Detection of Social Network Mental Disorder via Online Social Media Mining

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ABSTRACT-- **The explosive growth in popularity of social networking results in the problematic usage. The increase in number of social network mental disorders (SNMDs), like Cyber-Relationship Addiction, Information Overload, and Net Compulsion, are very much observable. Symptoms of those mental disorders are usually observed passively today, leading to delayed clinical intervention. In this paper, we argue that mining online social behavior provides a chance to actively identify SNMDs at an early stage. It is challenging to detect SNMDs because the mental status can't be directly observed from online group action logs. A new and innovative approach to the practice of SNMD detection, doesn't believe self-revealing of those mental factors via questionnaires in Psychology. Instead, we initiate a machine learning framework, namely, By extracting the features from social data we detect the potential cases of SNMD. We also exploit multi-source learning in SNMDD and propose a replacement SNMD-based Tensor Model(STM)to improve the accuracy. To increase the scalability of STM, we further try to increase the efficiency with performance guarantee.**

I.INTRODUCTION:

With the explosive growth in popularity of social networking and messaging apps, online social networks (OSNs) became a neighborhood of the many people's daily lives [1]. Most research on social network mining focuses on discovering the knowledge behind the info for improving people's life. While OSNs seemingly expand their users' capability in increasing social contacts, they'll actually decrease the face-to-face interpersonal interactions within the world . Due to the epidemic scale of these phenomena, new terms like Phubbing (Phone Snubbing) and Nomophobia (No mobile Phobia) [1] are created to elucidate people who cannot stop using mobile social networking apps. In fact, some social network mental disorders (SNMDs) [1], such as Information Overload and Net Compulsion, have been recently noted.1 For example, studies point out that 1 in 8 Americans suffer from problematic Internet use2. Moreover, leading journals in mental health, such as the American Journal of Psychiatry, have reported that the SNMDs may incur excessive use, depression, social withdrawal, and a range of other negative repercussions. Indeed, these symptoms are important components of diagnostic criteria for SNMDs e.g., excessive use of social networking apps – usually associated with a loss of the sense of your time or a neglect of basic drives, and withdrawal – including feelings of anger, tension, and/or depression when the computer/apps are inaccessible. SNMDs are social-oriented and tend to happen to users who usually interact with others via online social media. Those with SNMDs usually lack offline interactions, and as a result seek cyber-relationships to compensate [1]. Today, identification of potential mental disorders often falls on the shoulders of supervisors (such as teachers or parents) passively. However, since there are very few notable physical risk factors, the patients usually do not actively seek medical or psychological services. Therefore, patients would only seek clinical interventions when their conditions become very severe.

II. RELATED WORK

Existing System:

Psychology has identified several crucial mental factors associated with SNMDs, they're mostly examined as standard diagnostic criteria in survey questionnaires. To automatically detect potential SNMD cases of OSN users, extracting these factors to assess users' online mental states is extremely challenging. For example, the extent of loneliness and the effect of disinhibition of OSN users are not easily observable.3 Therefore, there is a need to develop new approaches for detecting SNMD cases of OSN users. We argue that mining the social network data of people as a complementary alternative to the traditional psychological approaches provides a superb opportunity to actively identify those cases at an early stage.

Disadvantages:

- Manually its very difficult to analysis the all post in large social media
- Its Difficult to monitor the stress of a person

Proposed System:

Specifically, we formulate the task as a semi-supervised classification problem to detect three sorts of SNMDs : i) Cyber-Relationship Addiction, which shows addictive behavior for building online relationships; ii)Net Compulsion, which shows compulsive behavior for online social gaming or gambling; and iii) Information Overload, which is related to uncontrollable surfing[1]. By exploiting machine learning techniques with the ground truth obtained via the current diagnostic practice in Psychology, we extract and analyze the following crucial categories of features from OSNs: 1) social comparison, 2) social structure, 3) social diversity, 4) para social relationships, 5) online and offline interaction ratio, 6) social capital, 7) disinhibition, 8) self-disclosure, and 9) bursting temporal behavior. These features capture important factors or serve as proxies for SNMD detection. For example, studies manifest that users exposed to positive posts from others on Facebook[2] with similar background are inclined to feel malicious envy and depressed due to the social comparison. The depression leads users to disorder behaviors, such as information overload or net compulsion.

Advantages:

- It take very less process time.
- It will predict more accurately.

III. LITERATURE SURVEY

1) Daily stress recognition from mobile data, weather and individual traits

AUTHORS: AndreyBogomolov, Bruno Lepri

Research has proven that stress reduces quality of life and causes many diseases. For this reason, several researchers devised stress detection systems supported physiological parameters. However, these systems require that obtrusive sensors are continuously carried by the user. Here an approach is proposed providing evidence that daily stress are often reliably recognized supported behavioral parameters, obtained from the user's mobile activity and from additional indicators, like the weather (data concerning transitory properties of the environment) and therefore the personality traits (data concerning permanent dispositions of individuals). The usage of multifactorial statistical model, which is person-independent, obtains the accuracy score of 72.28% for a 2-class daily stress recognition problem. The model is efficient to implement for many of multimedia applications thanks to highly reduced low-dimensional feature space (32d). Moreover, we identify and discuss the indications which have strong predictive power.

2) Retrieval evaluation with incomplete Information

AUTHORS: Chris Buckley and EllenM Voorhees

This paper tests whether the Cranfield evaluation methodology is robust to gross violations of the assumption of completeness (i.e., the thought that every one relevant documents within a test collection are identified and are present in the collection). We show that current evaluation measures aren't robust to substantially incomplete relevance judgments. A measure of both highly correlated with existing measures when complete judgments are available and more robust to incomplete judgment sets is done.

Measure value suggests that gradually larger or dynamic test collections built using present pooling practices must be available for laboratory tools, despite the actualundeniable fact that the relevance information are going to be incomplete and imperfect.

3) Measuring post traumatic stress disorder in twitter

AUTHORS: Glen Coppersmith, Craig Harman

Traditional psychological state studies believe information primarily collected through personal contact with a health care professional. Recent work has shown the utility of social media data for studying depression,but there are limited evaluations of other psychological state conditions. We consider post traumatic stress

disorder (PTSD), a significant condition that affects millions worldwide, with especially high rates in military veterans. We also present a completely unique method to get a PTSD classifier for social media using simple searches of obtainable Twitter data, a big reduction in training data cost compared to previous work. Demonstration of its utility by examining differences in language use between PTSD and random individuals, building classifiers to separate these two groups and by detecting elevated rates of PTSD at and around U.S. militarybases using classifiers is done.

4) Mental Disorder Detection and Measurement using Latent Dirichlet Allocation and SentiWordNet

AUTHORS:Chih-Hua Tai , Zheng-Han Tan, Yung-Sheng Lin, Yue-Shan Chang

With the upcoming of social platforms, people tend to posting their diaries and feeling online for sharing with others. In this paper, we aim to predict whether a user is getting depressed or not through his blog posts on the web . For this purpose, we use Latent Dirichlet Allocation (LDA) to seek out out top frequency words appearing during a user's diaries and use SentiWordNet to calculate the emotion score of the user. Experimental results show that our method is useful in the diagnosis of mental disorder detection in social platforms. In this paper, we proposed a method to measure and detect one's mental disorder though his online diaries using LDA and SentiWordNet. In the proposed method, words other than sentiment words were removed first. LDA was then used to extract the concept keywords of the diaries so that even later, we can focus on these representative sentiment keywords to evaluate one's emotion score with the help of SentiWordNet. The experimental results on real datasets collected from online depression forums and general social platforms show that the proposed method achieved at least 80% correct rates in the diagnosis of depression.

5) X-A-BiLSTM: a Deep Learning Approach for Depression Detection in Imbalanced Data

AUTHORS: Qing Cong, Zhiyong Feng, Fang Li

An increasing number of people suffering from mental health conditions resort to online resources (specialized websites, social media, etc.) to share their feelings. Early depression detection using social media data through deep learning models can help to vary life trajectories and save lives. But the accuracy of these models was not satisfying due to the real-world imbalanced data distributions. To tackle this problem, we propose a deep learning model (X-A-BiLSTM) for depression detection in imbalanced social media data. The X-ABiLSTM model consists of two essential components: the first one is XGBoost, which is used to reduce data imbalance; and the second one is an Attention-BiLSTM neural network, which enhances classification capacity. Results demonstrate that our approach significantly out performs the previous state-of-the-art models on the RSDD dataset. This approach focused on solving the problem caused by data imbalance in the real world. The X-A-BiLSTM model consisted of two essential components: the first XGBoost component, which permitted acquiring balanced data by means of an end-to-end scalable tree boosting system, and the second component, BiLSTM with the attention mechanism, which achieved good classification performance. Results on the RSDD dataset showed that our model significantly outperformed the previous state-of-the-art models. To the best of our knowledge, this is the first time such an effective combinational model has been proposed.

IV. METHODOLOGY

1)System Framework:

In this framework we propose a novel hybrid model - a factor graph model combined with Convolution Neural Network to leverage tweet content and social interaction information for stress detection. On experimenting the results show that the proposed model can improve the performance of detection by 6-9% in F1-score. By further analyzing the social interaction data, we also discover several serious situations, i.e. the number of social structures of sparse connections (i.e. with no delta connections)[1] which clearly states that the difference between stressed users and unstressed users is 14% indicating that the social organisation of stressed users' friends tend to be less connected and fewer complicated than that of non-stressed users.

By making use of Leacock chordorow algorithm, the tweets are classified as positive or negative based on the stress level analysis. Mutual information correlation feature extraction algorithm concept concerns the outcome of two variables. It will measure the reduction in uncertainty for predicting the outcome of the system.

2) Social Interactions:

We analyze the correlation of users' stress states and their social interactions on the networks, and react to the matter from the viewpoint of: (1) social interaction content, by investigating the content differences between stressed and normal users' social interactions; and (2) social interaction structure, by investigating the structure differences in terms of structural diversity, social influence, and strong/weak tie. Our investigation unveils some intriguing social phenomena. For example, we find that the number of social structures of sparse connection (i.e. with no delta connections4) of stressed users is around 14% above that of non-stressed users, indicating that the social organization of stressed users' friends tend to be less connected and sophisticated , compared thereto of non-stressed users.

3) Attributes categorization

We first define two sets of attributes to live the differences of the stressed and non-stressed users on social media platforms: 1) tweet-level attributes from a user's single tweet; 2) user level attributes analysed from a user's per week tweets.

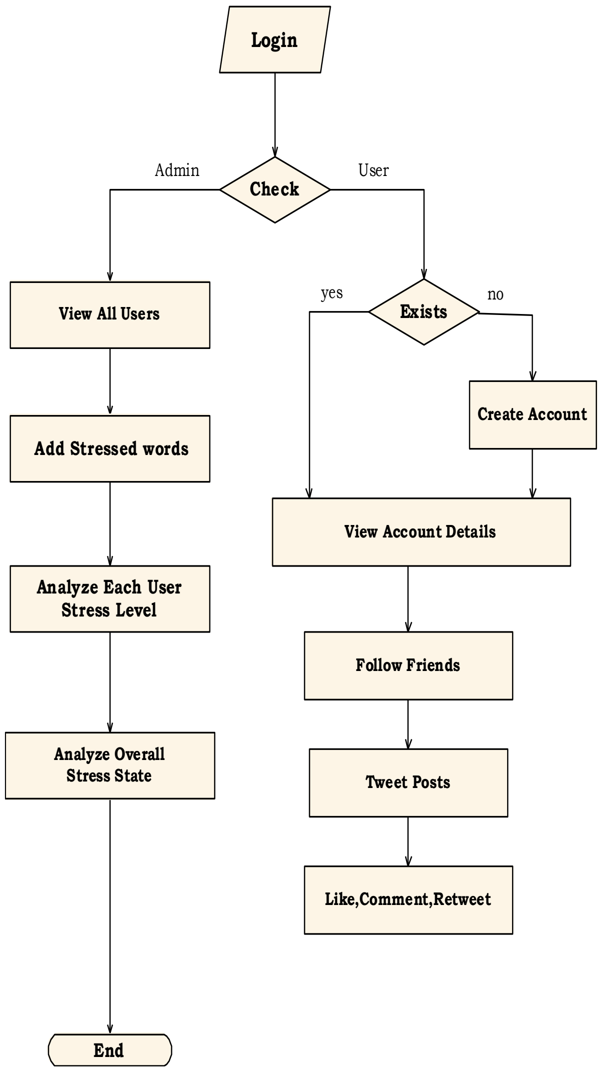
Tweet-level Attributes

Tweet-level attributes describe the linguistic and visual content, also as social attention factors (being liked, commented, and retweeted) of one tweet. We can classify words into different categories, e.g. positive/negative emotion words, degree adverbs. Furthermore, we extract linguistic attributes of emoticons, so we can map the keyword in square brackets to find the emoticons. Twitter adopts Unicode as the representation for all emojis, which can be extracted directly.

User-Level Attributes

Compared to tweet-level attributes extracted from one tweet, user-level attributes are extracted from an inventory of user's tweets during a specific sampling period. We use one week because the sampling period during this paper. On one hand, psychological stress often results from series of events or mental states. On the opposite hand, users may express their chronic stress during a series of tweets instead of one. Besides, the aforementioned social interaction patterns of users during a period of your time also contain useful information for stress detection. Moreover, as aforementioned, the knowledge in tweets is restricted and sparse. We need to add additional information around tweets, e.g., users' social interactions with friends.

V. Flow Chart



VI. CONCLUSION

In this paper, we presented a framework users'psychological stress states detection from users' per week social media data, leveraging tweets' content also as users' social interactions.Employing real-world social media data as the basis,we studied the correlation between user' psychological stress states and their social interaction behaviours. To gain total access of both content and social interaction information of users' tweets, we proposed a hybrid model which combines the factor graph model (FGM) with a convolutional neural network (CNN).In this work, we also discovered several intriguing phenomena of stress. We found that the number of social structures of sparse connection (i.e. with no delta connections)is the difference of 14% between stressed users and unstressed users, indicating that the social organisation of stressed users' friends tend to be less connected and fewer complicated than that of non-stressed users. These phenomena might be useful references for future related studies.

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