A HYBRID MODEL TO ANALYSE STRESS ON SOCIAL INTERCOMMUNICATION IN SOCIAL MEDIA

[1]Dr. C.Anuradha,
Assistant Professor and Head, Department of computer application,
S.S.B.S. Tamil, Arts & Science College, Tamilnadu, India.

[2]M. Muthulakshmi,
Assistant Professor, Department of Computer Science,
SrimathSivagnanaBalayaSwamigal Tamil Arts and Science College
Mailam, Tindivanam, Villupuram– India

[3]B.Ishwarya,
PG-M.Sc (CS),
S.S.B.S. Tamil, Arts & Science College, Tamilnadu, India.

Abstract

Psychological stress is aggressiveto people's health. It is non-trivial to find stress timely for proactive care. With the advancement in social media, humans are used to share their day-to-day activities and communicate with friends on social media platforms, making it conveniently to leverage online social network data for stress recognition. This research paper, 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 analytically study the correlation of users' stress states and social interactions. This article first define a set of stress-related textual, visual, and social attributes from various aspects, and then propose a hybrid model - a factor graph model combined with Convolutional Neural Network to leverage tweet content and social inter communication information for stress detection. Experimental results show that the proposed model can improve the detection performance by 6-9 percent in F1-score. Moreover, by analyzing the social interaction data, discovered severalinteresting factors, i.e., the number of social structures of sparse connections (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.

Keywords

Stress Detection, Data mining, random forest, Neural Network, Factor graph model.

1. Introduction

Psychological stress is becoming a Threat to people's health now a days. With the rapid pace of life, more and more people are feeling stressed. According to a worldwide survey reported by new business in 2010 over half of the population have experienced an appreciable rise in stress over the last two years. Through 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 existing research works, long-term stress has been found to be related to many diseases, e.g., clinical depressions, insomnia.For example, [1] 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, [2] proposed to leverage Twitter data for real-time disease surveillance; while [3] tried to bridge the vocabulary gaps between health seekers and providers using the community generated health data. There are also some research works [4], [5] using user tweeting contents on social media platforms. [6] Proposed a system called Mood Lens 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.

2. Literature Review

Fan et al. [7] studied the emotion propagation problem in social networks, and found that anger has as 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.While large-scale information technology has been evolving separate transaction and analytical systems, data mining provides the link between the two. Data mining software analyzes relationships and patterns in stored transaction data based on open-ended user queries. Several types of analytical software are available: statistical, machine learning, and neural networks.

Neil et al. had proposed a research work for findingStress and Health. The association between psychosocial stressors and disease is artificial by the nature, number, and resolution of the stressors as well as by the individual's biological exposure, psychosocial resources, and learned the copying pattern.Huijie Lin et al. [8]had proposed a research in Detecting Stress Based on Social Interactions in Social Networks. A set of stress-related textual, 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.

3. Problem of Statement

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 Mood Lens 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 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.

This process used in Random forest Algorithm. The best solution of the classification problem was found using an ensemble of tree classifiers based on Random Forest algorithm.Ensembleof tree classifiers based on a Random Forest algorithm, (ii) a Generalized Boosted Model (GBM) [9], (iii)Support Vector Machines with linear and Gaussian radial basis kernels, and (iv) Neural Networks. The best solution of the classification problem was found using an ensemble of tree classifiers based on RandomForestalgorithm.

4. Proposed Methodology

Inspired by psychological theories, we first define a set of attributes for stress detection from tweet-level and user-level aspects respectively.

4.1 Tweet-Level Attributes

Tweet-level attributes describe the linguistic and visual content, as well as social attention factors (being liked, commented, and retweeted or commented) attributes extracted from a single-tweet's text, image, and attention list of a single tweet. Tweet-level attributes from content of user's single tweet. Tweet's Content and Social Interactions:The social correlation between users and time-dependent correlation are hard to be modeled using classic classifiers such as Support Vector Machine (SVM), we use a partially-labeled factor graph model (PFG), which was first proposed in [10], to incorporate social interactions and tweets' content for learning and detecting user-level stress states.

4.2 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, they mentioned social interaction patterns of users in a period of time also contain useful information for stress detection. The user-level attributes however are composed into two categories.

(a)Posting behavior attributes as summarized from a user's weekly tweet postings

(b)Social interaction attributes extracted from a user's social interactions with friends. In particular, the social interaction attributes can further be broken into two steps.

Step 1:social-interaction content attributes extracted from the content of users' social interactionswith friends.

Step 2:social interaction structure attributes extracted from the structures of users' social interactions with friends.

The architecture of the proposed methodology is shown graphically in the figure 1. This shows that how the information system is changed by a series of transformations.

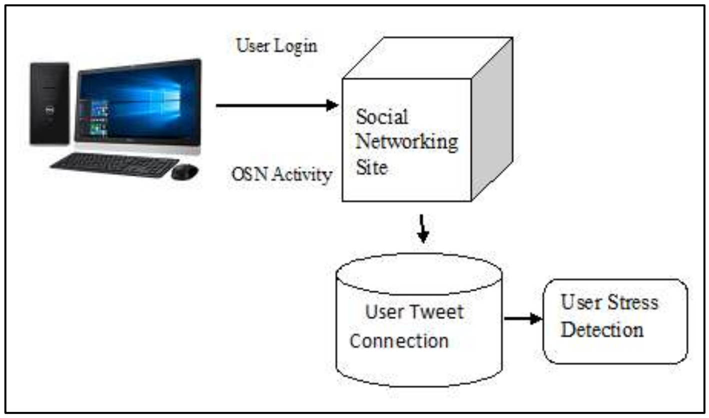

Figure 1: **Proposed Architecture**

4.3 Factor Graph Algorithm

Learning and Inference by Factor Graph:

Input: a series of time-varying attribute augmented network Gwith stress states on some of the user nodes, learning rate h;
Output: parameter value u ¼ fa; fb$_c$g; gg and full stress state vector Y;
Randomly initialize Y;
Initialize model parameters u;
repeat
Compute gradient ra; rb$_c$; r$_g$;

Update a a þ h ra;
Update b$_c$b$_c$ þ h rb$_c$;
Update g g þ h rg;
Update g g þ h rg

5.Experimental Setup

5.1 JavaRun time environment

Java technology is both a programming language and a platform.The Java programming language, is unusual in that a program is both compiled and interpreted. With the compiler, first you translate a program into an intermediate language called Java byte codes —the platform-independent codes interpreted by the interpreter on the Java platform. The interpreter parses and runs each Java byte code instruction on the computer. Compilation happens just once; interpretation occurs each time the program is executed. The following figure illustrate show this works.This functions in shown in figure 2.

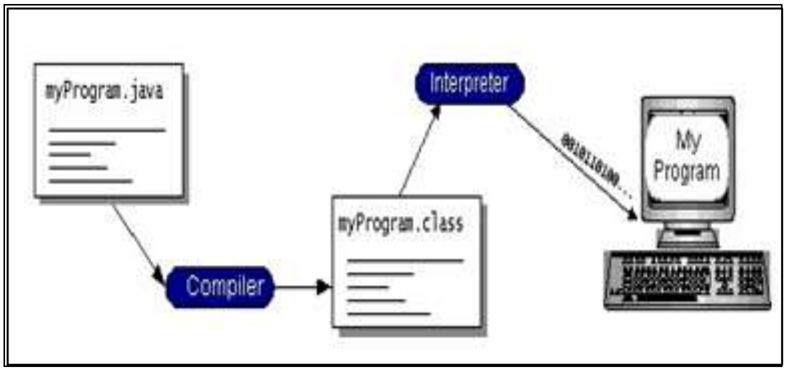

Figure 2: **Java Run-time Environment**

5.2 MySQL

SQL calls used by the programmer are simple SELECT's, INSERT's, DELETE's and UPDATE's, these queries should be simple with JDBC perform.

- However, more complex SQL statements should also be possible.
- Finally we decided to proceed the implementation using JavaNetworking.

6. Result and Discussion

Experimental results show that by exploiting the users' social interaction attributes, theproposed 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 andtheir social interactions on the networks, and address the problem from the stand points of: (1) social interaction content, by investigating the content differences between stressed and non-stressed users' social interactions; and (2) social interaction structure, by investigating the structure differences in terms of structural diversity, social influence, and strong/weak tie.

- The proposed method, build several stressed-twitter-posting datasets by different ground-truth labelingmethods 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 oncorrelations between social interactions and stress, as well as social structures of stressed users.

The pictorial representation shows a weekly over all end result of the Users Stress level. Theproposed model can improve the detection performance to 30 members of their Twitter level. The results shows that, 38% of usersin Stressed Tweet, and 62% of users in Normal Tweet’s and same is shown graphically in figure 3.

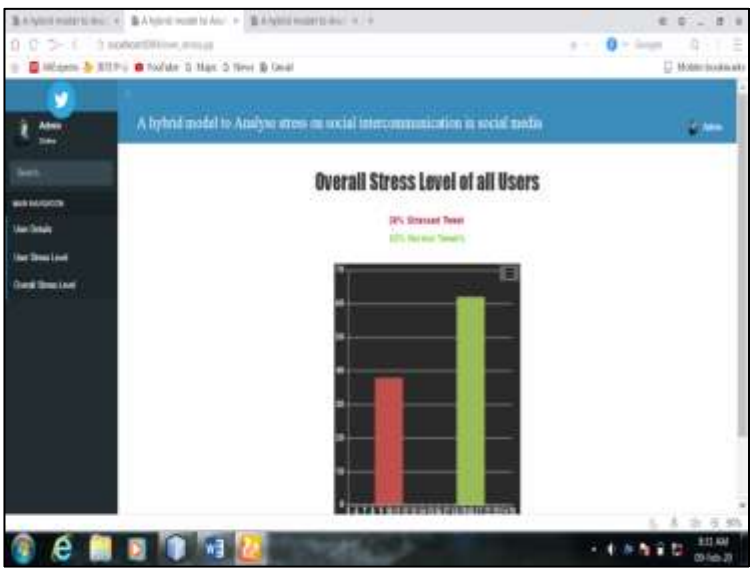

*Figure 3:***Overall end result of the user stress level.**

7. Conclusion

This manuscript presented a framework study details between users' psychological stress states by detecting users' psychological stress states from 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. To fully leverageboth content and social interaction information of users' tweets, here proposed a hybrid model which combines the factor graph model (FGM) with a convolutional neural network (CNN).

The results derived from the sample data set of 30 tweet members. It shows that, 38% of users in Stressed Tweet, and 62% of users in Normal Tweet's.By this studies,discovered various intriguingfeatures of stress. Also found that the number of social structures of sparse connectionof stressed users is around 14% higher than that of non stressed users, indicating that thesocialstructure of stressed users' friends tend to be less connected and less difficult than that of non-stressed users. These occurrences could be useful references for future related studies.

Reference

[1] Cohen, Sheldon, and Thomas A,Wills, "Stress, social support, and the bufferinghypothesis",Psychological Bulletin,Vol.98,No.2,1985,pp.310-357.

[2] Lee, Kathy, A kit Agrawal, and Alok Choudhary, "Real-time disease surveillance using twitter data: Demonstration on FLU and cancer",in Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2013, pp. 1474-1477.

[3] Nie,Liqiang, Yi-Liang Zhao, Mohammad Akbari, Jialie Shen, and Tat-Seng Chua, "Bridging thevocabulary gap between health seekers and healthcare knowledge",IEEE Transactions on Knowledge and Data Engineering, vol. 27, No. 2,2014, pp. 396-409.

[4] Lin, Huijie, Jia Jia, Quan Guo, Yuan Yuan Xue, Jie Huang, Lianhong Cai, Ling Feng,"Psychological stress detection from cross-media microblog data using deep sparse neural network", IEEE International Conference on Multi-media Expo, 2014, pp. 1-6.

[5]Xue, Yuanyuan, Qi Li, Li Jin, Ling Feng, David A. Clifton,Gari D. Clifford, “Detecting adolescent psychological pressures from micro-blog”, In International Conference on Health Information Science Springer, 2014, pp. 83-94.

[6] Zhao, Jichang, Li Dong, Junie Wu, and Ke Xu, “Mood lens: An emotion based sentiment analysis system for Chinese Tweets”, In Proceeding of the 18thACM SIGKDD International Conference on Knowledge Discovery Data Mining, 2012, pp. 1528-1531.

[7] Fan,Rui, Jichang Zhao, Yan Chen,Yan Chen, and Ke Xu, “Anger is more influentialthan joy: Sentiment correlation in weibo”, PLoS One, vol. 9,No 10, 2014, pp. e110184.

[8]Huijie Lin, Jia Jia, Jiezhong Qiu, Yongfeng Zhang, Guangyao Shen, Lexing Xie, Jie Tang, Ling Feng, and Tat-Seng Chua,”Detecting stress based on social interactions in social network”,IEEE transactions on knowledge and Data Engineering, vol.29,No.9,September 2017,pp.1820-1833.

[9]Freund Y, R.E.Schapire,“Adecision-theoretic generalization of on-line learning and an application to boosting”, Journal of Computer System Sciences, vol.55,No.1,1997,pp.119 – 139.

[10] Wenbin, Tang, Honglei Zhuang, and Jie Tang, “Learning to inter-social ties in large networks”,Proceeding European Conference, on machine learning and knowledge discovery in database,2011, pp. 381-397.