Detecting Stress Based on Social Interactions in Social Network

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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.**

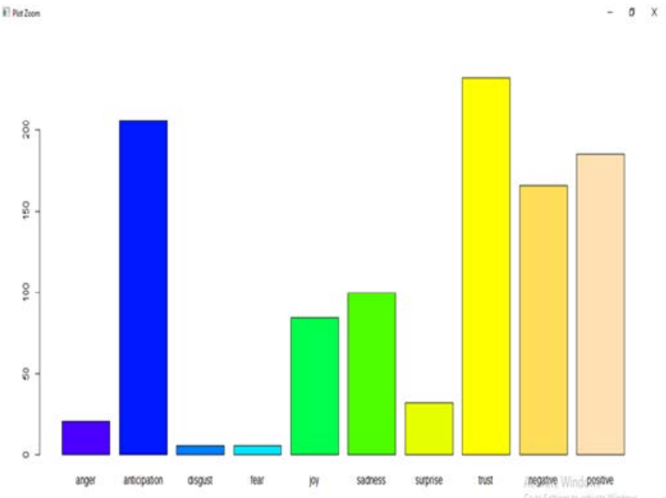
Index Terms—Stress detection, micro-blog, social media, social interaction , factor graph model.

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 2010[1], 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 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 is 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.

1.2 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.

2 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 cross-media data.

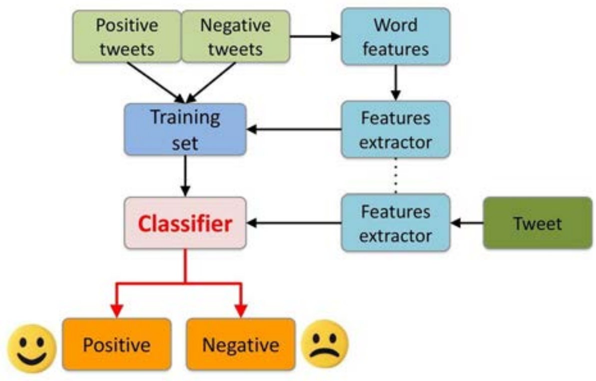
Research on user-level emotion detection in social networks. While tweet-level emotion detection reflects the instant emotion expressed in a single tweet, people's emotion or psychological stress states are usually more enduring, changing over different time periods. In recent years, extensive research 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*.

3 MODEL FRAMEWORK:

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.

ARCHITECTURE



3.1 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.

4 EXPERIMENTS

i) Dataset collection

Data collection is the process of gathering and measuring information on targeted variables in an established systematic fashion, which then enables one to answer relevant questions and evaluate outcomes.

ii) Pick the model

Preparation starts with simple steps, like loading data, but quickly gets difficult with cleaning tasks that are very specific to the data you are working with. You need help as to where to begin and what order to work through the steps from raw data to data ready for modeling

KEY FEATURES:

- How to load text data and clean it to remove punctuation and other non-words.
- How to develop a vocabulary, tailor it, and save it to file.
- How to prepare movie reviews using cleaning and a pre-defined vocabulary and save them to new files ready for modeling
- The goal for all data collection is to capture quality evidence that allows analysis to lead to the formulation of convincing and credible answers to the questions that have been posed.

iii)Train the model

Sentiment Analysis (SA) is an ongoing field of research in text mining field. SA is the computational treatment of opinions, sentiments and subjectivity of text. It tackles a comprehensive overview of the last update in this field. Many recently proposed algorithms' enhancements and various SA applications are investigated and presented briefly in this survey. These are categorized according to their contributions in the various SA techniques. The related fields to SA (transfer learning, emotion detection, and building resources) that attracted researchers recently are discussed. The main target is to give nearly full image of SA techniques and the related fields with brief details.

iv)Test the model

Once you have created a sentiment model and its entries you can test it with any of the services that support sentiment analysis. The Build action is a way to ensure that the most recent version of the model is the one used by any of those services.

5 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.

6 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.

7 REFERENCES

[1] Ben Verhoeven, Walter Daelemans, and Barbara Plank. Twisty: A multilingual twitter stylometry corpus for gender and personality profiling. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation LREC*, pages 1632–1637, 2016

[2] Andrey Bogomolov, Bruno Lepri, Michela Ferron, Fabio Pianesi, and Alex Pentland. Daily stress recognition from mobile phone data, weather conditions and individual traits. In *ACM International Conference on Multimedia*, pages 477–486, 2014.

[3] Chris Buckley and Ellen M Voorhees. Retrieval evaluation with incomplete information. In *Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 25–32, 2004.

[4] Xiaojun Chang, Yi Yang, Alexander G Hauptmann, Eric P Xing, and Yao-Liang Yu. Semantic concept discovery for large-scale zero-shot event detection. In *Proceedings of International Joint Conference on Artificial Intelligence*, pages 2234–2240, 2015.

[5] Wanxiang Che, Zhenghua Li, and Ting Liu. Ltp: A chinese language technology platform. In *Proceedings of International Conference on Computational Linguistics*, pages 13–16, 2010.

[6] Chih chung Chang and Chih-Jen Lin. Libsvm: a library for support vector machines. *ACM TRANSACTIONS ON INTELLIGENT SYSTEMS AND TECHNOLOGY*, 2(3):389–396, 2001.

[7] Dan C Ciresan, Ueli Meier, Jonathan Masci, Luca Maria Gambardella, and Jurgen¨ Schmidhuber. Flexible, high performance convolutional neural networks for image classification. In *Proceedings of International Joint Conference on Artificial Intelligence*, pages 1237–1242, 2011.

[8] Sheldon Cohen and Thomas A. W. Stress, social support, and the buffering hypothesis. *Psychological Bulletin*, 98(2):310–357, 1985.

[9] Glen Coppersmith, Craig Harman, and Mark Dredze. Measuring post traumatic stress disorder in twitter. In *Proceedings of the International Conference on Weblogs and Social Media*, pages 579–582 , 2014.

[10] Rui Fan, Jichang Zhao, Yan Chen, and Ke Xu. Anger is more influential than joy: Sentiment correlation in weibo. *PLoS ONE*, 2014.

[11] Zhanpeng Fang, Xinyu Zhou, Jie Tang, Wei Shao, A.C.M. Fong, Longjun Sun, Ying Ding, Ling Zhou, , and Jarder Luo. Modeling paying behavior in game social networks. In *In Proceedings of the Twenty-Third Conference on Information and Knowledge Management (CIKM'14)*, pages 411–420, 2014.

[12] Golnoosh Farnadi, Geetha Sitaraman, Shanu Sushmita, Fabio Celli, Michal Kosinski, David Stillwell, Sergio Davalos, Marie Francine Moens, and Martine De Cock. Computational personality recognition in social media. *User Modeling and UserAdapted Interaction*, pages 1–34, 2016.

[13] Eileen Fischer and A. Rebecca Reuber. Social interaction via new social media: (how) can interactions on twitter affect effectual thinking and behavior? *Journal of Business Venturing*, 26(1):1–18 , 2011.

[14] Jerome H. Friedman. Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29(5):1189–1232, 1999.

[15] Rui Gao, Bibo Hao, He Li, Yusong Gao, and Tingshao Zhu. Developing simplified chinese psychological linguistic analysis dictionary for microblog. pages 359–368, 2013.

[16] Johannes Gettinger and Sabine T. Koeszegi. *More Than Words: The Effect of Emoticons in Electronic Negotiations*.

[17] Jennifer Golbeck, Cristina Robles, Michon Edmondson, and Karen Turner. Predicting personality from twitter. In *Passat/socialcom 2011, Privacy, Security, Risk and Trust*, pages 149–156, 2011.

[18] Mark S. Granovetter. The strength of weak ties. *American Journal of Sociology*, 1973.

[19] Quan Guo, Jia Jia, Guangyao Shen, Lei Zhang, Lianhong Cai, and Zhang Yi. Learning robust uniform features for cross-media social data by using cross autoencoders. *Knowledge Based System*, 102:64– 75, 2016.

[20] David W. Hosmer, Stanley Lemeshow, and Rodney X. Sturdivant. Applied logistic regression. *Wiley series in probability and mathematical statistics*, 2013.

[21] Sung Ju Hwang. Discriminative object categorization with external semantic knowledge. 2013.

[22] Sepandar D. Kamvar. We feel fine and searching the emotional web. In *In Proceedings of WSDM*, pages 117–126, 2011.

[23] Herbert C. Kelman. Compliance, identification, and internalization: Three processes of attitude change. *general information*, 1(1):51–60, 1958.

[24] Shigenobu Kobayashi. The aim and method of the color image scale. *Color research & application*, 6(2):93–107, 1981.

[25] Novak P Kralj, J Smailovi, B Sluban, and I Mozeti. Sentiment of emojis. *Plos One*, 10(12), 2015.

[26] Frank R Kschischang, Brendan J Frey, and H-A Loeliger. Factor graphs and the sum-product algorithm. *Information Theory, IEEE Transactions on*, 47(2):498–519, 2001.

[27] Yann LeCun and Yoshua Bengio. Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks*, 3361, 1995.

[28] Kathy Lee, Ankit Agrawal, and Alok Choudhary. Real-time disease surveillance using twitter data: demonstration on flu and cancer. In *Proceedings of ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1474–1477, 2013.

[29] H. Lin, J. Jia, Q. Guo, Y. Xue, J. Huang, L. Cai, and L. Feng. Psychological stress detection from cross-media microblog data using deep sparse neural network. In *proceedings of IEEE International Conference on Multimedia & Expo*, 2014.

[30] H. Lin, J. Jia, Q. Guo, Y. Xue, Q. Li, J Huang, L. Cai, and L. Feng. User-level psychological stress detection from social media using deep neural network. In *Proceedings of ACM Int. Conference on Multimedia*, 2014.

[31] Li Liu and Ling Shao. Learning discriminative representations from rgb-d video data. In *Proceedings of International Joint Conference on Artificial Intelligence*, pages 1493–1500, 2013.

[32] H-A Loeliger. An introduction to factor graphs. *Signal Processing Magazine, IEEE*, 21(1):28–41, 2004.

[33] Jana Machajdik and Allan Hanbury. Affective image classification using features inspired by psychology and art theory. In *Proceedings of the international conference on Multimedia*, pages 83–92, 2010.

[34] Kevin P Murphy, Yair Weiss, and Michael I Jordan. Loopy belief propagation for approximate inference: An empirical study. In *Proceedings of the Fifteenth conference on Uncertainty in artificial intelligence*, pages 467–475, 1999.

[35] Cristian Danescu niculescu mizil, Lillian Lee, Bo Pang, and Jon Kleinberg. Echoes of power: Language effects and power differences in social interaction. *eprint arXiv:1112.3670*, 2011.

[36] Liqiang Nie, Yi-Liang Zhao, Mohammad Akbari, Jialie Shen, and Tat-Seng Chua. Bridging the vocabulary gap between health seekers and healthcare knowledge. *Knowledge and Data Engineering, IEEE Transactions on*, 27(2):396–409, 2015.

[37] Federico Alberto Pozzi, Daniele Maccagnola, Elisabetta Fersini, and Enza Messina. Enhance user-level sentiment analysis on microblogs with approval relations. In *AI* IA 2013: Advances in Artificial Intelligence*, pages 133–144. 2013.

[38] Neumann R and Strack F. "mood contagion": the automatic transfer of mood between persons. *Journal of Personality and Social Psychology*, pages 211–223, 2000.

[39] Chenhao Tan, Lillian Lee, Jie Tang, Long Jiang, Ming Zhou, and Ping Li. User-level sentiment analysis incorporating social networks. In *Proceedings of the SIGKDD international conference on Knowledge discovery and data mining*, pages 1397–1405, 2011.

[40] Wenbin Tang, Honglei Zhuang, and Jie Tang. Learning to infer social ties in large networks. In *Machine Learning and Knowledge Discovery in Databases*, pages 381–397. 2011.

[41] Y. R. Tausczik and J. W. Pennebaker. The psychological meaning of words: Liwc and computerized text analysis methods. *Journal of Language and Social Psychology*, 29(1):24–54, 2010.

[42] Mike Thelwall, Kevan Buckley, Georgios Paltoglou, Di Cai, and Arvid Kappas. Sentiment strength detection in short informal text. *Journal of the American Society for Information Science and Technology*, 61(12):2544–2558, 2010.

[43] Svetnik V. Random forest: a classification and regression tool for compound classification and qsar modeling. *Journal of Chemical Information and Computer Sciences*, 43(6):1947–1958, 2003.
.

[44] Chi Wang, Jie Tang, Jimeng Sun, and Jiawei Han. Dynamic social influence analysis through time-dependent factor graphs. *Advances in Social Networks Analysis and Mining (ASONAM), 2011 International Conference on*, pages 239 – 246, 2011.

[45] Xiaohui Wang, Jia Jia, Peiyun Hu, Sen Wu, Jie Tang, and Lianhong Cai. Understanding the emotional impact of images. In *Proceedings of the 20th ACM International Conference on Multimedia*, MM '12, pages 1369–1370, 2012.

[46] Lexing Xie and Xuming He. Picture tags and world knowledge: learning tag relations from visual semantic sources. In *ACM Multimedia Conference*, pages 967–976, 2013.

[47] Yuanyuan Xue and et al. Detecting adolescent psychological pressures from micro-blog. *Health Information Science. Springer International Publishing*, pages 83–94, 2014.

[48] Jian Bo Yang, Minh Nhut Nguyen, Phyo Phyo San, Xiao Li Li, and Shonali Krishnaswamy. Deep convolutional neural networks on multichannel time series for human activity recognition. In *Proceedings of International Joint Conference on Artificial Intelligence*, pages 3995–4001, 2015.
[49] Yang Yang, Jia Jia, Shumei Zhang, Boya Wu, Qicong Chen, Juanzi Li, Chunxiao Xing, and Jie Tang. How do your friends on social media disclose your emotions? In *Proceedings of the 28th AAAI Conference on Artificial Intelligence (AAAI'14)*, pages 306–312, 2011.
[50] Shuo Zeng, Mingfeng Lin, and Hsinchun Chen. Dynamic userlevel affect analysis in social media: Modeling violence in the dark web. In *IEEE International Conference on Intelligence and Security Informatics (ISI)*, pages 1–6, 2011.
[51] Qian Zhang and Bruno Goncalves. Topical differences between chinese language twitter and sina weibo. *Computer Science*, 2015.
[52] Yuan Zhang, Jie Tang, Jimeng Sun, Yiran Chen, and Jinghai Rao. Moodcast: Emotion prediction via dynamic continuous factor graph model. *2013 IEEE 13th International Conference on Data Mining*, pages 1193–1198, 2010.
[53] Jichang Zhao, Li Dong, Junjie Wu, and Ke Xu. Moodlens: an emoticon-based sentiment analysis system for chinese tweets. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1528–1531, 2012.