### Assessment of social network public anxiety

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ABSTRACT— These days, it seems like everyone uses social media, and unfortunately, some people's postings, messages, and remarks may really bring on some serious emotional distress. There has been a lot of research on assessing individual anxiety, but much less on assessing public anxiety of groups, particularly in the form of online communities that may be used to gauge society's mental health. The following considerations, however, prevent us from just averaging individual anxiety levels in order to assess the public anxiety of a community:-(1) the Structural component, which deals with the effects of interpersonal connections on the anxiety levels of each group member. (2) Conversations centred on certain topics that reveal the level of concern in a society (the Topical component). The evaluation of topic-based social network communities' (TSNC) public anxiety is the primary focus

of this project. We develop an assessment methodology that can convert a TSNC's anxiety level into a numeric value between zero and one. In order to calculate individual anxiety ratings dynamically utilizing the Structural effect, we use a cascade model. In order to successfully calculate the anxiety score of a TSNC from the Topical aspect, we construct a tree structure (MC-Tree) and apply a fuzzy model to evaluate the anxiety score of social network communications using a generalized user.

#### INTRODUCTION

As a result of their varied interests, social media users create distinct communities online. People who suffer from social anxiety disorder may find that social media has an impact on them. Anxieties about how others may perceive one's decisions or looks may intensify in certain situations. The

comparison of the emotional states of internet communication gives birth to this, which may have far-reaching consequences for society. While at work, I find myself engrossed in social media. There is an overpowering want to post everything on every social networking platform. Being unable to check your social media status for a while causes you to feel very worried or agitated. You shouldn't be concerned about seeming foolish or ashamed. Severe anxiety when confronted with new people. That other people would see your fear as a sign of weakness. Anxieties about potentially humiliating physical manifestations. B. Red face, perspiration, nervousness, quivering speech. Thus, it has become a significant challenge in social network analysis to analyze the emotional state of topic-based social network communities (TSNC)[3], particularly dread. All users who contribute to a topic-specific conversation make up such a community. Platform for social network involvement. Traditional approaches include administering a questionnaire that includes the Self-Rating Anxiety Scale (SAS) in order to gauge the degree of anxiety experienced by individuals. It is not feasible to have a big number of people fill out SAS surveys indicating their degree of anxiety in order to track who uses media.Important social social network

analysis tasks will revolve on topic-based analysis, in which the whole user community discusses a certain issue. Assessing an individual's anxiety level via the Self-Rating Anxiety Scale (SAS) involves conventional procedures. The foundation of one network's attitude or conduct towards another actor, according to social influence theory, are social interactions. A persistent and extreme aversion to interacting with other people is characterized by social anxiety disorder (or social phobia). This is a typical issue that often manifests itself throughout adolescence. The effects on your life might be profoundly negative and painful. It improves over time for some individuals. Anxiety disorders associated with mental and physical stress affect around 30% of people, according to the American Association. **Psychiatric** The term "community public anxiety" describes how a group of people respond to difficult events, which in turn influences their collective mindsets about the importance of community involvement. How Social Anxiety Relates to Online Platforms In the ever-growing realm social media, users able are instantaneously exchange photos and thoughts with their entire buddy circle via a complex web of websites. Billion people use these sites daily, and their popularity

skyrocketed. Despite appearances, these interactive platforms have the potential to amplify societal instability. A lot of people's mental health is suffering because of these social networks. More than fifteen million Americans suffer from social anxiety, and the prevalence of online platforms is a major contributing factor.

#### RELATED WORK

## 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 vears. Relationships between psychological stress and personality traits can be an interesting issue to consider. For example, 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, classifying the emotion categories into four types, i.e., angry, disgusting, joyful, and sad. 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 4Meaning that three points are connected with each other 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 interconnected 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. Our recent work 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, incorporated social relationships to improve user-level sentiment analysis in

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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 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 analyzed the relationships between social interactions and users' thinking and behaviors, and found out that Twitter-based interaction can trigger effectual cognitions. 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.

#### **METHODOLOGY**

- 1. **Topical Anxiety:** Using this module, we have to enter some keywords like anxiety and it will shows the data related to particular keyword and we can sort that data based on the anxiety score value.
- 2. **Structural Anxiety:** Using this module, Evaluating Public Anxiety for Topic-based Communities in Social Networks and the anxiety result is displayed in the pie chart format and we will get overall anxiety score value also.
- 3. Comparison graph: Using this module, we can compare accuracy, precision, recall values of our model with reference model. By comparing their model with our model in many test cases we came to know that the accuracy of reference is come out to be 80%, their precision is come out to be 89% and their recall is come out to be 85% and our model's accuracy is came out to be 88%, our models precision is came out to be 92% and recall is 84%.

#### RESULT AND DISCUSSION



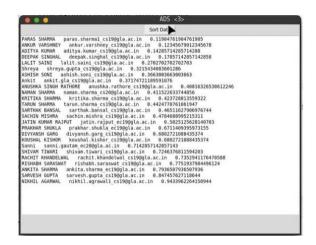
In above screen, showing two different modes such as structural anxiety and topical anxiety for detecting anxiety.



In above screen, showing Topical anxiety mode and entering anxiety keyword for getting data for anxiety.

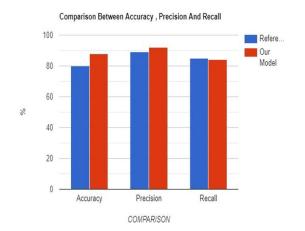


In above screen, showing Topical anxiety results and for each record its showing anxiety score value also.



In above screen, showing Topical anxiety results in sorting order based on anxiety score value.

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In above screen, showing comparison between their model with our model in many test cases we came to know that the accuracy of reference is come out to be 80%, their precision is come out to be 89% and their recall is come out to be 85% and our model's accuracy is came out to be 88%, our models precision is came out to be 92% and recall is 84%.

#### **CONCLUSION**

We investigate and resolve the issue of topicbased public anxiety estimation in social media communities using fuzzy tree in this research work. Using Structural and Topical components, we provide a useful paradigm for estimating topic-based public anxiety levels in social network communities. We compute the Structural component anxiety score iteratively to assess the anxiety levels of community members. We like a troublesome approach to assess the anxiety score of the social communities' comments and messages for the topical components. In order to make calculation easier, we create an MC Tree structure, which stands for message-comment tree, to estimate the public anxiety score inside the social media community. In a similar vein, we breakdown huge communities into smaller ones in order to assess and measure the public worry. A research using real-world datasets shows that our technique for measuring the social media anxiety score is quite accurate and precise.

#### REFERENCES

- [1] Craske, Michelle G., Scott L. Rauch, Robert Ursano, Jason Prenoveau, Daniel S. Pine, and Richard E. Zinbarg. "What is an anxiety disorder?." Focus 9, no. 3 (2011): 369388.
- [2] Boulianne, Shelley. "Revolution in the making? Social media effects across the globe."

  Information, communication & society 22, no. 1 (2019): 39-54.
- [3] Ta, N., Li, K., Yang, Y., Jiao, F., Tang, Z. and Li, G., 2020. Evaluating public anxiety for topic-based communities in social

- networks.IEEE Transactions on Knowledge and Data Engineering.
- Agarwal, S., Milner, H., Kleiner, [4] A., Talwalkar, A., Jordan, M., Madden, S., ... & Stoica, I. (2014, June). Knowing when you're wrong: building fast and reliable approximate query processing systems. In Proceedings of the 2014 ACM **SIGMOD** conference international on Management of data (pp. 481-492).
- [5] Alkis, Y., Kadirhan, Z., & Sat, M. (2017). Development and validation of social anxiety scale for social media users. Computers in Human Behavior, 72, 296-303.
- [6] Walsh, C. G.,Ribeiro, J. D., & Franklin, J. C. (2017). Predicting risk of suicide attempts over time through machine learning. Clinical Psychological Science, 5(3), 457-469.
- [7] Park, M., McDonald, D., & Cha, M. (2013). Perception differences between the depressed and non-depressed users in twitter. In

- Proceedings of the International AAAI Conference on Web and Social Media (Vol. 7, No. 1, pp. 476-485).
- [8] Memmedova, Konul. "Fuzzy logic modelling of the impact of using technology on anxiety and aggression levels of students."

  Procedia computer science 120 (2017): 495-501.
- [9] Almadi, Abdulla IM, Rabia Emhamed Al Mamlook, Yahya Almarhabi, Irfan Ullah, Arshad Jamal, and Nishantha Bandara.

  "A fuzzy-logic approach based on driver decision-making behavior modeling and simulation."

  Sustainability 14, no. 14 (2022): 8874.
- [10] Singh, Harpreet, Madan M. Gupta, Thomas Meitzler, Zeng-Guang Hou, Kum Kum Garg, Ashu MG Solo, and Lotfi A. Zadeh. "Real-life applications of fuzzy logic." Advances in Fuzzy Systems 2013 (2013): 3-3.
- [11] Zhang, Junbo, Yu Zheng, Dekang Qi, Ruiyuan Li, and Xiuwen Yi. "DNN-based prediction model for

spatio-temporal data." In Proceedings of the 24th ACM SIGSPATIAL international conference on advances in geographic information systems, pp. 1-4. 2016.

- [12] Metz, CE (October 1978). "Basic principles of ROC analysis" (PDF). Semin Nucl Med. 8 (4): 283–98. doi:10.1016/s0001-2998(78)80014-2. PMID 112681
- [13] Bzdok, Danilo, and Andreas Meyer-Lindenberg. "Machine learning for precision psychiatry: opportunities and challenges." Biological Psychiatry: Cognitive Neuroscience and Neuroimaging 3, no. 3 (2018): 223-230.
- [14] Buckland, Michael, and Fredric Gey. "The relationship between recall and precision." Journal of the American society for information science 45, no. 1 (1994): 12-19.
- [15] Goutte, Cyril, and Eric Gaussier.

  "A probabilistic interpretation of precision, recall and F-score, with implication for evaluation." In Advances in Information

Retrieval: 27th European Conference on IR Research, ECIR 2005, Santiago de Compostela, Spain, March 21-23, 2005. Proceedings 27, pp. 345-359. Springer Berlin Heidelberg, 2005.

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