**Detecting Stress Based on Social Interactions inSocial Networks**

**ABSTRACT:**

Psychological stress is threatening people’s health. It is non-trivial to detect stress timely for proactive care. With thepopularity of social media, people are used to sharing their daily activities and interacting 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 state is closelyrelated to that of his/her friends in social media, and we employ a large-scale dataset from real-world social platforms to systematicallystudy the correlation of users’ stress states and social interactions. We first define a set of stress-related textual, visual, and socialattributes from various aspects, and then propose a novel hybrid model - a factor graph model combined with Convolutional NeuralNetwork to leverage tweet content and social interaction information for stress detection. Experimental results show that the proposedmodel can improve the detection performance by 6-9% in F1-score. By further analyzing the social interaction data, we also discoverseveral intriguing phenomena, i.e. the number of social structures of sparse connections (i.e. with no delta connections) of stressedusers is around 14% higher than that of non-stressed users, indicating that the social structure of stressed users’ friends tend to beless connected and less complicated than that of non-stressed users.

**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.

**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.

**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 our 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.

**SYSTEM ARCHITECTURE:**

**User Stress Detection**

User Login

**Social Networking Site**

C:\Program Files\Microsoft Office\MEDIA\CAGCAT10\j0292020.wmf

**User Tweet Collection**

OSN Activity

**SYSTEM REQUIREMENTS:**

**HARDWARE REQUIREMENTS:**

* System : Pentium Dual Core.
* Hard Disk : 120 GB.
* Monitor : 15’’ LED
* Input Devices : Keyboard, Mouse
* Ram : 1 GB

**SOFTWARE REQUIREMENTS:**

* Operating system : Windows 7.
* Coding Language : JAVA/J2EE
* Tool : Netbeans 7.2.1
* Database : MYSQL

**REFERENCE:**

Huijie Lin, JiaJia, JiezhonQiu, Yongfeng Zhang, LexingXie, Jie Tang, Ling Feng, and Tat-Seng Chua, “Detecting Stress Based on Social Interactions inSocial Networks”, **IEEE Transactions on Knowledge and Data Engineering, 2017.**