International Journal of Scientific Research in Computer Science, Engineering and Information Technology
© 2018 IJSRCSEIT | Volume 4 | Issue 2 | ISSN : 2456-3307

An Efficient Analysis of Psychological Stress Prediction Technique Using Social Interaction of Social Networks

G. Prashanti [*1], Mujafar Abdul Ghani [2]

[1*]prashantiguttikonda77@gmail.com, abdulghani.mujafar@gmail.com[2]

ABSTRACT

Mental general despondency is weakening people's prosperity. It is non-immaterial to perceive push propitious for proactive care. With the reputation of online organizing, people are familiar with offering their step by step activities and working together to associates through electronic systems administration media stages, making it conceivable to utilize online relational association data for extend ID. In this paper, we find that customers push state is about related to that of his/her mates in web-based systems administration, and we use a tremendous scale dataset from certifiable social stages to systematically mull over the association of customers' tension states and social co-activities. We at first describe a plan of pressure related artistic, visual, and social characteristics from various points and after that propose a novel cream show - a factor chart show joined with Con-volition Neural System to utilize tweet substance and social affiliation information for extending area. Test happens exhibit that the proposed model can upgrade the area execution by 6-9% in F1-score. By furthermore separating the social affiliation data, we moreover locate a couple of spellbinding wonders, i.e. the amount of social structures of sparse affiliations (i.e. with no delta relationship) of centered customers is around 14% higher than that of non-concentrated on customers, exhibiting that the social structure of concentrated on customers' mates tend to be less related and less jumbled than that of non-concentrated on customers.

Keywords: *Stress detection, factor graph model, micro-blog, social media, healthcare, social interaction.*

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 New business in 20101, 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 Chinese Centre for Disease Control and Prevention, suicide has become the top cause of death among Chinese youth, and excessive stress is considered 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. Are there any timely and proactive methods for stress detection? 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 Sine Weibo2.

Fig. 1. Sample tweets from Sina Weibo. In each tweet, the top part is tweet content with text and an image; the bottom part shows the social interactions of tweets where there are multiple indicators of stress: mentions of '*busy*' and '*stressed*', '*working overtime*', '*failed the exam*', '*money*' and a stressed emoticon.

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 user's 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],

Using user tweeting contents on social media platforms to detect users' psychological stress. Existing works [28], demonstrated that leverage social media for healthcare, and in particular stress detection, is feasible.

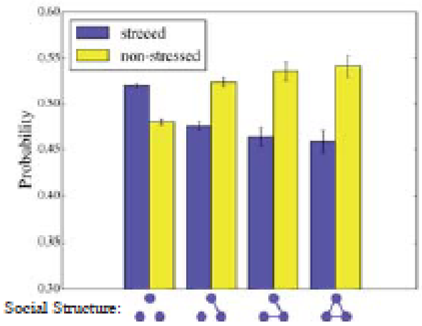


Fig. 2. The sampling test results of the diversity of users' social struc-tures from Sina Weibo, by using the top 3 interacted friends of the users.

Limitations exist in tweeting content based stress de-tection. Firstly, tweets are limited to a maximum of 140 characters on social platforms like Twitter and Sina Weibo, 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, as reported by a recent study in Pew Research Center3. These phenomena incur the inherent data sparsity and ambiguity problem,which may hurt the performance of tweeting content based stress detection performance. For illustration, let's see a Sina Weibo tweet example in Figure 1. The tweet contains only 13 characters, saying that the user wished to go home for the Spring Festival holiday. Although no stress is revealed from the tweet itself, from the follow-up interactive comments made by the user and her friends, we can find that the user is actually stressed from work. Thus, simply relying on a user's tweeting content for stress detection is insufficient. Users' social interactions on social networks contain useful cues for stress detection. Social psychological stud-ies have made two interesting observations. The first is mood contagion [37]: a bad mood can be transferred from one person to another during social interaction.

The second is linguistic echoes [34]: people are known to mimic the style and affect of another person. These observations motivate us to expand the scope of tweet-wise investigation by incorporating follow-up social interactions like comments and retweeting activities in user's stress detection. This may actually help to mitigate the single user's data sparsity problem. Another reason for considering social interactions in stress detection is based on our empirical findings on a large-scale dataset crawled from Sina Weibo that the social structures of stressed users are less connected and thus less complicated than those of non-stressed users. This is con-sistent with the Pew Research Center's finding that stressed users are less active than non-stressed ones. The bottom of Figure 2 illustrates four social interaction structure patterns.

Each node in a structure pattern represents a user's interacting friend (who either commented or retreated the tweets).

If two nodes are also friends on social network, there is an edge linking both; otherwise, there is none. We examined 3000 users on Sina Weibo. For each user, we collected and merged his/her one week tweets into one and sense stress from it. Meanwhile, we captured the top-3 most active friends the user interacted with. As shown in Figure 2,stressed users' interaction structures are less connected, and thus less complicated than those of non-stressed users.

II. LETERECTURE SURVY

1.“Researching Mental Health Disorders in the Era of Social Media: Sys-tematic Review.” 2017, Author's:Munmun De Choudhury, Glen Copper-smith, and Christophe Giraud-Carrier Assembling large, high-quality datasets of social media users with mental dis-order is problematic, not only due to biases associated with the collection methods, but also with regard to managing consent and selecting appropriate analytics techniques.

2.“Social Networks Under Stress.2016”, Author's:Daniel M. Romero, Brian Uzzi Network science has examined the reaction of networks to internal stresses, particularly nodal loss, but has given considerably less attention to the rela-tionship between external shocks in a network of stable members .

3.Flexible, High Performance Convolutional Neural Networks for Image Classification. 2011 We presented high-performance GPU-based CNN variants trained by on-line gradient descent. Principal advantages include state-of-the-art generalization capabilities, great flexibility and speed.

4.Measuring Post Traumatic Stress Disorder in Twitter, Author's:Glen A. Coppersmith Craig T. Harman Mark H. Dredze We have presented the first analysis of social media for the study of individuals with post traumatic stress disorder.

III. 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 applica-tion of emotion, especially in social networks, have drawn much attention in recent years [8], [9], [28], [41],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. proposed a system called *MoodLens* to perform emotion analysis on the Chinese micro-blog platform Weibo, clas-sifying the emotion categories into four types, i.e., angry, disgusting, joyful, and sad. [9] studied the emotion propaga-tion problem in social networks, and found that anger has a stronger correlation among different users than joy, indicat-ing 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 com-posed of sequential and inter-connected items from diverse sources and modalities, making it be actually cross-media data.

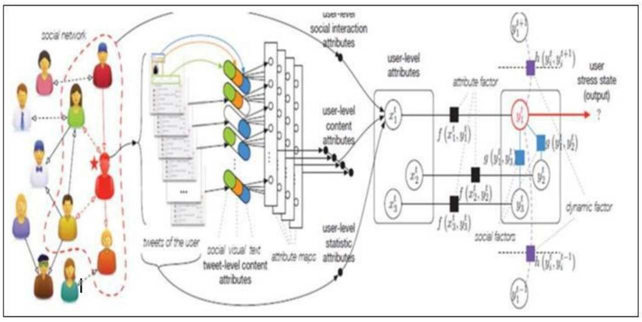
Research on user-level emotion detection in social networks. While tweet-level emotion detection reflects the instant emotion expressed in a single tweet, people's emo-tion or psychological stress states are usually more endur-ing, changing over different time periods. In recent years, extensive research starts to focus on user-level emotion detection in social networks [29], [36], [38]. 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 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.

Research on leveraging social interactions for social media analysis. Social interaction is one of the most im-portant features of social media platforms. Now many researchers are focusing on leveraging social interaction information to help improve the effectiveness of social me-dia analysis. [12] analyzed the relationships between social interactions and users' thinking and behaviors, and found out that Twitter-based interaction can trigger effectual cog-nitions. [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 inter-actions, e.g., textual comment content, while ignoring the inherent structural information like *how users are connected.*

IV. PROPOSED SYSTEM

First we design a CNN with cross auto encoders (CAE) to generate user-level interaction content attributes from tweet-level attributes. The CNN has been found to be effective in learning stationary local attributes for series like images and audios. Then, we design a partially-labelled factor graph (PFG) to incorporate all three aspects of user-level attributes for user stress detection. Factor graph model has been widely used in social network modelling. It is effective in leveraging social correlations for different prediction tasks.



1. Data collection

To lead perceptions and assess our successive model, we initially gather a set of data sets utilizing diverse naming techniques

2. CNN+ FGN

We propose a bound together hybrid model incorporating CNN with FGM to use both tweet content properties and social connections to upgrade stress discovery.

3.Tweet Classification

we utilize a cross auto-encoder (CAE) to take in the methodology invariant representation of each single tweet with various modalities. Indicating the content, visual, and social traits of a tweet by vT , vI , and vS, the CAE is planned.

4.Attribute Categorization

To address the issue of stress recognition, we initially characterize two arrangements of ascribes to quantify the distinctions of the stressed and non-stressed on user via web-based networking media stages.

APPLICATION

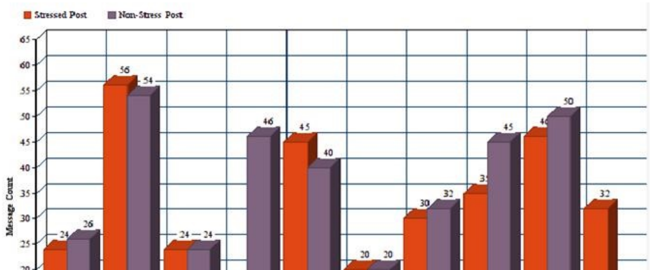
The patterns that emerge through collective human mobility behaviour are now understood for wide ranging and important.

ADVANTAGES

- ✓ Democratization of media can be used to gain fame.
- ✓ Social media helps users to connect with strong and weak ties.
- ✓ Creativity and re-mix culture.
- ✓ It can be used to embrace your passion and identity.
- ✓ Community, sharing, and connecting are integral part of social media.

RESULT ANALYSIS

In below graphical analysis we have tested our system on n number of users, X-axis shows the user name and Y-axis shows the message count of that social user. the analysis shows that there are 50% online social user are in stress.



CONCLUSION

In this PAPER , we showed a framework for recognizing clients mental extend states from customers' week after week web based systems administration data, using tweets' substance and moreover customers' social affiliations. Using genuine online system ing data as the commence, we considered the association between's customer' mental uneasiness states and their social correspondence rehearses. To totally utilize both substance and social correspondence information of customers' tweets, we proposed a creamer show which joins the factor graph show (FGM) with a convolution neural framework (CNN).

V. REFERENCES

1. 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 Interna-tional Conference on Multimedia, pages 477–486, 2014.
2. Chris Buckley and Ellen M Voorhees. Retrieval evaluation with in-complete information. In Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval, pages 25–32, 2004.
3. 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.

4. Wanxiang Che, Zhenghua Li, and Ting Liu. Ltp: A chinese language technology platform. In Proceedings of International Con-ference on Computational Linguistics, pages 13–16, 2010.
5. Chih chung Chang and Chih-Jen Lin. Libsvm: a library for sup-port vector machines. ACM TRANSACTIONS ON INTELLIGENT SYSTEMS AND TECHNOLOGY, 2(3):389–396, 2001.
6. Dan C Ciresan, Ueli Meier, Jonathan Masci, Luca Maria Gam-bardella, and Jurgen¨ Schmidhuber. Flexible, high performance convolutional neural networks for image classification. In Proceed-ings of International Joint Conference on Artificial Intelligence, pages 1237–1242, 2011.
7. Sheldon Cohen and Thomas A. W. Stress, social support, and the buffering hypothesis. Psychological Bulletin, 98(2):310–357, 1985.
8. 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.
9. Rui Fan, Jichang Zhao, Yan Chen, and Ke Xu. Anger is more influential than joy: Sentiment correlation in weibo. PLoS ONE, 2014.
10. 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.
11. 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 User-Adapted Interaction, pages 1–34, 2016.
12. 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.
13. Jerome H. Friedman. Greedy function approximation: A gradient boosting machine. Annals of Statistics, 29(5):1189–1232, 1999.
14. Rui Gao, Bibo Hao, He Li, Yusong Gao, and Tingshao Zhu. Developing simplified chinese psychological linguistic analysis dictionary for microblog. pages 359–368, 2013.
15. Johannes Gettinger and Sabine T. Koeszegi. More Than Words: The Effect of Emoticons in Electronic Negotiations.
16. 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.
17. Mark S. Granovetter. The strength of weak ties. American Journal of Sociology, 1973.
18. 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.
19. David W. Hosmer, Stanley Lemeshow, and Rodney X. Sturdivant. Applied logistic regression. Wiley series in probability and mathemat-ical statistics, 2013.
20. Sung Ju Hwang. Discriminative object categorization with exter-nal semantic knowledge. 2013.
21. Sepandar D. Kamvar. We feel fine and searching the emotional web. In In Proceedings of WSDM, pages 117–126, 2011.
22. Herbert C. Kelman. Compliance, identification, and internal-ization: Three processes of attitude change. general information, 1(1):51–60, 1958.
23. Shigenobu Kobayashi. The aim and method of the color image scale. Color research & application, 6(2):93–107, 1981.

24. Novak P Kralj, J Smailovi, B Sluban, and I Mozeti. Sentiment of emojis. Plos One, 10(12), 2015.
25. 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.
26. Yann LeCun and Yoshua Bengio. Convolutional networks for images, speech, and time series. The handbook of brain theory and neural networks, 3361, 1995.
27. 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.
28. H. Lin, J. Jia, Q. Guo, Y. Xue, J. Huang, L. Cai, and L. Feng. Psy-chological stress detection from cross-media microblog data using deep sparse neural network. In proceedings of IEEE International Conference on Multimedia & Expo, 2014.
29. 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.
30. Li Liu and Ling Shao. Learning discriminative representations from rgb-d video data. In Proceedings of International Joint Confer-ence on Artificial Intelligence, pages 1493–1500, 2013.
31. H-A Loeliger. An introduction to factor graphs. Signal Processing Magazine, IEEE, 21(1):28–41, 2004.
32. Jana Machajdik and Allan Hanbury. Affective image classification using features inspired by psychology and art theory. In Proceed-ings of the international conference on Multimedia, pages 83–92, 2010.
33. 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.
34. Cristian Danescu niculescu mizil, Lillian Lee, Bo Pang, and Jon Kleinberg. Echoes of power: Language effects and power differ-ences in social interaction. eprint arXiv:1112.3670, 2011.
35. Liqiang Nie, Yi-Liang Zhao, Mohammad Akbari, Jialie Shen, and Tat-Seng Chua. Bridging the vocabulary gap between health seek-ers and healthcare knowledge. Knowledge and Data Engineering, IEEE Transactions on, 27(2):396–409, 2015.
36. 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.
37. Neumann R and Strack F. ”mood contagion”: the automatic transfer of mood between persons. Journal of Personality and Social Psychology, pages 211–223, 2000.
38. 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.
39. 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.
40. 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.

41. 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.
42. 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.
43. 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.

AUTHOR DETAILAS

G.PRASHANTI is working an assistant professor in VIGNAN'S LARA INSTITUTE OF TECHNOLOGY & SCIENCE. Vadlamudi-522213 Guntur Dist.She has Experience in the teaching field For 7 years and her interested in research areas are network security Steganography and data mining.

MUJAFAR ABDUL GHANI he is Currently pursuing MCA in MCA Department,Vignan's Lara Institute Of Technology&Science,Vadlamudi, Guntur(Dt), Andhra Pradesh, India.

He received Bachelor of science from ANU