IDENTIFYING STRESS BASED ON COMMUNICATIONS IN SOCIAL NETWORKS

[1]Manimegalai. C and [2]Prakash Narayanan. C
manimegalaic153@gmail.com and cprakashmca@gmail.com
[1]PG Student and [2]Assistant Professor, Department of Computer Science and Engineering
P.S.V. College of Engineering & Technology, Krishnagiri

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Abstract - Mental pressure is compromising individuals' wellbeing. It is non-unimportant to recognize pressure convenient for proactive consideration. With the fame of web based life, individuals are accustomed to sharing their every day exercises and cooperating with companions via web-based networking media stages, making it doable to use online informal community information for stress discovery. In this paper, we find that clients stress state is firmly identified with that of his/her companions in web-based social networking, and we utilize an extensive scale dataset from genuine social stages to efficiently think about the relationship of clients' pressure states and social connections. We initially characterize a lot of pressure related literary, visual, and social properties from different viewpoints, and after that propose a novel half and half model - a factor chart display joined with Convolutional Neural Network to use tweet substance and social collaboration data for stress recognition. Exploratory outcomes demonstrate that the proposed model can improve the location execution by 6-9% in F1-score. By further examining the social communication information, we likewise find a few captivating wonders, for example the quantity of social structures of scanty associations (for example with no delta associations) of focused on clients is around 14% higher than that of non-focused on clients, demonstrating that the social structure of focused on clients' companions will in general be less associated and less confused than that of non-focused on clients.

Key Words: (Size 10 & Bold) Key word1, Key word2, Key word3, etc (Minimum 5 to 8 key words)…

1. INTRODUCTION

Psychological stress is becoming a threat to people's health nowadays. With the rapid pace of life, more and more people are feeling stressed. According to a worldwide survey reported by New business in 20101, over half of the population have experienced an appreciable rise in stress over the last two years. Though stress itself is nonclinical and common in our life, excessive and chronic stress can be rather harmful to people's physical and mental health. According to existing research works, long-term stress has been found to be related to many diseases, e.g., clinical depressions, insomnia etc.. Moreover, according to Chinese Center for Disease Control and Prevention, suicide has become the top cause of death among Chinese youth, and excessive stress is considered to be a major factor of suicide .All these reveal that the rapid increase of stress has become a great challenge to human health and life quality. Thus, there is significant importance to detect stress be-fore it turns into severe problems. Traditional psychological stress detection is mainly based on face-to face interviews, self-report questionnaires or wearable sensors. However, traditional methods are actually reactive, which are usually labor-consuming, time-costing and hysteretic.

2. OUR WORK

Inspired by psychological theories, we first define a set of at-tributes 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.

3. RELATED WORK

Psychological stress detection is related to the topics of sentiment analysis and emotion detection. Research on tweet-level emotion detection in social networks. Computer-aided detection, analysis, and application of emotion, especially in social networks, have drawn much attention in recent years. Relationships between psychological stress and personality traits can be an interesting issue to consider. For example, providing evidence that daily stress can be reliably recognized based on behavioral metrics from users mobile phone activity. Many studies on social media based emotion analysis are at the tweet level, using text-based linguistic features and classic classification approaches. proposed a system called Mood Lens to perform emotion analysis on the Chinese micro-blog platform We classifying the emotion categories into four types, i.e., angry, disgusting, joyful, and sad. studied the emotion propagation problem in social networks, and found that anger has a stronger correlation among different users than joy, indicating that negative emotions could spread more quickly and broadly in the network. As stress is mostly considered as a negative emotion, this conclusion can help us in combining the social influence of users for stress detection.

4. PROBLEM FORMULATION

Before presenting our problem statement, let's first define some necessary notations. Let V be a set of users on a social network, and let |V |denote the total number of users. Each user vi ∈ V posts a series of tweets, with each tweet containing text, image, or video content; the series of tweets contribute to users social interactions on the social network.

Definition:1

Stress state. The stress state y of user vi ∈ V at time t is represented as a triple (y, vi, t), or briefly yti. In the study, a binary stress state yti ∈ {0, 1} is considered, where y t i = 1 indicates that user vi is stressed at time t, and y ti = 0indicates that the user is non-stressed at time t, which can be identified from specific expressions in user tweets or clearly identified by user himself, as explained in the experiments. Let Yt be the set of stress states of all users at time t.

Definition: 2

Time-varying user-level attribute matrix. Each user in V is associated with a set of attributes A. Let Xt be a |V | × |A| attribute matrix at time t, in which every row xti corresponds to a user, each column corresponds A user-level attribute matrix describes user-specific features, and can be defined in different ways. This study considers user-level content attributes, statistical attributes, and social interaction attributes.

Definition: 3

Time-varying edge set. Users are linked by edges of certain types. Let Et ⊆ V ×V ×C be a set of edges between users at time t. Three types of edges are considered in the study. For an edge e = (vi, vj , c) ∈ Et, c = 0 indicates that vi follows or is followed by vj at time t, c = 1 indicates that there are positive words in comments between user viand vj at time t, and c = 2 indicates that there are negative words in comments between them at time t.

Definition: 4

Time varying attribute augmented network. An attribute-augmented network at time t is comprised of four elements, including 1) a user set Vt, 2) an edge set Et,3) a user-level attribute matrix set Xt, and 4) a stress state set for all users Yt at time t, denoted as Gt = (Vt, Et, Xt, Y t).

5. ATTRIBUTES CATEGORIZATION AND DEFINITION

To address the problem of stress detection, 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.

6. TWEET-LEVEL ATTRIBUTES

Tweet-level attributes describe the linguistic and visual content, as well as social attention factors (being liked, commented, and re tweeted) of a single tweet. For linguistic attributes, we take the most commonly used linguistic features in sentiment analysis research. Specifically, we first adopt LTP — A Chinese Language Technology Platform — to perform lexical analysis, e.g., tokenize and lemmatize, and then explore the use of a Chinese LIWC dictionary — LIWC2007, to map the words into positive/negative emotions. LIWC2007 is a dictionary which categorizes words based on their linguistic or psychological meanings, so we can classify words into different categories, e.g. positive/negative emotion words, degree adverbs. We have also tested other linguistic re-sources including NRC5and HowNet6, and found that the performances were relatively the same, so we adopted the commonly used LIWC2007 dictionary for experiments. Furthermore , we extract linguistic attributes of emoticons (e.g., and) and punctuation marks ('!', '?', '...', '.'). We defines every emoticon in square brackets (e.g., they use [ha ha] for "laugh"), so we can map the keyword in square brackets to find the emoticons. Twitter adopts Unicode as the representation for all which can be extracted directly.

7. 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 aforementioned social interaction patterns of users in a period of time also contain useful information for stress detection. Moreover, as aforementioned, the information in tweets is limited and sparse, we need to integrate more complementary information around tweets, e.g., users' social interactions with friends. Thus, appropriately designed user-level attributes can provide a macro-scope of a user's stress states, and avoid noise or missing data. Here, we define user-level attributes from two aspects to measure the differences between stressed and non-stressed states based on users' weekly tweet postings: 1) user-level posting behavior attributes from the user's weekly tweet postings; and 2) user-level social interaction attributes from the user's social interactions beneath his/her weekly tweet postings.

8. MODEL FRAMEWORK

Two challenges exist in psychological stress detection.

1)How to extract user-level attributes from user's tweeting series and deal with the problem of absence of modality in the tweets?

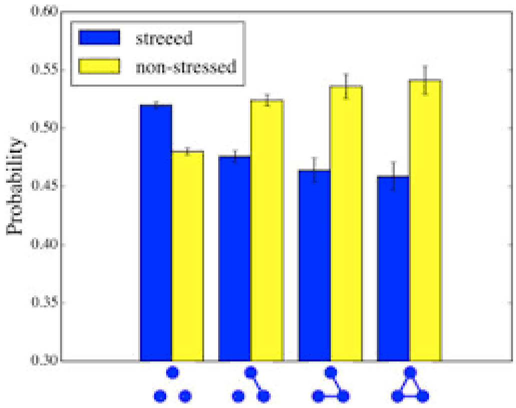
2) How to fully leverage social interaction, including interaction content and structure patterns, for stress detection?

9. ARCHITECTURE

The architecture of our model. There are three types of information that we can use as the initial inputs, i.e., tweet-level attributes, user-level posting behavior attributes, and user-level social interaction attributes, whose detailed computation will be described later. We address the solution through the following two key components:

• First, we design a CNN with cross auto encoders (CAE) to generate user-level interaction content at-tributes from tweet-level attributes. The CNN has been found to be effective in learning stationary local attributes for series like images and audios.

• Then, we design a partially-labeled factor graph (PFG) to incorporate all three aspects of user-level attributes for user stress detection. Factor graph model has been widely used in social network modeling. It is effective in leveraging social correlations for different prediction tasks.



11. CONCLUSION

We presented a framework for detecting users psychological stress states from users' weekly social media data, leveraging tweets' content as well as users' social inter-actions. Employing real-world social media data as the ba-sis, we studied the correlation between user' psychological stress states and their social interaction behaviors. To fully leverage 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)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. These phenomena could be useful references for future related studies.

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