STRESS BASED DETECTION ON SOCIAL INTERACTIONS IN SOCIAL NETWORKS
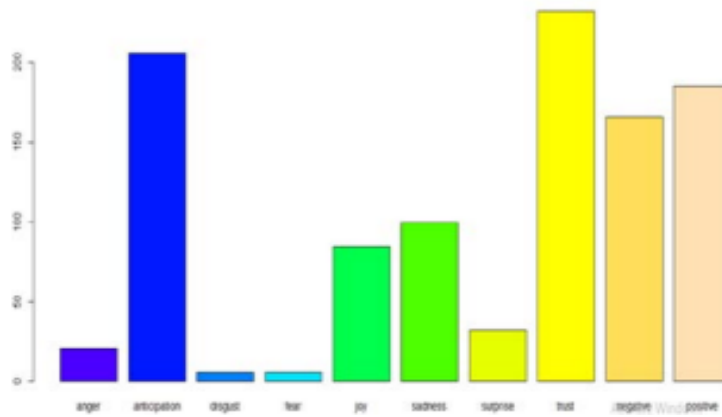
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ABSTRACT - Psychological stress is threatening people's health. It is non-trivial to detect stress timely for proactive care. With the popularity of social media, people are used to share their daily activities and interact with friends on social media platforms, making it feasible to leverage online social network data for stress detection. We find that users stress state 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 study the correlation of users' stress states and social interactions. We first define a set of stress-related textual, visual, and social attributes from various aspects, and then proposed a plot .Experimental results show that the proposed model can improve the detection performance .With the help of enumeration we build a website for the users to identify their stress rate level and can check other related activities.

Index Terms—Stress detection, micro-blog, social media, social interaction, factor graph model.

I. 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 Newbusiness in 20101, over half of the population has experienced an appreciable rise in stress over the last two years. Though stress itself is non-clinical 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 survey, 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 before 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 labour-consuming, time-costing and hysteretic. 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 more and more people are willing to share their daily events and moods, and interact with friends through the social networks. As these social media data timely reflect users' real-life states and emotions in a timely manner, it offers new opportunities for representing, measuring, modeling, and mining users behavior patterns through the large-scale social networks, and such social information can find its theoretical basis in psychology research. For example, [7] found that stressed users are more likely to be socially less active, and more recently, there have been research efforts on harnessing social media data for developing mental and physical healthcare tools. For example, [27] proposed to leverage Twitter data for real-time disease surveillance; while [35] tried to bridge the vocabulary gaps between health seekers and providers using the community generated health data. There are also some research works [28] [47] using user tweeting contents on social media platforms to detect users' psychological stress. Existing works [28], [47] demonstrated that leverage social media for healthcare, and in particular stress detection, is feasible.

Limitations in existing system are that stress analysis is a crucial tool for designing structurally sound shapes. However, the expensive computational cost has hampered its use in interactive shape editing tasks. We augment the existing

Example-based shape editing tools, and propose a fast subspace stress analysis method to enable stress-aware shape editing. In particular it is constructed by a reduced stress basis from a small set of shape exemplars and possible external forces. This stress basis is automatically adapted to the current user edited shape on the fly, and thereby offers reliable stress estimation. We then introduce a new finite element discretization scheme to use the reduced basis for fast stress analysis. Some Limitations exist in tweeting content based stress detection Firstly, tweets are limited to a maximum of 140 characters on social platforms like Twitter and users do not always express their stressful states directly in tweets. Secondly, users with high psychological stress may exhibit low activeness on social networks. These phenomena incur the inherent data sparsity and ambiguity problem, which may hurt the performance of tweeting content based stress detection performance

PROPOSED SYSTEM Sentiment analysis is to define automatic tools able to extract subjective information from texts in natural language, such as opinions and sentiments, in order to create structured and actionable knowledge to be used by either a decision support system or a decision maker.In Social Networks begins with an overview of the latest research trends in the field. Sentiment analysis has gained even more value with the advent and growth of social networking. It explores both semantic and machine learning models and methods that address context-dependent and dynamic text in online social networks, showing how social network streams pose numerous challenges due to their large-scale, short, noisy, context- dependent and dynamic nature. The contributions of this paper are as following:
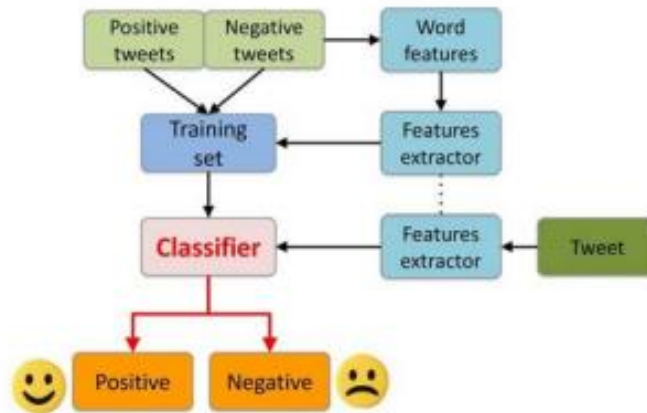
• We propose a unified factor graph model in R studio to leverage both tweet content attributes and social interactions to enhance stress detection.

• We build several stressed-twitter-posting datasets by different ground-truth labeling 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

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 [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 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. [53] proposed 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. [9] 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. 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 crossmedia 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 psychological 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 networks [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 network on sequential tweet series in a certain time period. Motivated by the principle of homophily, [38] incorporated social relationships to improve user-level sentiment analysis in Twitter. Though some userlevel 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. Research on leveraging social interactions for social media analysis. Social interaction is one of the most important features of social media platforms. Now many researchers are focusing on leveraging social interaction information to help improve the effectiveness of social media analysis. [12] analyzed the relationships between social interactions and users' thinking and behaviors, and found out that Twitter-based interaction can trigger effectual cognitions. [49] leveraged comments on Flickr to help predict emotions expressed by images posted on Flickr. However, these work mainly focused on the content of social interactions, e.g., textual comment content, while ignoring the inherent structural information like how users are connected.

MODEL FRAMEWORK: 3 Challenges exist in psychological stress detection. 1) How to extract users 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? To tackle these challenges, we propose a factor graph model

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Sentiment extraction of tweets sentence extraction Fig 3 represents how to review all the datas, that are initially collected and how all the sentence are extracted using sentiments. After the extraction of sentences part-of-speech tagging is done in order to determine the sentences after phrase is identified then score has been computed for each sentiments with each of polarities has categorized and result has been categorized. • We proposed a method in which we extracted tweets from twitter and categorizes each of the data with different sentiments. • We can identify the structure of each of the tweets and class of each tweets. After classifying all of the tweets with each of the sentences it has been sentimented. • With the help of sentiment extraction it is easy to leverage each of the tweets, so that it is easy to classify each of the stress rate level.

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 interactions. Employing real-world social media data as the basis, we studied the correlation between user' psychological stress states and their social interaction behaviors. In this work, we also discovered several intriguing phenomena of stress.

FUTURE WORK The future scope of the project is to develop a system that not only detecting the stress and also able to analyze people mind means that it will play as a survey system. So that it may provide a better solution on behalf of people of the society for every debatable concepts and also it will indirectly play an important role in political, government and also social media. So we may efficiently analyze stress and also find solution to every social issue by means of polling and analyzing comments.

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