A Novel Hybrid Model for Stress Detection with Convolutional Neural Networks

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Abstract

Psychological wellness conditions influence a noteworthy level of the world's population every year. The stress investigation of emotional wellness phenomena in openly accessible social networking sites like Twitter,Sina Weibo and Facebook. A set of stress-related textual, visual, and social attributes from various aspects are first defined and then propose a novel hybrid model. The work has demonstrated the utility of online social information for contemplating despondency, be that as it may, there have been limited assessments of other mental wellbeing conditions. It is not easy to access the user posts on their Facebook page. In order to obtain the user data from Facebook, system have to get the access token from Facebook developer page. The API act as an intermediate system that will help the system to analysis the user information from the Facebook page. The system will also help to Recommending users with different links for psychological counselling centers, soft music or articles to help release their stress according to users' stress level

Key words: *Stress detection, social media, microblog, access tokens, and face book.*

1. Introduction

More and more teenagers today are overloaded with adolescent stress from different aspects: academic future, self-cognition, interpersonal, and affection. Long-lasting stress may lead to anxiety, withdrawal, aggression, or poor coping skills such as drug and alcohol use, threatening teenagers' health and development. Hence, it is important for both teenagers and their guardians/teachers to be aware of the stress in advance and manage the stress before it becomes severe and starts causing health problems. The current social media micro-blog offers an open channel for us to timely andunobtrusively sense teenager's stress based on his/her tweeting contents and behaviours. This study describes a framework to further predict teenager's future adolescent stress level from micro-blog and discusses how we address the challenges (data incompleteness and multifaceted prediction) using machine learning and multi-variant time series prediction techniques. Forthcoming events that may possibly influence teenager's stress levels are also incorporated into our prediction method. Our experimental results demonstrate the effectiveness of considering correlated features and event influence in prediction. To the best of our knowledge, this is the first work on predicting teenager's future stress level via micro-blog. College can be stressful for many freshmen as they cope with a variety of academic, personal, and social pressures. Although not all stress is negative, a certain level of stress can be beneficial to help improve performance. However, too much stress can adversely affect health in the annual survey of the American Freshman; the number of students reported feeling overwhelmed and stressed has increased steadily in the last decade. Over 50% of college students suffer significant levels of stress during a typical college semester.

Consequently, there is a need to find innovative and cost-effective strategies to help identify those students experiencing high levels of stress and negative emotions early on so that they can receive the appropriate treatment in order to prevent future mental illnesses. Social media use, such as Twitter and Facebook, has been rapidly growing, and research has already shown that data from these technologies can be used for novel approaches to public health surveillance . Twitter usage among young adults has increased 16% from 2012 to 2014. Currently, 32% of adults of the ages 18-29 years use Twitter, and the usage is expected to increase steadily in the future. People often have the need to share their emotions and experiences . Researchers have theorized that emotional sharing may fulfil a socio-affective need by eliciting attention, affection, and social support. Consequently, this may help individuals cope with their emotions and provide an immediate relief . Users often share their thoughts, feelings, and opinions on these social media platforms, and as a result, social media data may be used to provide real-time monitoring of stress and emotional state among college students.

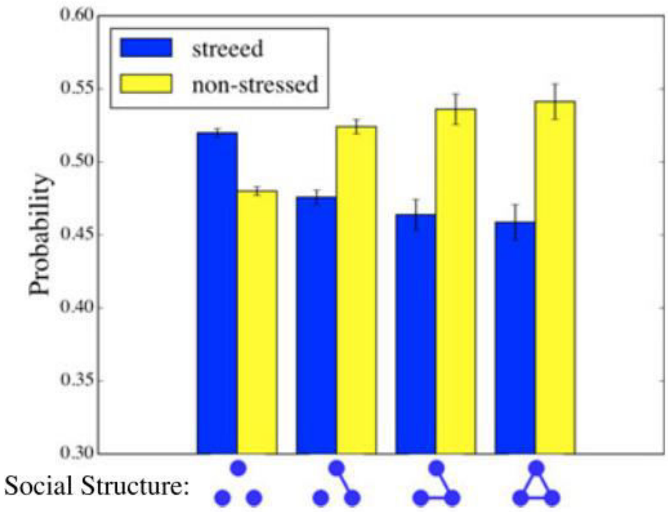

Figure 1. The sampling test results of the diversity of the user's social structures form Sina Weibo

Previous studies have shown that Twitter data can be used to monitor a wide range of health outcomes, such as detecting human immunodeficiency virus infection outbreaks and predicting an individual's risk of depression . For example, De Choudhury et al conducted one of the first studies that used an individual's tweets to predict the risk of depression . The authors found that certain features extracted from a person's tweets collected over a 1-year period were highly associated with the risk of depression in adults, such as raised negative sentiment in the tweets, frequent mentions of antidepressant medication, and greater expression of religious involvement. Currently, no studies have examined whether Twitter data can be used to monitor stress level and emotional state among college students. Studying this topic is important because the large amount of social media data from college students' frequent use of social media can be used to helpuniversity officials and researchers monitor and reduce stress among college students.

2. Proposed System

Inspired by psychological theories, we first define a set of attributes for stress detection from tweet-level and user-level aspects respectively: 1) tweet-level attributes from content of user's single tweet, and 2) user level attributes from user's weekly tweets. ❑ The tweet-level attributes are mainly composed of linguistic, visual, and social attention (i.e., being liked, retweeted, or commented) attributes extracted from a single-tweet's text, image, and attention list. The user-level attributes however are composed of: (a) posting behavior attributes as summarized from a user's weekly tweet postings; and (b) social interaction attributes extracted from a user's social interactions with friends. ❑ In particular, the social interaction attributes can further be broken into: (i) social interaction content attributes extracted from the content of users' social interactions with friends; and (ii) social interaction structure attributes extracted from the structures of users' social interactions with friends.

2.1. Advantages

Experimental results show that by exploiting the users' social interaction attributes, the proposed model can improve the detection performance (F1-score) by 6-9% over that of the state-of-art methods. This indicates that the proposed attributes can serve as good cues in tackling the data sparsity and ambiguity problem. Moreover, the proposed model can also efficiently combine tweet content and social interaction to enhance the stress detection performance.

Beyond user's tweeting contents, we analyzed the correlation of users' stress states and their social interactions on the networks, and address the problem from the standpoints of:

(1) social interaction content, by investigating the content differences between stressed and non-stressed users' social interactions; and

(2) social interaction structure, by investigating the structure differences in terms of structural diversity, social influence, and strong/weak tie.

We build several stressed-twitter-posting datasets by different ground-truth labelling methods from several popular social media platforms and thoroughly evaluate our proposed method on multiple aspects.

We carry out in-depth studies on a real-world large-scale dataset and gain insights on correlations between social interactions and stress, as well as social structures of stressed users.

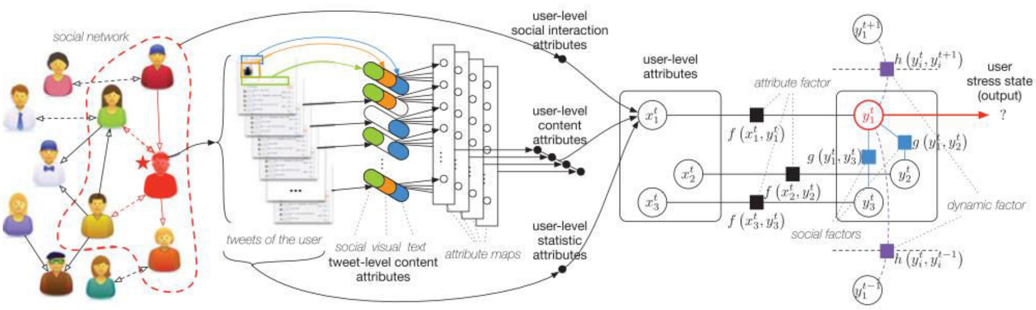

Figure. 2 Architecture of proposed stress detection model

3. Implementation

3.1. 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. Experimental results show that the proposed model can improve the detection performance by 6-9% in F1-score. By further analysing the social interaction data, we also discover several intriguing phenomena, i.e. the number of social structures of sparse connections (i.e. with no delta connections) of stressed users is around 14% higher than that of non-stressed users, indicating that the social structure of stressed users' friends tend to be less connected and less complicated than that of non-stressed users.

3.2. Social Interactions

We analyzed the correlation of users' stress states and their social interactions on the networks, and address the problem from the standpoints of:

(1) social interaction content, by investigating the content differences between stressed and non-stressed 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% higher than that of non-stressed users, indicating that the social structure of stressed users' friends tend to be less connected and complicated, compared to that of non-stressed users.

3.3. Attributes categorization

We first define two sets of attributes to measure 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 summarized from a user's weekly tweets.

3.4. Tweet-level Attributes

Tweet-level attributes describe the linguistic and visual content, as well as social attention factors (being liked, commented, and retweeted) of a single 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.

3.5. User-Level Attributes

Compared to tweet-level attributes extracted from a single tweet, user-level attributes are extracted from a list of user's tweets in a specific sampling period. We use one week as the sampling period in this paper. On one hand, psychological stress often results from cumulative events or mental states. On the other hand, users may express their chronic stress in a series of tweets rather than one. Besides, the social interaction patterns of users in a period also contain useful information for stress detection. Moreover, as aforementioned, the information in tweets is limited and sparse. We needto integrate more complementary information around tweets, e.g., users' social interactions with friends.

4. Conclusion

Psychological stress is threatening people's health. It is non-trivial to detect stress timely for proactive care. Therefore, we have presented a framework for detecting user's psychological stress states from user's monthly social media data, leveraging Facebook post content as well as user's social interactions. Employing real-world social media data as the basis, we studied the correlation between user's psychological stress states and their social interaction behaviours. We recommend the user for health consultant or doctor. We show the hospitals for further treatment on a graph which locate shortest path from current location of user to that hospital. We recommended the user for health precaution and send mail for user interaction purpose.

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