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Efficient Detecting Of Stress Based On Social Communication In Social Networks

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***Abstract*— —** 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 over half of the population have experienced an appreciable rise in stress over the last two years. Though stress itself is non-clinical and common in life, excessive and chronic stress can be rather harmful to people's physical and mental health. The rise of social media is changing people's life, as well as research in healthcare and wellness. With the development of social networks like Twitter and Sina Weibo, more and more people are willing to share their daily events and moods, and interact with friends through the social networks.

Keywords – *psycholoigcla stress, population, social networks*

I INTRODUCTION

Computer systems can access a constant stream of public social web texts and those that are embedded within communication applications may also store private messages. Harnessing this information to detect stress within individuals or specific groups could allow more intelligent decisions to be made in a wide variety of different contexts. For example, Intelligent Transportation Systems (ITS) harness information from traffic sensors, road monitoring cameras, mobile phone GPS signals, and number plate recognition technology in order to support traffic management (e.g., Wen, Lu, Yan, Zhou, Von Deneen, & Shi, 2011; Knorr, Baselt, Schreckenberg, & Mauve, 2012). There is a constant need to improve the range of sources of evidence for these systems. Stress is indirectly taken into account within ITS through predictable knowledge about stressful times, such as rush hour, and stressful journeys, such as travel to sports events, but accidents or random traffic jams cannot be predicted. To exploit the wealth of text information available to computing systems to improve the predictive power of ITS and other systems, a fast effective method is needed to detect expressions of stress within short informal messages. The task of deducing affective states from text is already partly solved for sentiment. Opinion mining programs can detect the opinions of users towards products and services from their online reviews or comments with a reasonable degree of accuracy in many contexts (Liu, 2012; Pang & Lee, 2008). Some sentiment analysis programs also attempt to detect a range of emotions, although with limited accuracy (Neviarouskaya, Prendinger, & Ishizuka, 2010). Other systems have also focused on stress detection (see below) but is seems that none harness social media text for this task.

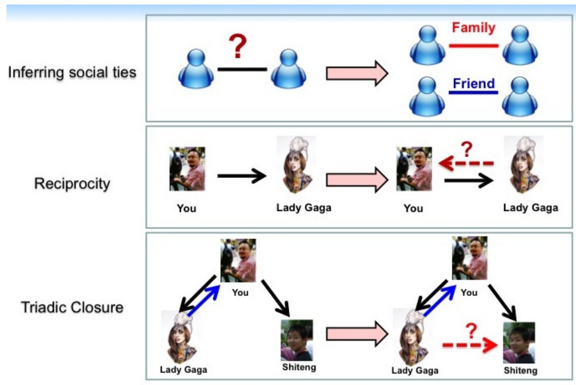

Fig: General Interaction between network users

With the invention of the web 2.0, the users of internet have not only become the consumers of information but also the producers of information. The users of world of web interact with each other, participate in online discussions, exchange different types of information and their views, they form social networks. The interaction among the users in the social networks can be characterized according on the basis of positions, behaviors or their virtual identities [1]. Social networking has become an extremely important application in the world of internet in the past few years, because of its capability to enable social contact over the internet for geographically dispersed users. A social network can be represented as a graph, in which nodes represent users (e.g. peoples, organizations, groups etc.) and links or edges represent the connections between the users. Social networks depict the interactions between individuals or entities and are represented by a graph of interconnected nodes. One of the

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important features of social networks is community structure, and the detection of communities in the area of social networking is an important problem. Till now, many approaches have been proposed to detect the hidden communities in a social network. So there is a high importance for discovering communities, for understanding the type's social networks and detecting the useful and hidden patterns in the aforementioned network [2]. In social networks, the term community has no unique definition till today which can be widely accepted. In Fig. 2, there are three communities in which all the nodes within a community are densely inter-connected with each other and have sparse inter-connection with the nodes belonging to another community. In a social network community, nodes are connected with each other based on their human relationship like friendship, colleague etc. [3].

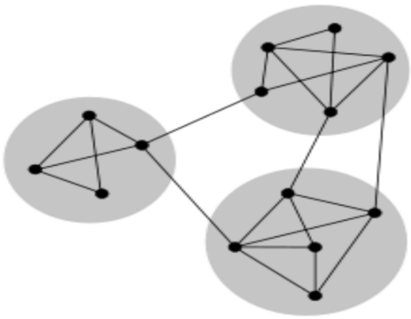

Fig: 2 Visualization of community structure with three groups of nodes with dense internal connections and sparser connections between groups.

II RELATED WORK

The task of deducing affective states from text is already partly solved for sentiment. Opinion mining programs can detect the opinions of users towards products and services from their online reviews or comments with a reasonable degree of accuracy in many contexts (Liu, 2012; Pang & Lee, 2008). Some sentiment analysis programs also attempt to detect a range of emotions, although with limited accuracy (Neviarouskaya, Prendinger, & Ishizuka, 2010). Other systems have also focused on stress detection (see below) but is seems that none harness social media text for this task.

This article introduces a new automated system, TensiStrength, to detect the strength of stress and relaxation expressed in short text messages. It uses a lexical approach to detect indicators of stress or its partial opposite, relaxation, combined with additional linguistic rules to accommodate common ways of modifying the meaning of expressions, such as negation. The result is score for each text on a scale of -1 (no stress) to -5 (extremely stressed) and a parallel score for relaxation from 1 (not relaxing) to 5 (completely relaxed or sleepy). The method is evaluated on a corpus of human-coded tweets and compared to a similar sentiment analysis approach and generic machine learning algorithms. Although TensiStrength is designed for general purpose stress/relaxation detection, its lexicon has additional travel-specific terms for two reasons. First, this research is part of a project to develop automated traffic management and information systems. Second, some stressors are context-specific and it is therefore important to assess whether a stress detection system can work well on a narrow topic

Psychological stress

Biological stress refers to changes within the body, such as heartrate increases, in response to an unusual stimulus or challenge and in order to prepare for a response (Goldstein & Kopin, 2007; see also: Carr & Umberson, 2013). At the physiological level, stress involves the release of a number of chemicals into the bloodstream to prepare for a fight or flight response, including the stress hormone cortisol (Dickerson & Kemeny, 2004), which increases the blood sugar level. This type of stress can be scientifically detected by heart rate measures or tests for cortisol in saliva, but can also be inferred through selfreport questionnaires (Arora et al., 2010). In contrast, psychological stress is a subjective feeling of pressure or strain as a result of a stressor in the external environment or internal perceptions of an inability to cope with a situation (Jones, Bright, & Clow, 2001). Stress and negative emotions often co-occur, with each able to be a cause and effect of the other (Lazarus, 2006). Nevertheless, since stress is most closely related to fear and anxiety, it might not be directly triggered by the negative emotion of disgust (e.g., Fredrikson & Furmark, 2006). Conversely, positive emotions have been proposed as an antidote to stress as part of a therapeutic regime for long term sufferers (McCraty & Tomasino, 2006) or as part of a coping strategy (Folkman & Moskowitz, 2000; Moskowitz, Shmueli-Blumberg, Acree, & Folkman, 2012). Other popular strategies for treating or managing stress include cognitive behavioural therapy (Granath, Ingvarsson, von Thiele, & Lundberg, 2006). Stress can be long term, for example as a by-product of long term medical conditions or psychiatric disorders (Hammen, 1991), or very short term, such as in the fraction of a second between first seeing a crocodile and rationalising that it is safely in a cage. Stress can be broken down into two types: negative stress is termed distress whereas positive stress is known as eustress (Lazarus, 1974). Positive stress is an important component of some activities that can lead to good outcomes (Simmons, & Nelson, 2001; c.f., Le Fevre, Matheny, & Kolt, 2003). Eustress typically occurs for challenges that are not overwhelming and have a positive outcome. Events, perceptions or experiences that can cause stress are called stressors. Stress is not only caused by immediate fears about physical survival or harm but also by threats to social esteem or successful performance of a task (in a social context), especially when the situation is judged to be uncontrollable (Dickerson & Kemeny, 2004). Hence, there are many factors that might trigger stress and so it would be difficult to precisely delineate all possible stressors. The most common general stressors seem to be interpersonal tensions, work, and ocial networks (Almeida, Wethington, & Kessler, 2002), but in narrower contexts, the main stressors can be very different (e.g., Aylott & Mitchell, 1999; Cupples, Nolan, Augustine, & Kynoch, 1998; Walker, Smith, Garber, & Claar, 2007). It is useful to distinguish between long term stressors, including divorce, illness, and major work projects, and transient stressors, which are annoyances or factors with a short term influence during daily life. Stressors of both types can be cumulative in the sense that multiple stressors, even of different types, can tend to aggregate the effect of each other (Pearlin, Schieman, Fazio, & Meersman, 2005). Stressors are subjective, however, and the reaction to a stressor partly depends upon personality type (Semmer, 2006) and the person's perceived ability to cope (Compas, Banez, Malcarne, & Worsham, 1991).

Psychological stress detection is related to the topics of sen-timent analysis and emotion detection. Research on Tweet-Level Emotion Detection in Social Networks. Computer-aided detection, analysis, and application of emo-tion, especially in social networks, have drawn much atten-tion in recent years [8], [9], [28], [41], [52], [53]. Relationships between psychological stress and personality traits can be an interesting issue to consider [11], [16], [43]. For example, [1] providing evidence that daily stress can be reliably recog-nized based on behavioral metrics from users mobile phone activity. Many studies on social media based emotion analy-sis are at the tweet level, using text-based linguistic features and classic classification approaches. Zhao et al. [53] 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, joy-ful, and sad. Fan et al. [9] studied the emotion propagation problem in social networks, and found that anger has a stron-ger 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. Meaning that three points are connected with each other.influence of users for stress detection. However, these work 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 be actually cross-media data. Research on User-Level Emotion Detection in Social Networks. While tweet-level emotion detection reflects the instant emotion expressed in a single tweet, people's emotion or psycho-logical stress states 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 [29], [36], [38], [50]. Our recent work [29] proposed to detect users psychological stress states from social media by learning user-level presentation via a deep convolution net-work on sequential tweet series in a certain time period. Moti-vated by the principle of homophily, [38] incorporated social relationships to improve user-level sentiment analysis in Twitter. Though some user-level emotion detection studies have been done, the role that social relationships plays in one's psychological stress states, and how we can incorporate such infor-mation into stress detection have not been examined yet. Research on Leveraging Social Interactions for Social Media Analysis. Social interaction is one of the most important fea-tures of social media platforms. Now many researchers are focusing on leveraging social interaction information to help improve the effectiveness of social media analysis. Fischer and Reuber [12] analyzed the relationships between social interactions and users' thinking and behaviors, and found out that Twitter-based interaction can trigger effectual cogni-tions. Yang et al. [49] 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.

III PROBLEM FORMULATION

Before presenting 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 vi 2 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.

(Time-varying user-level attribute matrix). Each user in V is associated with a set of attributes A. Let Xt be a jV j jAj attribute matrix at time t, in which every row xti corresponds to a user, each column corresponds to an attribute, and an element xti;j is the jth attribute value of user vi at time t. A user-level attribute matrix describes user-specific featu res, and can be defined in different ways. This study consid-ers user-level content attributes, statistical attributes, and social interaction attributes. A detailed discussion of the matrix can be found in Section 4. The column "#" indicates the feature vector length for each type of feature.

IV PROPOSED WORK IMPLEMENTATION

ATTRIBUTES CATEGORIZATION AND DEFINITION

To address the problem of stress detection, 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

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attributes summarized from a user's weekly tweets.

4.1 **Tweet-Level Attributes** describe the linguistic and visual con-tent, as well as social attention factors (being liked, com-mented, and retweeted) of a single tweet. For linguistic attributes, take the most commonly used linguistic features in sentiment analysis research. Spe-cifically, first adopt LTP [4]—A Chinese Language Tech-nology Platform—to perform lexical analysis, e.g., tokenize and lemmatize, and then explore the use of a Chinese LIWC dictionary—LIWC2007 [14], to map the words into posi-tive/negative emotions. LIWC2007 is a dictionary which categorizes words based on their linguistic or psychological meanings, so can classify words into different categories, e.g., positive/negative emotion words, degree adverbs. have also tested other linguistic resources including NRC5 and HowNet,6 and found that the performances were relatively the same, so adopted the commonly used LIWC2007 dictionary for experiments. Furthermore, extract linguistic attributes of emoticons (e.g., and) and punctuation marks ('!', '?', '...', '.'). Weibo defines every emoticon in square brackets (e.g., they use [haha] for "laugh"), so can map the keyword in square brackets to find the emoticons. Twitter adopts Unicode as the represen-tation for all emojis [15], [24], which can be extracted directly. The list of linguistic attributes and descriptions are shown in Table 1. As for the visual attributes, use API from OpenCV7 to perform picture processing and colorrelated attributes computation, e.g., saturation, brightness, warm/cool color, clear/dull color in Table 1. For a special class of attributes named five-color theme, adopt algorithm from papers on affective image classification [32] and color psychology theories [23], [45]. In this work, did not adopt the direct emotional detection results as visual features because need multi-dimensional visual features for deep model learning, while a direct visual emotional classification result only gives a single or very few dimensions as features. However, with the development of emotion-sensitive visual representation techniques, it would be possibility to adopt automatic visual features in the future. The details of tweet-level attributes are summarized .

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. 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, need to integrate more complementary information around tweets, e.g., users' social interactions with friends.

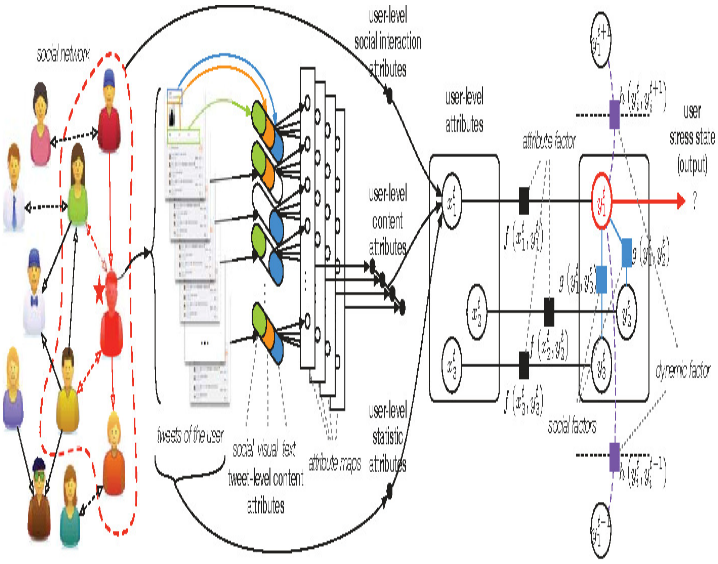

Fig: Social Network User interfaces

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.

A existing system 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.

DISADVANTAGES OF EXISTING SYSTEM:

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.

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 be actually cross-media data.

Though some user-level emotion detection studies have been done, the role that social relationships plays in one's psychological stress states, and how we can incorporate such information into stress detection have not been examined yet.

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PROPOSED SYSTEM:

Inspired by psychological theories, 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.

ADVANTAGES OF PROPOSED SYSTEM:

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 analyze the correlation of users' stress states and theirsocial interactions on the networks, and address the problemfrom the standpoints of: (1) social interaction content,by investigating the content differences between stressedand non-stressed users' social interactions; and (2) socialinteraction structure, by investigating the structure differencesin terms of structural diversity, social influence, andstrong/weak tie.

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

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

VI. EXPERIMENTAL RESULTS

Fig: User Details in network

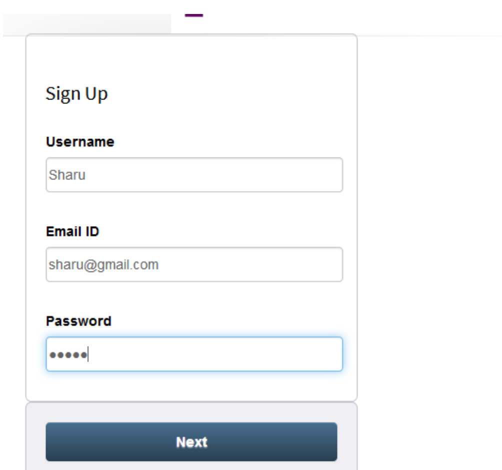

Fig: Sign Up page work

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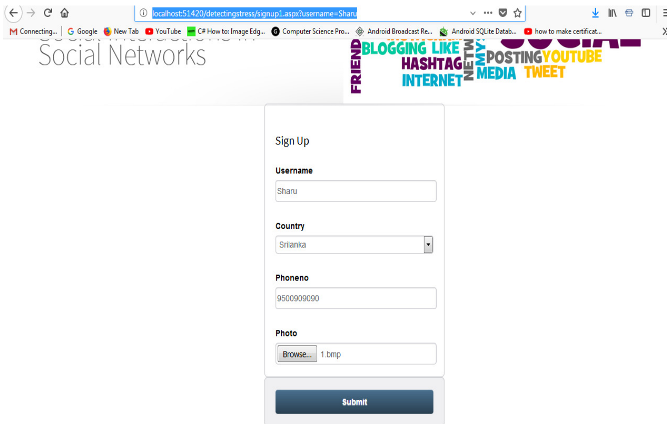

Fig: uploading files to social network GUI

V CONCLUSION

In this paper, presented a framework for detecting users' psychological stress states from users' weekly social media data, leveraging tweets' content as well as users' social interactions. Employing real-world social media data as the basis, studied the correlation between user' psy-chological stress states and their social interaction behav-iors. To fully leverage both content and social interaction information of users' tweets, proposed a hybrid model which combines the factor graph model (FGM) with a con-volutional neural network (CNN). In this work, also discovered several intriguing phe-nomena of stress. found that the number of social struc-tures of sparse connection (i.e., with no delta connections) of stressed users is around 14 percent 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 phenom-ena could be useful references for future related studies

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International and National Journals and presented in the National and International conferences. His areas of research interests Data Mining, Network Security and Big Data & Analytics.

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