. Hovy, "Personality Traits on Twitter —or— How to Get 1,500 Personality Tests in a Week," in Proc. of the 6th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, 2015, pp. 92–98.	1. The personality distinctions, namely INTROVERT–EXTROVERT (I–E) and THINKING–FEELING (T–F), can be predicted from social media data with high reliability. 2. The large-scale, open-vocabulary analysis of user attributes can help improve classification accuracy.	1.The resulting accuracy is 54.0	In this 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.	1. Applying the k-NN classifier machine learning algorithm which gives more accurate results as well as fast emotion recognition system.
4	X. Liu, J. Gao, X. He, L. Deng, K. Duh, and Y.-Y. Wang,	1. The MT-DNN robustly outperforms strong baselines across	1. The query classification incorporated	Develop a multi-task DNN for learning representations across multiple tasks, not only	1. Applying the k-NN classifier machine learning

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	"Representation Learning Using Multi-Task Deep Neural Networks for Semantic Classification and Information Retrieval," Proc. of the 2015 Conf. of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pp. 912–921, 2015.	all web search and query classification tasks. 2. Multi-task DNN model successfully combines tasks as disparate as classification and ranking.	either as classification or ranking tasks not comprehensive exploration work. 2. The resulting accuracy is 66.5	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.	algorithm which gives more accurate results as well as fast emotion recognition system.
5	O. Irsoy and C. Cardie, "Ozpinion Mining with Deep Recurrent Neural Networks," in Proc. of the Conf. on Empirical Methods in Natural Language Processing. ACL, 2014, pp. 720–728.	1.Deep RNNs outperformed previous (semi)CRF baselines; achieving new state-of-the-art results for fine-grained on opinion expression extraction.	1.RNNs do not have access to any features other than word vectors 2.The resulting accuracy is 58.2	In this 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.	1. POMS classifies the emotions with the help of bag-of-words and LSI algorithm.

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