IJRSET JUNE 2021 Volume 8, Issue 6 Pages: 1-7

ISSN 2394-739X

International Journal for Research in Science Engineering and Technology

DEPRESSION DETECTION FROM SOCIAL NETWORK DATA USING ML

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ABSTRACT - Social networks have been developed as a great point for its users to communicate with their interested friends and share their opinions, photos, and videos reflecting their moods, feelings and sentiments. This creates an opportunity to analyze social network data for user's feelings and sentiments to investigate their moods and attitudes when they are communicating via these online tools. This study used data from social media networks to explore various methods of early detection of depressive tweets based on machine learning. We performed a thorough analysis of the dataset to characterize the subjects' behavior based on different aspects of their writings: textual spreading, time gap, and time span. In this study, we aim to perform depression analysis on Twitter data collected from an online public source. To investigate the effect of depression detection, we propose machine learning technique as an efficient and scalable method. The evaluation follows a time-aware approach that rewards early detections and penalizes late detections. Given the results, we consider that this study can help in the development of new solutions to deal with the early detection of depression on social networks.

Keywords: [Social Media Analytics, Depression Detection, Machine Learning, Opinion Mining, Mental health, Prediction, Naïve Bayes.]

1. INTRODUCTION

The widespread use of social media may provide opportunities to help reduce undiagnosed mental illness. A growing number of studies examine mental health within social media contexts, linking social media use and behavioral patterns with stress, anxiety, depression, suicidality, and other mental illnesses. The greatest number of studies of this kind focus on depression. Depression continues to be under-diagnosed, with roughly half the cases detected by primary care physicians and only 13–49% receiving minimally adequate treatment.

Automated analysis of social media potentially provides methods for early detection. If an automated process could detect elevated depression scores in a user, that individual could be targeted for a more thorough assessment, and provided with further resources, support, and treatment. Studies to date have either examined how the use of social media sites correlates with mental illness in users [3] or attempted to detect mental illness through analysis of the content created by users. This review focuses on the latter: studies aimed at predicting mental illness using social media. We first consider methods used to predict depression, and then consider four approaches that have been used in the literature. We compare the different approaches, provide direction for future studies, and consider ethical issues.

In this study, we aim to analyze Twitter data to detect any factors that may reflect the depression of relevant Twitter users. Various machine learning techniques are employed for such purpose. Considering the key objective of this study, the following are subsequent research challenges addressed in paper.

(i). What depression is and what are the common factors contributing toward depression?

(ii). What are the factors to look for depression detection in tweets?

(iii). How to extract these factors from tweets?

(iv). What is the relationship between these factors and attitudes toward depression?

(v). When is the most influential time to communicate within depressive Indicative Twitter user?

(vi). What are the most influential machine learning techniques for detection of depression in Tweets?

In the context of above mentioned challenges, we analyze depression from Twitter users' data. As users express their feeling as a post in the Twitter platform, sometimes their posts and comments refer to as emotional state such as 'joy', 'sadness', 'fear', 'anger', or 'surprise'. We analyze various features of Tweets by collecting data through an effective method of machine learning classification techniques and to make overall judgements regarding their various parts. In this study, we used publically available twitter data containing users' tweets. Once we access the data, it was cleaned from any inconsistency and then analyzed by machine learning techniques.

2 LITERATURE REVIEW

Although diagnosis of depression using social networks data has picked an established position globally, there are several dimensions that are yet to be detected. In this study, we aim to perform depression analysis on Facebook data collected from an online public source. To investigate the effect of depression detection, we propose machine learning technique as an efficient and scalable method. We report an implementation of the proposed method. We have evaluated the efficiency of our proposed method using a set of various psycholinguistic features. We show that our proposed method can significantly improve the accuracy and classification error rate. In addition, the result shows that in different experiments Decision Tree (DT) gives the highest accuracy than other ML approaches to find the depression. Machine learning techniques identify high quality solutions of mental health problems among Facebook users. (1.Md. Rafiqul Islam 2. Muhammad Ashad KabirAshir Ahmed 3. Abu Raihan M. Kamal 4.Hua Wang 5.Anwaar Ulh - Depression detection from social network data using machine learning techniques) [1]Depression is viewed as the largest contributor to global disability and a major reason for suicide. It has an impact on the language usage reflected in the written text. The key objective of our study is to examine Reddit users' posts to detect any factors that may reveal the depression attitudes of relevant. The best single feature is bigram with the Support Vector Machine (SVM) classifier to detect depression with 80% accuracy and 0.80 F1 scores. The strength and effectiveness of the combined features (LIWC+LDA+bigram) are most successfully demonstrated with the Multilayer Perceptron (MLP) classifier resulting in the top performance for depression detection reaching. 91% accuracy and 0.93F1 scores. According to our study, better performance improvement can be achieved by proper feature selections and their multiple feature combinations. Forum. (1. MICHAEL M.

TADESSE 2. HONGFEI LIN 3. BO XU 4. LIANG YANG – Detection of Depression-Related Posts in Reddit Social Media forum) [2] Datasets originating from social networks are valuable to many fields such as sociology and psychology. But the supports from technical perspective are far from enough, and specific approaches are urgently in need. This paper applies data mining to psychology area for detecting depressed users in social network services. Firstly, a sentiment analysis method is proposed utilizing vocabulary and man-made rules to calculate the depression inclination of each micro-blog. Secondly, a depression detection model is constructed based on the proposed method and 10 features of depressed users derived from psychological research. Then 180 users and 3 kinds of classifiers are used to verify the model, whose precisions are all around 80%. Also, the significance of each feature is analyzed. Lastly, an application is developed within the proposed model for mental health monitoring online. This study is supported by some psychologists, and facilitates them in data-centric aspect. (1. Xinyu Wang 2. Chunhong Zhang 3.Yang Ji Li Sun Leijia Wu 6. Zhana Ba – a DEPRESSION DETECTION DEL BASED ON SENTIMENT ANALYSIS ON MICRO BLOG SOCIAL NETWORK) [3] Social networks contain a tremendous amount of node and linkage data, providing unprecedented opportunities for a wide variety of fields. As the world's fourth largest disease, depression has become one of the most significant research subjects. Previously, a depression classifier has been proposed to classify the users in online social networks to be depressed or not, however, the classifier takes only node features into account and neglects the influence of linkages. This paper proposes an improved model to calculate the probability of a user being depressed, which is based on both node and linkage features. The linkage features are measured in two aspects: tie strength and interaction content analysis. Moreover, the propagation rule of depression is considered for improving the prediction accuracy. Finally, our experiments on the data derived from Sina Micro-blog shows that the highest accuracy of the improved model is 95%, increasing by 15% compared to the classifier with node features considered only. In this paper, it is well proved that adding linkage features analysis performs much better than node features analysis only. It also implies that tie strength and interaction content have different effects on depression probability estimation. Although this model is proposed for depression detection, the basic idea of linkage features analysis could be explicitly used in a wide scenario. (1 Xinyu Wang 2. Chunhong Zhang 3. Li Sun - AN IMPROVED MODEL FOR DEPRESSION DETECTION IN MICRO BLOG SOCIAL NETWORK) [4] Depression detection is a significant issue for human well-being. Conventional diagnosis of depression requires a face-to-face conversation with a doctor, which limits the likelihood of the identification of potential patients. We instead explore the potential of using only the textual information to detect depression based on the content users posted on social media sites. Since users may post a variety of different kinds of content, only a small number of posts are relevant to the signs and symptoms of depression. We propose the use of reinforcement learning method to automatically select the indicator posts from the historical posts of users. Our experimental results demonstrate that the proposed method outperforms both feature-based and neural network-based methods (over 14.6% error reduction). In addition, a series of experiments demonstrate that our model can deal with the noise of data effectively and can generalize to more complex situations.(1. Tao Gui 2. Qi Zhang 3.Liang Zhu 4.Xu Zhou 5. Minlong Peng 6.Xuanjing Huan - Depression Detection on Social Media with Reinforcement Learn)[5]

3. METHODOLOGY

3.1. Problem Statement

Depression is a mental illness that is not taken seriously in some countries. According to Our World in Data Website, Depressive disorders occur with varying severity. The WHO's International Classification of Diseases (ICD-10) defines this set of disorders ranging from mild to moderate to severe. The Institute for Health Metrics and Evaluation (IHME) adopt such definitions by disaggregating to mild, persistent depression (dysthymia) and major depressive disorder (severe).

All forms of depressive disorder experience some of the following symptoms:

(a) reduced concentration and attention.
(b) reduced self-esteem and self-confidence.
(c) ideas of guilt and unworthiness (even in a mild type of episode).
(d) bleak and pessimistic views of the future.
(e) ideas or acts of self-harm or suicide.
(f) disturbed sleep.
(g) diminished appetite.

3.2. Proposed Approach

Creating a model to detect depression in tweets

In Machine Learning, there are many ways for sentiment analysis such: decision-based systems, Bayesian classifiers, support vector machine, neural networks and sample-based methods. We are going to apply sentiment analysis through a powerful theorem from probability theory called Bayes Theorem. The model will be written in python and it will tell whether a given tweet is depressive or not.

Datasets

Sentiment140: The Sentiment140 dataset contains 1,600,000 tweets extracted using the Twitter API. The tweets have been annotated (0 = negative, 2 = neutral, 4 = positive) and they can be used to detect sentiment.

Web scraping depressive Tweets

Twint is an advanced Twitter scraping tool written in Python that doesn't use Twitter's API, allowing you to scrape a user's followers, following, Tweets and more while evading most API limitations.

Analyzing the data

After cleaning the data and concatenating depressive and positive tweets, to generate a single CVS, decided to analyze the data with wordcloud.

Training and Testing Data

Split the dataset as follows: 98 % for the Training Data and 2% for Testing Data, where polarity "0" means positive and polarity "1" means depressed.

4. EXPERIMENT AND RESULTS

4.1. Data Collection

We use a dataset for Twitter users who suffer from depression. The self-reports are collected by searching Twitter using a regular expression. Candidate users are filtered manually, and then, all their recent tweets are continuously crawled using the Twitter Search API.

4.2 Evaluation Measures

Accuracy: the simplest and mostly used measure to evaluate a classifier. It is defined as the degree of right predictions of a model (or contrarily, the percentage of misclassification errors).

$$Acc = \frac{TP+TN}{TP+TN+FP+FN}$$

Here, TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative
Acc = Accuracy

Precision: It is defined as the fraction of correctly classified positives to the total predicted positives. Under our condition, it aims to find how many of the users identified as depressed are actually depressed.

$$P = \frac{TP}{TP+FN}$$

Recall: It is defined as the fraction of correctly classified positives to total positives [37]. Within our situation, it aims to determine that of all depressed users, how many are properly detected.

$$R = \frac{TP}{TP+TN}$$

F1 Score (F-measure): It is the harmonic mean of precision and recall; it weighs each metric evenly, and therefore, is commonly utilized as a classification evaluation metric.

$$F1 = \frac{2*P*R}{P+R}$$

Hence, it is important to achieve both high recall and high precision.

Confusion Matrix: It is a form of contingency table that presents the differences between the true and predicted classes for a set of labeled instances. It has four categories: true positives (TP), which refers to positives that are identified correctly; false positives (FP),which are positives identified incorrectly and supposed to be negatives; true negatives (TN), which refer to negatives that are correctly labeled as negative, and false negatives (FN),correspond to positives that are incorrectly labeled as negative .

4.3 Results

After training the model, the results are:
Precision: 0.9
Recall: 0.43902439024390244
F-score: 0.5901639344262295
Accuracy: 0.8756218905472637
we can improve the accuracy of the model by feeding it with more data.

5. CONCLUSION AND FUTURE WORK

5.1. CONCLUSION

This project defines a binary classification problem as identifying whether a person is depressed, based on his tweets and Twitter profile activity. Different machine learning algorithms are exploited and different feature datasets are explored. Many preprocessing steps are performed, including data preparation and aligning, data labeling, and feature extraction and selection. We created a closer connection between depression and a language usage by applying NLP and text classification techniques. We identified a lexicon of words more common among the depressed accounts. According to our findings, the language predictors of depression contained the words related to preoccupation with themselves, feelings of sadness, anxiety, anger, hostility or suicidal thoughts, with a greater emphasis on the present and future.
We applied Linguistic Inquiry and Word Count (LIWC) on our data set. The LIWC2015 dictionary is the heart of the text analysis strategy. It processes our tweets on a 'line by line' basis within and across columns of spreadsheet and accesses a single text within a spreadsheet and analyzes each line sequentially and reads one target word at a time. The SVM model has achieved optimal accuracy metric combinations; it converts an extremely nonlinear classification problem into a linearly separable problem. Although the DT model is comprehensive and follows understandable steps, it can fail if exposed to brand-new data. This study can be considered as a step toward building a complete social media-based platform for analyzing and predicting mental and psychological issues and recommending solutions for these users. The main contribution of this study lies in exploiting a rich, diverse, and discriminating feature set that contains both tweet text and behavioral trends of different users.
In this project, we tried to identify the presence of depression in social media, and searched for affective performance increase solutions of depression detection. We characterized a closer connection between depression and a language usage by applying NLP and text classification techniques. We identified a lexicon of words more common among the depressed accounts. According to our findings, the language predictors of depression contained the words related to preoccupation with themselves, feelings of sadness, anxiety, anger, hostility or suicidal

thoughts, with a greater emphasis on the present and future.

5.2. Future Work

This study can be extended in the future by considering more ML models that are highly unlikely to over-fit the used data and find a more dependable way to measure the features' impact. Depression can be detected in other features, such as the time when a person tweet something. People with depression usually post late night tweets. There are many factors we can analyze in order to make better conclusions.

In future work, we plan to use more dataset to verify our techniques efficiency and effectiveness. We are in agreement with the existing body of literature that suggests that more focused studies in depression analysis are needed.

As you can see, the model works good in predicting some tweets sentiment but it can get better with more data. The difficult part was finding an annotated dataset. Cleaning the data to get it ready for analysis took me some sometime.

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