

EMOTION RECOGNITION ON TWITTER: COMPARATIVE STUDY AND TRAINING A UNISON MODEL

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Abstract — In this paper, propose designing a sentiment analysis by extracting a vast amount of tweets. Prototyping is used in this development. Results classify customers' perspective via tweets into positive, negative and neutral, which is represented in an html web page. However, the program has planned to develop on a web application system, using Natural Language Processing and Deep Learning integrated with JSP, Servlet web stack.

Keywords — social media, **Twitter**, **Emotion Recognition**.

INTRODUCTION

Due to the vast number of texts, manual inspection for emotion classification is infeasible, hence the need for accurate automatic systems. Although in many cases people can easily spot whether the

author of a text was angry or happy, the task is quite challenging for a computer - mainly due to the lack of background knowledge that is implicitly considered by humans. Given some text, emotion recognition algorithms detect which emotions the writer wanted to express when composing it. To treat this problem as a special case of text classification, we need to define a set of basic emotions. Although emotions have long been studied by psychologists, there is no single, standard set of basic emotions. Therefore, we decided to 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. Each dimension is defined by a set of emotional adjectives, like bitter, and the individual's mood is assessed by how strongly (s)he experienced such a feeling in the last month. Majority of previous studies predict either Ekman's or Plutchik's classifications, while POMS's adjectives had only been used in simple keyword spotting algorithms. We are not aware of any studies that tackle the problem of predicting POMS's categories from the text. Methodologically, they mainly used simple classification algorithms, like logistic regression or support vector machines, on top of word and n-gram counts, and other custom engineered features (capturing the use of punctuation, the presence or absence of negation, and counts of words from various emotion lexicons).

PROPOSED METHOD

The existing system works only on the dataset which is constrained to a particular topic. The existing systems also do not determine the measure of impact the results determined can have on the particular field taken into consideration and it does not allow retrieval of data based on the query entered by the user i.e. it has constrained scope. In simple words, it works on static data

rather than dynamic data. Unsupervised algorithms like Vector Quantization, are used for data compression, pattern recognition, facial and speech recognition, etc and therefore cannot be used in determining sentiment in Twitter data. Aprox algorithm fails to handle large datasets and as a result can generate faulty results.

Disadvantages of Existing System:

1. Existing system takes a stored dataset on a particular topic into consideration.
2. It fails to determine the impact the results might or will have in the respective field.
3. Existing system does not allow the retrieval of data based on the query entered by the user.
4. Existing system does not provide accurate feature selection.

Proposed System:

In the proposed system, we will retrieve tweets from twitter using twitter API based on the query. The collected tweets will be subjected to preprocessing. We will then apply the supervised algorithm on the stored data. The supervised algorithm used in our system is Support Vector Machine (SVM). The results of the algorithms i.e. the sentiment will be represented in graphical manner (pie charts/bar charts). The proposed system is more effective than the existing one. This is because we will be able to know how the

statistics determined from the representation of the result can have an impact in a particular field.

Advantages of Proposed System:

1. Proposed system gives you the freedom to choose the data of any topic.
2. The proposed system, gives you the impact the results and statistics will have on the respective field.
3. Proposed system allows retrieval of data based on the query entered by the user.
4. Proposed system will provide accurate feature selection.

LITERATURE SURVEY

S. M. Mohammad and S. Kiritchenko, "Using Hashtags to Capture Fine Emotion Categories from Tweets," Computational Intelligence, vol. 31, no. 2, pp. 301–326, 2015.

Detecting emotions in microblogs and social media posts has applications for industry, health, and security. Statistical, supervised automatic methods for emotion detection rely on text that is labeled for emotions, but such data are rare and available for only a handful of basic emotions. In this article, we show that emotion-word hashtags are good manual labels of emotions in tweets. We also propose 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. We begin with experiments for six basic emotions and show that the hashtag annotations are consistent and

match with the annotations of trained judges. We also show how the extracted tweet corpus and word–emotion associations can be used to improve emotion classification accuracy in a different nontweet domain.

J. Bollen, H. Mao, and X. J. Zeng, "Twitter mood predicts the stock market," J. of Computational Science, vol. 2, no. 1, pp. 1–8, 2011.

Behavioral economics tells us that emotions can profoundly affect individual behavior and decision-making. Does this also apply to societies at large, i.e. can societies experience mood states that affect their collective decision making? By extension is the public mood correlated or even predictive of economic indicators? Here we investigate whether measurements of collective mood states derived from large-scale Twitter feeds are correlated to the value of the Dow Jones Industrial Average (DJIA) over time. We analyze the text content of daily Twitter feeds by two mood tracking tools, namely OpinionFinder that measures positive vs. negative mood and Google-Profile of Mood States (GPOMS) that measures mood in terms of 6 dimensions (Calm, Alert, Sure, Vital, Kind, and Happy). We cross-validate the resulting mood time series by comparing their ability to detect the public's response to the presidential election and Thanksgiving day in 2008. A Granger causality analysis and a Self-Organizing Fuzzy Neural Network are then used to investigate the hypothesis that public mood states, as measured by the

View All Sentiments Emotions				
All Anger Tweets Details				
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Anger Tweets of : Kerala_Flood [tweet owner: tmksmanju]				
Reviewed User	Review	Emotion	Date	View the Details
Mahan	Kerala Flood is very angry and #Sadness news in an indian history		21/06/2018 15:03:07	View
Anger Tweets of : Kerala_Flood [tweet owner: tmksmanju]				
Reviewed User	Review	Emotion	Date	View the Details
govan1	Kerala Flood is very angry and #Sadness news in an indian History		17/07/2019 12:29:05	View

Sample results



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adjectives and later grouping them according to POMS factor structure yields a coherent data set whose labels can be predicted with the same accuracy as other classifications.

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