Detecting Stress Based on Social Interactions in Social Networks

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Abstract—Psychological stress is ominous person's health. It is non-trivial to detect stress timely for proactive care. With the attractive of social media, person are used to sharing their daily task and communicating with friends on social media platforms, making it feasible to leverage online social network data for stress detection. In this paper, we find that users stress condition is closely related to that of his/her friends in social media, and we employ a large-scale dataset from real-world social platforms to systematically examine the connection of users' stress condition's and social interactions. We first define a set of stress-related textual analysis, visual, and social attributes from various aspects, and then propose a novel hybrid model – a factor graph model combined with Convolutional Neural Network to leverage tweet content and social interaction information for stress detection. Experimental results show that the proposed model can better 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% more 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 us.

***Keywords*- Stress detection, factor graph model, micro-blog, social media, healthcare, social interaction**

I. INTRODUCTION

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. Currently, no studies have examined whether Twitter data can be used to monitor stress level and emotional situation among college students. Studying this topic is important because the large volume of social media data from college students' habitual use of social media can be used to help university officials and researchers monitor and reduce stress among college students. User's social interactions on social networks contain useful cues for stress detection.

The second is Social Interconnection: people are known to social interconnection of user in social media. The advancement of social networks like Twitter, Facebook and Sina Weibo2, an ever increasing number of people will share their every day events and moods, and interact with friends over the social networks. After getting stress level, system can recommended user hospital for further treatment, we can show that hospital on map and system also recommends taking precaution to avoid stress. The advancement of social networks like Twitter, Twitter and Sina Weibo2, an ever increasing number of people will share their every day events and moods, and interact with friends over the social networks. (a) Social interconnection attributes extracted from a user's social interconnections with friends. (i) Social interconnection content attributes extracted from the content of users' social interconnections with friends; and (ii) Social interconnection structure attributes extracted from the structures of users' social interconnection with friends.

Due to advantage of both Twitters post content attributes and social interconnections to enlarge stress detection. In existing system, it is not easy to detect stressed and non-stressed users due to interconnection of social network.so we propose framework for detecting user's psychological stress condition's from user's weekly social media data, leveraging Twitter post content as well as user's social interconnection then we can find out user are stress or not. To study framework for detecting users psychological stress condition's from user's weekly social media data, leveraging Twitter post content as well as users social interconnections. From social interconnection of user we find out user are in stress or not.

II.LITERATURE SURVEY

Psychological stress detection is related to the topics of sentiment analysis and emotion detection. Research 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 [1], [2], [3], [4], [5], [6]. Correlation between psychological stress and character traits can be an interesting issue to consider [7], [8], and [9]. For example, [10] providing evidence that daily stress can be reliably recognized based on behavioural 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. Zhao et al. [6] pro-posed a system called MoodLens to perform emotion analysis on the Chinese micro-blog platform Weibo, classifying the emotion categories into four types, i.e., angry, disgusting, joyful, and sad. Fan et al. [2] studied the emotion propagation problem in social networks, and found that anger has a stronger connection 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. Concepts are three points are connected with each and every one and impact of users for stress detection. However, these works mainly leverage the textual contents in social networks. In reality, data in social networks is usually composed of sequential and inter-connected items from diverse sources and modalities, making it are actually cross-media data. Research user-Level Emotion Detection in Social Networks. While tweet-level emotion detection reflects the instant emotion expressed in a single tweet, person's emotion or psycho-logical stress conditions are usually more enduring, changing over different time periods. In recent years, extensive research starts to focus on user-level emotion detection in social net-works. Recent work proposed to detect users psychological stress conditions from social media by learning user-level presentation via a deep convolution net-work on sequential tweet series in a certain time period. Motivated by the principle of homophily, [11] incorporated social interconnections to improve user-level sentiment analysis in Twitter.

Though some user-level emotion detection studies have been done, the capacity that social interconnections plays in one's psychological stress conditions, and how we can incorporate such information into stress detection have not been examined yet. Study on leveraging social interconnections for social media evaluation. Social interconnection is one of the most important features of social media platforms. Now many researchers are focusing on leveraging social interconnection information to help improve the effectiveness of social media analysis. Fischer and Reuber [12] analysed the interconnections between social interconnections and users' thinking and behaviour's, and found out that Twitter-based interconnection can trigger effectual cognitions. Yang et al. [13] leveraged comments on Flickr to help predict emotions expressed by images posted on Flickr. How-ever these work mainly focused on the content of social inter-actions, e.g., textual comment content, while ignoring the inherent structural information like how users are connected.

Huijie Lin, Jia Jia, Quan Guo, Yuanyuan Xue, Qi Li, Jie Huang, Lianhong Cai, Ling Feng et al. the study of "User-Level Psychological Stress Detection From Social Media Using Deep Neural Network" .The paper employs real online micro blog data to investigate the connections between users' stress and their tweeting content. It also defines two types of stress related attributes: - Low-level content attributes from a single tweet, including text, images and social interconnections; and User scope statistical attributes over their weekly micro-blog postings, mapping information of tweeting time, tweeting types and linguistic styles.

Li-fang Zhang et al. proposed the study on titled Occupational stress and teaching approaches among Chinese academics (2009). Researcher suggested that, controlling the self-rating abilities of the participants, the favourable conceptual changes in teaching approach and their role insufficiency predicated that the conceptual change in teaching strategy is negative.

Another approach for stress analysis is Kavitha et al. in her research titled -Role of stress among female employees forming majority workforce at IT sector in Chennai and Coimbatore (2012), she has focuses on the organizational role stress for the employees in the IT sector. She found in her research that, female face more stress than men in the organization and she viewed to be more specific married female faces more stress than the unmarried female.

Another approach is Amir Shani and Abraham Pizam (2009) et al. [14] -Work-Related Depression among Hotel Employees has conducted a study on the depression of work among hotel employees in Central Florida. They have found that, event of depression among workers in the hospitality industry by evaluating the interconnection between the occupational stress and work characteristics.

Another approach is Kayoko Urakawa and Kazuhito Yokoyam et al in their work on Sense of Coherence (SOC) may Reduce the impact of Occupational Stress on Mental Health Status among Japanese Factory Workers (2009) has found the result i.e. adverse impact on mental health due to the job demand and job stress was positively related with SOC, the mental health status of males in managerial work was adversely negative, where as it was positive among the female co-workers. Finally they found that, SOC is an important factor determining the coping ability over the job stress for both the genders.

III.PROBLEM STATEMENT

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 jV j denote the total number of users. Each user v_i 2 V posts a series of tweets, with each tweet containing text, image, or video content; the series of tweets contribute to users social interconnections on the social network.

Definition 1(Stress state)

The stress state y of user v_i 2 V at time t is represented as a triple ðy; v_i; tÞ, or briefly $y^t{}_i$. In the study, a binary stress state $y^t{}_i$ 2 f0; 1g is considered, where $y^t{}_i$ ¼ 1 indicates that user v_i is stressed at time t, and $y^t{}_i$ ¼ 0 indicates 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 Y^t 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 X^t be a jV j jAj attribute matrix at time t, in which every row $\mathbf{x^t{}_i}$ corresponds to a user, each column corresponds to an attribute, and an element $x^t{}_{i;j}$ is the jth attribute value of user v_i at time t.

Problem 1 (Psychological stress detection)

Given a series of T partially labelled time-varying attribute-augmented net- works fG^t ¼ ð$V_L{}^t$; $V_U{}^t$; E^t; $Y_L{}^t$Þ j t 2 f1; 2; . . . ; T g g, $V_L{}^t$ is a set of users with labelled stress states $Y_L{}^t$ at time t, and $V_U{}^t$ is a set of unlabelled users, the objective is to learn a function f : fG^1; G^2; . . . G^T g ! f$Y_U{}^1$; $Y_U{}^2$; . . . $Y_U{}^T$ g to predict unlabelled users stress states.

IV.EXISTING SYSTEM

Many studies on social media based emotion analysis are at the tweet level, using text-based linguistic features and classic classification approaches. A system called MoodLens to perform emotion analysis on the Chinese micro-blog platform Weibo, classifying the emotion categories into four types, i.e., angry, disgusting, joyful, and sad. An existing system studied the emotion propagation problem in social networks, and found that anger has a stronger connection 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 impact of users for stress detection.

1. Disadvantages of Existing System:

Traditional psychological stress detection is mainly based on face-to face interviews, self-report questionnaires or wearable sensors. However, traditional approaches are actually reactive, which are usually labour-consuming, time-costing and hysteretic. These works mainly leverage the textual contents in social networks. In reality, data in social networks is usually composed of sequential and inter-connected items from diverse sources and modalities, making it are actually cross-media data. Though some user-level emotion detection studies have been done, the role that social interconnections plays in one's psychological stress conditions, and how we can incorporate such information into stress detection have not been examined yet.

V.PROPOSED SYSTEM:

Motivated 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 extracted from a user's weekly tweet postings; and (b) social interconnection attributes extracted from a user's social interconnections with friends. In particular, the social interconnection attributes can further be breakdown into: (i) Social interconnection content attributes extracted from the content of users' social interconnections with friends; and (ii) social interconnection structure attributes extracted from the structures of users' social interconnections with friends.

1. Advantages of Proposed System:

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

Beyond user's tweeting contents, we analyse the connection of users' stress conditions and their social interconnections on the networks, and address the problem from the standpoints of: (1) social interconnection content, by investigating the content differences between stressed and non-stressed users' social interconnections; and (2) social interconnection structure, by investigating the structure differences in terms of structural diversity, social impact, and strong/weak tie. We build several stressed-twitter-posting datasets by different ground-truth labelling approaches from several popular social media platforms and thoroughly evaluate proposed approach on multiple aspects. We carry out in-depth studies on a real-world large scale dataset and gain insights on connections between social interconnections and stress, as well as social structures of stressed users.

Table: Comparison of Efficiency and Effectiveness Using Different Models (%)

Approach	Accuracy	Recall	Precision.	F1 score	CPU time
Logistic Regression (LRC)	76.18	87.94	78.58	83.00	39.43 s
Support Vector Machine (SVM)	72.58	87.39	75.16	80.82	10 min
Random Forest (RF)	77.73	89.63	79.35	84.18	67.71 s
Gradient Boosted Decision Tree (GBDT)	79.75	82.99	85.90	84.43	262.86 s
Factor Graph Model (FGM)	91.55	96.56	90.44	93.40	20 min

VI.CONCLUSION

Psychological stress is ominous person’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 conditions from user’s monthly social media data, leveraging Twitter post content as well as user’s social interconnections. Employing real-world social media data as the basis, we examine the connection between user’s psychological stress situation and their social interconnection 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 dealing purpose.

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