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SOCIAL MEDIA EMOTIONAL PATTERNS FOR DETECTING MENTAL DISORDERS

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Abstract: Lot of people around the world are affected by one or more mental disorders that involve in their thinking and behavior. A timely finding of these problems is challenging but important, since it could open the possibility to offer a bid to people before the illness gets worst. Another Approach is to realize this is to monitor how people communicate themselves, that is,what and how they write, or even a step further, what emotions they accomplish in their social media communications. In this study, we estimate two computational representations that aim to design the presence and changes of the emotions communicated by social media users. In our approach we use two recent public data sets for two important mental disorders: Depression and Anorexia. The acquired results suggest that the presence and variability of emotions, apprehend by the proposed representations, allow to highlight main information about social media users suffering from depression or anorexia. Furthermore, the combination of both representations can enhance the performance, equaling the best reported approach for depression.

Index Terms - Social media, Mental Disorders

I. Introduction

A mental disorder affects several interferences in the thinking and behavior of the affected person.These Changes could vary from low to high, which could result in an inaptitude to live routines indaily life and general demands [2]. Common mental disorders such as depression and anorexia effect several millions of people around the world. They may be connected to a single incident

which can cause more stress on the person or by a combination of several stressful events. It is also known that mental disorders tend to grow in countries containing generalized violence or recurrent natural disasters. For example, in 2018 a study of mental disorders in Mexico revealed that 19% of its population has at least mental disorder and one in four will contain a mental disorder at least once in their life [3]. In another, in the modern world, we take social life could be knowledgeable either in the physical world or in a virtual world designed by social media platforms. This reality presents some problems, but also great opportunities which, if properly addressed, could grant to the understanding of what and how we interact. In this regard, the goal of this study is to estimate, via the automatic detection of emotional patterns, social media documents 1 with the purpose of finding the presence of signs of depression or anorexia in the population of that area. Existing studies focused on the identification of depression and anorexia have mainly considered linguistic and sentiment analysis [2]-[4]. Note that the utilize of sentiments, i.e. polarity, was the notable for the later use of emotions for the same task [5]. This line of thought un cover the potential of utilizing emotions as features, such as" anger"," surprise" or joy", insteadof linguistic features or general sentiments like positive and negative. In this direction, in our existing work [6], we implemented a novel representation that was built using information extracted from emotions lexicons aggregated with word embedding as a way to represent the information contained in users' documents. Then, utilizing a clustering algorithm, we generated sub-groups of emotions, that conveniently renamed as sub-emotions. These discovered sub- emotions gives a more convenient and fine-grained representation of users and a more performancefor the detection of depression. In a few words, the objective behind this representation was to collect the presence of sub-emotions in users' posts. The objective of our approach is that users suffering from depression would show a distribution of emotions different from healthy users. Considering by the encouraging results of the representation based on sub-emotions. In particular, we propose a new representation,that not only collects the presence of sub-emotions, but also design their changes over time. The intuition is to design emotional fluctuations that users with mental disorders could continuously present. This temporal information is later combined to enhance the original approach. That is, we design a fusion of both representations, that at the end attains very competitive results, practicallyequal to those of the state of-the-art approaches. Finally, we visualize how these two representations can be applied beyond detecting depression to also detect other important mental disorder such as anorexia. Using this new representation, we contrast emotional patterns between the two disorders, possibly finding what could be described as their emotional" silhouette".

II. LITERATURE SURVEY

Depression is a mental health disorder characterized by persistent loss of interest in activities, which can cause more difficulties in everyday life [1], [7]. Studies focusing on the automatic detection of this disorder have used crowdsourcing as their main strategy to capture data from users who have reported more being treated with clinical depression [8]. Among these researches,the most important approach considers words and word n-grams as features and employs existingclassification algorithms. The main idea is to collect the most frequent words used by individualseffected by depression and compare them against the more frequent words used by healthy users.This approach suffers because there is usually a high overlap in the vocabulary of users with and without depression. Another group of works utilized a LIWC-based representation [2], aiming to represent users' posts by a group of psychologically meaningful categories like social relationships, thinking styles, or individual differences [8], [3]. These works have allowed a better characterization of the mental disorder conditions, nevertheless, they have only obtained moderately better results than using only the words.

Recent works have considered ensemble approaches, which aggregrate word and Linguistic Inquiry and Word Count (LIWC) basedrepresentations with deep neural models such as LSTM and CNN networks [2]. These works showthat in social media texts exist useful data to tell if a person suffers from depression, but the resultsare sometimes hard to predict. This is a main limitation since these types of tools are naturally aimed to support health professionals and not to take the final decisions. In [2], the authors conductstudies to deal this issue. They characterize users affected by mental disorders and propose methods for visualizing the data in order to give useful insights to psychologists. Lastly, some works have also considered representations based on sentiment analysis techniques. These works have shown interesting results, indicates that negative comments are more abundant in people withdepression than in users who do not suffer from this disorder to detect depression on Twitter users.

III. PROPOSED SYSTEM

To offer a glimpse of the data sets, we demonstrate some examples of posts from the different classes of users. Our goal is to show that users who effect from a mental illness as well as controlusers share their experiences and personal feelings about them, which for both can be positive andnegative, making their detection a great challenge.

Depression

1) After coming home from a road trip with a group of friends to celebrate my birthday.

2) Sometimes I can’t help but think that they will be so much better off without me, and they knowthat they would be happier without me.

Anorexia

1) I’m happy to hear that you’re okay with realizing you’ll be on anti-depressants for the rest of your life.

2) My coach looked over at me then muttered; "It’s a shame. If she wasn’t so BIG I’d consider herfor the team.

Control

1) Nice job; it’s not always easy with the clouds. I love the colors of those waters with the glacialmoraine. Beautiful image.

2) It was difficult, I do not expect it to be well-received here, but even if one person find it usefulį will continue.

The steps of proposed system are as follows:

Preprocessing: The texts were normalized by lowercasing all words and eliminating special characters like URLs, emoticons, and #; the stop words were kept. Then, the preprocessed texts werehidden using the created sub-emotions.

Classification: The main goal is to divide users into one of the two classes (Depressed / Control or Anorexia / Control).

The BoSE (Bag of Sub Emotions) approach consists of three main steps: first, a set of fine-grained emotions are tested using unsupervised learning from a lexical resource that contains words associated to different emotions and sentiments, this is achieved using a clustering technique that separates the distribution of each emotion e in Ke sub-groups also known as sub-emotions. Second, the fine-grained emotions are used to represent the documents, each word is masked or substitute by its closer sub-emotion, and each document is represented by a frequency histogram of their sub-emotions. Third, the histogram representation is used to train a classification model that predicts the depression label. On the other hand, the involvement of a dynamic analysis over the sub-emotions, called Δ-BoSE, which helps to improve in finding the users having signs of anorexia and depression.

After developing the BoSE representation, the most relevant features of the sequences of sub-emotions were taken using the term frequency – inverse document frequency(tf-idf) representation and chi2 distribution X2 k [9]. With the chosen features we give a Support Vector Machine (SVM) with a linear kernel, C = 1, L2 normalization and weighted for class imbalance. We utilized the same number of features for BoSE and Δ-BoSE. The final prediction is utilizing the whole post history of the users and we divide the user as positive if the SVM decidesthe example is closer to this class.

Baselines: Inspired in [15], we generalized a slightly different approach. That is, the original approach counts the correct presence of words from each emotion in each one of the posts, in ourcase we applied an approach similar to BoSE, masking the words with their more same emotion. In other words, the original approach considers a hard matching of words from the lexicons, whileours considers a soft matching procedure which can be referred as Bag-of-Emotions (BoE). Also, the results are compared to the existing Bag-of-Words representation. Both representations were generated using word unigrams and n-grams; these are common baseline approaches for text classification.

IV. RESULT AND DISCUSSION

Bag of Emotions (BoE) acts like a description which are used to measure the emotional valence or polarity in the posts. A Bag of words (BoW) is a representation of text that describes the occurrence of words within a document. We just keep track of word counts and ignores the grammatical details and the word order. In this study, we exhaustively evaluate BoSE-based representations, and we contrast them againstthe BoE and BoW schemes (using both unigrams and bigrams) and also against Deep Learning models (using Glove and word2vec) for the detection of Depression (eRisk '18) and Anorexia (eRisk '18). Surprisingly, the performance of deep learning models is remarkably low; to some extent this could be attributable to the small size of the employed data sets. Indeed, most participants of eRisk 2018 that employed this kind of models combined them with traditional approaches to leverage their results. In order to analyze the obtained results, we plotted the users in a plane using both the BoW and the BoSE representations. To generate these visualizations. weused the T-distributed Stochastic Neighbor Embedding (T-SNE) algorithm [5], which is a nonlinear dimensionality reduction technique well-suited for plotting high-dimensional spaces in a low dimensional space. For this analysis we used the vector representation of 3000/1500 features obtained using tf-idf with chi2 distribution for both BoSE and BoW. Figure 2 offers an interestingperspective of the advantage of using BoSE over BoW to allow the classifier to build a better classification function. We even analyzed the boundary cases and found similar distribution in thesub emotions, this could be due to the similarity in the topics captured by the

sub-emotions that users posted and shared.

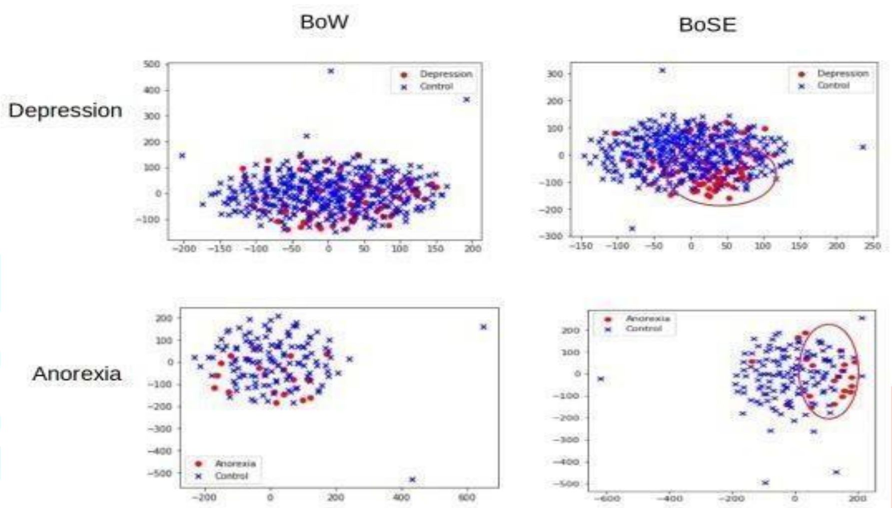

Figure 2. Experimental Result

V. *CONCLUSION*

In this work, we shown that representations which can be based on fine grained emotions can collect more particular topics and issues that are generalized in social media documents done by users that unfortunately affected by depression or anorexia. That is, the automatically divided fromsub-emotions which can present useful information that a bid the finding of these two mental disorders. On the one hand, the BoSE representation gets better results than the traditional baselines, that consists of some deep learning approaches, and also enhanced the results of only utilizing broad emotions as features. On the other hand, the including of a dynamic analysis over the sub-emotions, called Δ-BoSE, improved the finding of users that presents signs of anorexia and depression, showing the usefulness of considering the changes of sub-emotions overtime.

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