Measuring the Impact of Anxiety on Online Social Interactions

Sarmistha Dutta , Jennifer Ma , Munmun De Choudhury
Georgia Institute of Technology
sdutta65, jennifer.ma, munmund@gatech.edu

Abstract

For individuals with anxiety disorders, maladaptive feelings and negative beliefs can interfere with daily activities and importantly, social relationships. Literature has examined both direct and indirect influences of an individual's anxiety on their social interactions, however, how they co-vary temporally remains less explored. As individuals appropriate social media platforms more pervasively, can anxiety play an equally significant role in impacting one's *online* social interactions? This paper seeks to answer this question. Employing a dataset of 200 Twitter users, their timeline, and social network data, we examine the relationship between manifested anxiety and various attributes of social interaction of a user by employing Granger causality and time series forecasting approaches. We observe that increases in anxiety levels of an individual result in increased future interaction with weak ties, indicating a tendency to seek support from the broader online community. We discuss how our findings provide novel insights and practical lessons around the impact of an individual's mental health state on their online social interactions.

Introduction

Anxiety disorders have the highest overall prevalence rate among psychiatric disorders (Grant et al. 2005). They are characterized by experiences of non-specific persistent fear and worry and excessive concern with everyday matters. What makes these disorders extremely challenging is the substantial negative impact they have on the sufferers' quality of life. Anxiety is known to result not only in negative self-image and maladaptive feelings, but also in reduced social engagement, reduced perceived quality of social relations, and reduced interest in social and leisure activities (Rapee and Heimberg 1997). Broadly, experiences of anxiety negatively impact an individual's interaction and manifest in the way an individual expresses themselves and interacts with others in their social environment.

However, how changes in anxiety experiences influence interpersonal and social dynamics via theoretically-grounded causal pathways remains under-explored, although prior work has recognized the value of strong social ties in mental wellbeing (Kawachi and Berkman 2001). Empirical examinations of the relationship between anxiety and the nature of impairments in social functioning can provide rich insights into the development and delivery of therapies and interventions, as well as into improving social support structures within the affected individuals' specific contexts.

Individuals are increasingly appropriating social media platforms to self-disclose about their mental illnesses (Coppersmith, Dredze, and Harman 2014), seek support (Burke, Marlow, and Lento 2010), and derive therapeutic benefits (Ernala et al. 2017). Social media, including the types of social interactions they facilitate, has also been established to be valuable in understanding and predicting different forms of mental illnesses like depression (De Choudhury et al. 2013) and suicidal ideation (De Choudhury and Kıcıman 2017). Nevertheless, little is understood in terms of how an individual's mental health status impacts the interactions they have on these platforms. With social interactions increasingly shifting online and complementing offline relationships (Perrin 2015) such an understanding can help evaluate and discover new and existing observations about how underlying mental health challenges like anxiety can affect social functioning, particularly around the varied social relations an individual might be embedded in. Moreover, identifying how an individual's mental health state impacts their interactions online can be valuable to social media users, managers, designers, and owners. In this paper, we leverage Twitter to examine the question: *How does anxiety impact an individual's forthcoming online interactions?*

Our study focuses on a sample of 200 Twitter users who, following expert-validation, had self-disclosed about experiencing an anxiety disorder. On their public timeline data, we model several social interactional attributes. Then, developing a Granger causality framework and time series forecasting models, we identify specific interaction patterns that were significantly affected by an individual's historical anxiety status. Our results provide novel insights into the manner in which online social networks and interactions are influenced by an individual's mental health state, specifically anxiety disorders. We conclude with the implications of our work for instrumenting online social platforms and tailoring their affordances in ways that yield positive outcomes for individuals vulnerable to mental health challenges.

Background and Related Work

A rich body of literature exists in psychiatry, psychology, and health to understand the social effects of anxiety disorders. Anxiety disorders are studied to be predictive of certain traits of personality and sociability in life (Brandes and Bienvenu 2009). For instance, individuals who experience high level of anxiety in social situations often underperform in work and find it difficult to develop and maintain close relationships (Caspi, Elder, and Bem 1988). Partners with generalized anxiety disorder perceived their marriages to be less satisfying than did other partners (McLeod 1994). Research in psychiatry further shows that anxiety disorder causes greater activity in brain structures linked to negative emotional responses to others (Etkin and Wager 2007). People also experience anxiety while interacting with outgroup members due to fear of negative psychological or behavioral consequences for the self and fear of negative evaluations by ingroup or outgroup members (Stephan and Stephan 1985). However, these studies have been largely cross-sectional in nature and similar studies on online interactions of individuals is under-explored. While prior work has examined the ability for online social interactions to predict risk to mental illness (De Choudhury et al. 2013), how mental illness influences the manifestations of individuals' interpersonal and social dynamics in the online context remains unexplored.

Drawing upon this work and existing gaps in the literature, we study if and how temporal changes in anxiety can predict the changes in the online interactions with strong (friends) and weak ties (contacts without bidirectional interaction) of people suffering from anxiety disorder.

Data

Towards our research question, we focused on the social media Twitter. We started by collecting Twitter users who had self-disclosed about their diagnosis or experience of anxiety through a public post. To identify self-disclosures, inspired from prior work (Coppersmith, Dredze, and Harman 2014; Ernala et al. 2017), we utilized a set of carefully curated search queries: "diagnosed [me]* with anxiety" and "i got/was/am/have been diagnosed with anxiety".

We used a web-based Twitter crawler called GetOldTweetsAPI to obtain tweets with self-disclosures of anxiety between 2013 and 2017. Our initial search based on the queries listed above gave us 3,856 tweets shared by 966 users. Thereafter, for each user, two human annotators familiar with social media content around mental health manually inspected the collected tweets to identify if they indicated a genuine self-disclosure of anxiety. Then we removed users who had less than 20 followers and followings as these networks were too small to compute meaningful social network metrics. We also removed accounts which had too few posts (less than 10) and with more than 10,000 followers or followings. Our final dataset at the conclusion of this data acquisition and curation contained 200 users.

For each of these users, we collected their entire timeline data again using the GetOldTweets API. This gave us 209,290 tweets with a median of 695 tweets per user. Additionally, we collected one-hop network data (followers and followings) of the 200 anxiety disclosing users; we obtained 41,557 users who had follower and following ties with the anxiety users. Thereafter, using the retweets, quotes, and replies contained in this tweet corpus, we categorized these social interactions into interactions with friends (strong ties) and non-friends (weak ties). Here, we define friends as any Twitter user who has bidirectional ties with an anxiety user i.e., users who follow the anxiety user and is also followed by the anxiety user. Anyone who does not fall in this category, is a non-friend and their interactions, via retweets, quotes, or replies are characterized as weak tie interactions.

Approach

To investigate whether changes in anxiety impacts individual's online social interactions, our computational approach involves the following components: 1) determining expressions of anxiety in tweets and their manifestation over time; 2) defining attributes of social interaction; and 3) developing a causal inference based time series approach (Geweke 1984) to gauge the relationship between historical anxiety and forthcoming interaction attributes. In Figure 1(a) we provide a schematic diagram of the overall approach.

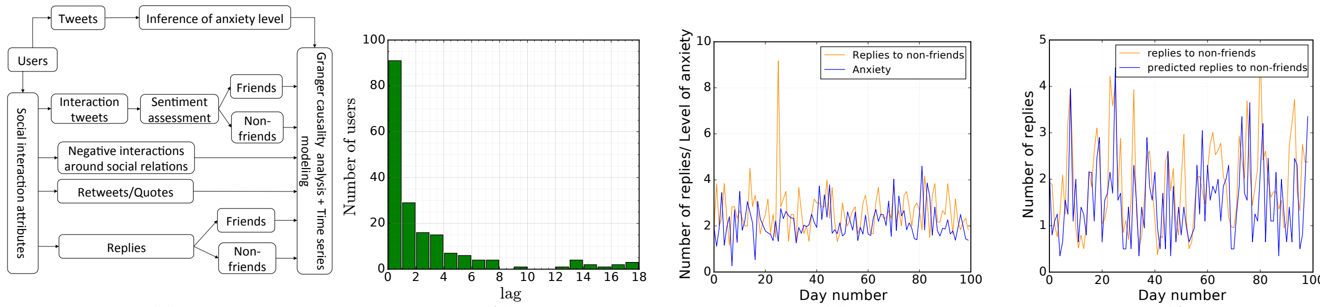
Inferring a Dynamic Measure of Anxiety

Due to our focus on understanding the temporal effects of anxiety on a user's online social interactions, and because not all tweets in an anxiety user's Twitter feed are likely to be anxiety-intensive, we begin by first presenting an approach to infer a dynamic measure of anxiety in a user's Twitter posts over time. In the absence of ground truth labels on anxiety levels in tweets, we adopt an ensemble approach to combine various noisy assessments of anxiety in tweets into a reliable composite measure.

Anxiety assessment with word embeddings. First we annotated the 209,290 tweets of the 200 anxiety users using the established psycholinguistic dictionary LIWC (Pennebaker, Francis, and Booth 2001). We started by focusing on all of the words and word stems given in the "anxiety" category, and expanded this list using neural word embeddings (Mikolov et al. 2013). We used the presence/absence of the stems of these words in the tweets to annotate the tweets as expressing anxiety (binary annotations).

Anxiety assessment with transfer learning. As a second method in our ensemble approach, we adopted a transfer learning approach, similar to (Saha and De Choudhury 2017). Specifically, we first built a supervised machine learning model on a large social media (Reddit) dataset containing labeled information on anxiety: positive class or "anxiety" examples came from posts shared in the r/anxiety subreddit, while negative class or "no anxiety" examples constituted posts, unrelated to mental health, that were randomly sampled from Reddit's homepage. Then we adopted this classifier, a binary Support Vector Machine (SVM) trained on the uni-, bi-, and tri-grams of posts as features, to machine label the tweets of the 200 anxiety users. On a hand-labeled validation set of tweets, the classifier was found to yield an accuracy of 87.59% and an F-1 score of 79.64% in detecting binary anxiety levels.

Inferring final anxiety label through voting. After each tweet in the dataset of all tweets of the 200 anxiety users was annotated separately by the above two approaches, we used unweighted ensemble of the results to finally annotate the



(a) (b) (c) (d)

Figure 1: (a) Schematic diagram of our overall approach. (b) Histogram of lags in predicting changes in interactions with non-friends using anxiety levels of users. (c) Time series showing changes in anxiety levels of users and interactions with non-friends. (d) Actual interactions with non-friends overlaid with values forecasted using anxiety levels of users.

tweet as anxiety. For each tweet, we assigned it to be an anxiety expression only if both the methods agreed on the anxiety label; all of the other tweets were annotated as non-expressions of anxiety. As a final step in this approach, in order to generate a time series representation of a user's anxiety measures for the ensuing causal analysis, we obtained daily aggregates of anxiety of a user by taking average over all of the tweets shared by them during a day.

Modeling Dynamic Social Interactions

Next, we focus on characterizing the nature of the different social interactions of an anxiety user. We first identified the interactions that could be dynamically calculated (that is, over time) — replies, retweets/quoted tweets directed to and received from friends, and the same involving non-friends. On these tweets, next, we quantified several attributes of the nature of social interaction. We assessed whether an interaction to or from an anxiety user expresses negative sentiment or not by using an ensemble of three methods: the VADER tool (Hutto and Gilbert 2014), Stanford CoreNLP sentiment analysis toolkit, and the Python NLTK sentiment analysis library. We then divided the sentiment labeled interactions in two attribute types—interactions with friends (strong ties), and interactions with non-friends (weak ties).

Additionally, prior literature (McLeod 1994) posits that, for people suffering from anxiety, the perceived quality of close relations is greatly reduced. Hence we define a final attribute of social interaction that captures the sentiment of tweets that discuss familial and related social issues and topics. For this, we first labeled the tweets to belong to the "family", "friends", or "social" categories by using the lexicon LIWC, and then used the above ensemble based sentiment inference approach to obtain the quality of interactions for an anxiety user centered around social relations.

Causality and Time Series Modeling

Following the above assessments of anxiety and social interactions, recall that we are ultimately concerned with the question whether temporal changes in the anxiety level of users predicts ensuing temporal changes in the various attributes of social interaction. For this we employ the Granger causality analysis (Granger 1988). Granger causality of two time series X and Y is a statistical hypothesis test to determine whether a time series X is useful in forecasting another time series Y. The analysis gives a p-value which attempts to reject the null hypothesis that X does not predict, i.e., Granger-cause, Y. The analysis also gives a lag value which is the number of unit time interval after which changes in X are manifested in Y.

In our approach, we paired up each of the social interaction attribute time series with the anxiety time series for each anxiety user. After that, we applied the Granger causality technique to each time series pair. This created six causality tests for each of the 200 anxiety users. For each social interaction attribute we considered it to be usefully predicted by a user's anxiety level if future time series values of that attribute are significantly ($p < 0.001$) Granger-caused by historical anxiety levels for at least half (100) of the anxiety users. In all, for the causal relationships, we did a Granger analysis for 1200 time series pairs.

Finally, following the Granger causality analysis, to examine if the social interaction attributes can be reliably predicted from the anxiety levels of an individual, we developed a vector autoregressive model (VAR) (Johansen 2000). VAR models are time series forecasting approaches that have previously been shown to work well in temporal prediction problems and work suitably in conjunction with Granger causality analysis (De Choudhury, Kumar, and Weber 2017). Our VAR model is meant to forecast changes in social interaction attributes on day t_k based on: (a) the attribute values over n previous days; and (b) the anxiety level of users over the same n previous days. We empirically choose $n = 20$ for our task. We forecast the predictions of the various social interaction attributes over 100 consecutive days using this method to create several predicted time series and then evaluate the models' predictive performance.

Results

We first present the outcomes of the Granger causality analysis. We observe that the social interactions with non-friends can be significantly predicted using the temporal anxiety changes for 186 users. However, the lag after which peaks in the anxiety time series Granger-cause peaks in the times series of interactions with non-friends is different for different users, indicating notable individual differences. The histogram of the Granger lags after which changes in interactions with non-friends follow the changes in anxiety levels is presented in Figure 1(b). We observe that most users show increased interaction with non-friends on the same day as increased levels of anxiety. To explore further, in Figure 1(c), we show the temporal changes in anxiety level of users and their interactions with non-friends over a period of 100 days. Both time series can be observed to follow each other closely, indicating strong Granger-causal relationship. Can these observations be extrapolated to social interactions with friends, or strong ties? Unexpectedly, we find that temporal changes in anxiety significantly predicts interactions with friends for only 18 of the anxiety users. This shows that following increases in anxiety levels, the users tend to seek support from the broader Twitter community in the near future—typically their weak ties, instead of strong ties.

Furthermore, we find that temporal changes of anxiety significantly Granger cause other social interaction attributes like retweets, interaction tweets expressing negative sentiment around social relations, negative interactions with friends, negative interactions with non-friends for 8 users, 67 users, 14 users and 22 users respectively (out of 200). As these numbers are much below are our chosen empirical threshold of 100 users, we do not conclude that they are reliably predictable from temporal changes of anxiety.

Finally, we apply the above described VAR models to forecast temporal changes in social interaction attributes from users' anxiety levels. We present the forecasted and observed time series of interactions with non-friends over 100 days in Figure 1(d), since the above Granger causality analysis indicated this interaction type to be the most affected by historical anxiety. Here we obtain a RMSE score of 0.98 and SMAPE of 24.44%, which indicate that our forecasting models can reliably predict to what extent interactions along weak ties are impacted by the users' historical anxiety.

Conclusion

Our study revealed that anxiety levels as manifested by individuals on Twitter satisfactorily predicted future social interactions with weak ties on the platform. This, we believe, may indicate a desire for individuals with heightened anxiety seeking out the broader social media community, predominating consisting of weak ties, for help, advice, solidarity, and support. It can also be because, unlike an offline context, these users believe that reaching out to weak ties online during times of vulnerability can enable them be more candid in their expressions, as these ties are likely to be non-judgmental towards their mental illness. Essentially, these findings suggest that Twitter users with self-disclosing manifestations of anxiety may not necessarily have reduced interest in online social interaction, but the reduction in interactions with strong ties (friends) that we observed could be due to a fear of negative self-evaluation. Summarily, the specific reasons driving this (Granger)-causal relationship is a topic ripe for future investigation.

One important practical implication can be that since individuals tend to reach out to weak ties in the broader online community during times of heightened anxiety, platforms can enable provisions to recommend specific groups or lists where individuals can be less concerned about impression management and can engage in more disinhibiting discourse about their condition and experiences.

References

Brandes, M., and Bienvenu, O. J. 2009. Anxiety disorders and personality disorders comorbidity.

Burke, M.; Marlow, C.; and Lento, T. 2010. Social network activity and social well-being. In *Proceedings of the SIGCHI conference on human factors in computing systems*, 1909–1912. ACM.

Caspi, A.; Elder, G. H.; and Bem, D. J. 1988. Moving away from the world: Life-course patterns of shy children. *Developmental psychology* 24(6):824.

Coppersmith, G.; Dredze, M.; and Harman, C. 2014. Quantifying mental health signals in twitter. In *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology*.

De Choudhury, M., and Kıcıman, E. 2017. The language of social support in social media and its effect on suicidal ideation risk. In *ICWSM*.

De Choudhury, M.; Gamon, M.; Counts, S.; and Horvitz, E. 2013. Predicting depression via social media. In *ICWSM*.

De Choudhury, M.; Kumar, M.; and Weber, I. 2017. Computational approaches toward integrating quantified self sensing and social media. In *CSCW*.

Ernala, S. K.; Rizvi, A. F.; Birnbaum, M.; Kane, J.; and De Choudhury, M. 2017. Linguistic markers indicating therapeutic outcomes of social media disclosures of schizophrenia. *PACM HCI* 1(1):43.

Etkin, A., and Wager, T. D. 2007. Functional neuroimaging of anxiety: a meta-analysis of emotional processing in ptsd, social anxiety disorder, and specific phobia. *American Journal of Psychiatry*.

Geweke, J. F. 1984. Measures of conditional linear dependence and feedback between time series. *J. American Statistical Assoc*.

Granger, C. W. 1988. Causality, cointegration, and control. *Journal of Economic Dynamics and Control*.

Grant, B. F.; Hasin, D. S.; Blanco, C.; Stinson, F. S.; Chou, S. P.; Goldstein, R. B.; Dawson, D. A.; Smith, S.; Saha, T. D.; and Huang, B. 2005. The epidemiology of social anxiety disorder in the united states: results from the national epidemiologic survey on alcohol and related conditions. *The Journal of clinical psychiatry*.

Hutto, C. J., and Gilbert, E. 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *ICWSM*.

Johansen, S. 2000. Modelling of cointegration in the vector autoregressive model. *Economic modelling*.

Kawachi, I., and Berkman, L. F. 2001. Social ties and mental health. *Journal of Urban health*.

McLeod, J. D. 1994. Anxiety disorders and marital quality. *Journal of Abnormal Psychology* 103(4):767.

Mikolov, T.; Chen, K.; Corrado, G.; and Dean, J. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.

Pennebaker, J.; Francis, M.; and Booth, R. 2001. Linguistic inquiry and word count: Liwc 2001. *Mahway: Lawrence Erlbaum Assoc*.

Perrin, A. 2015. Social media usage: 2005-2015.

Rapee, R., and Heimberg, R. 1997. A cognitive-behavioral model of anxiety in social phobia. *Behaviour research & therapy*.

Saha, K., and De Choudhury, M. 2017. Modeling stress with social media around incidents of gun violence on college campuses.

Stephan, W. G., and Stephan, C. W. 1985. Intergroup anxiety. *Journal of social issues* 41(3):157–175.