Understanding and Quantifying patterns of mental health issues in Bangladesh

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1 Abstract

Suicide and mental illness are major public health issues. Every year, approximately 800,000 people die by suicide, with an additional 16 million attempting suicide (World Health Organization, 2013). Mental illness is a similar widespread issue, affecting nearly one in every four people worldwide during their lifetime (World Health Organization, 2013). Mental illness (including suicide) has a negative impact on quality of life, accounting for the fourth-highest contributor to disability-adjusted life years (Vigo et al., 2016). Furthermore, mental illness was responsible for five of the top twenty causes of global disease burden (Vigo et al., 2016). Little progress has been made in improving these figures over the last fifty years (Franklin et al., 2016). Current care systems struggle with scalability and long-term efficacy measures. Given recent advances in many industries by ubiquitous technology and data science, many people believe that a similar revolution in mental health is possible.

2 Introduction

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2.1 Why Social Media?

Language is a particularly compelling and rich source of data for digital phenotyping. Language provides a window into a person's perception, cognition, and other psychological processes, and thus serves as a useful lens through which we can understand, quantify, and ultimately improve mental health. Social media, in particular, offers a treasure trove of language data in a format suitable for computational analysis. It also includes the time that a specific piece of language was authored by the user, which is critical for this work. Thus, social media is one data source that can detect early signs of mental illness and suicide. In social media data, micropatterns in short sequences of emotion, cognition, behavior, and symptoms relevant to specific psychological states may be visible, reflecting dynamic shifts in internal situational factors. Many social media users post enough personal information on public feeds to capture brief shifts in behaviors, cognitions, emotions, and symptoms associated with specific psychological states. A seesaw-like effect was observed one month prior to a suicide death between social media posts about a maladaptive coping behavior and a negative belief, and this negative relationship grows stronger one week prior to a suicide death. We supplement this work by automating labeling and exploring micropatterns directly, rather than embedded in a larger system. Other than suicidality, no prior research has examined micropatterns in social media post content for psychological disorders. Broadly, the motivation for exploring micropatterns and data on the timescale of minutes and hours stems from the importance of temporal information in the assessment of psychological symptoms. Knowledge of symptom cooccurrence over specified time periods can determine whether a mental illness diagnosis is received, as well as inform assessments of treatment responsiveness and relapse.

2.2 Related Work

There is rich literature on the interaction between mental health and language (Tausczik and Pennebaker, 2010; Ramirez-Esparza et al., 2008; Chung and Pennebaker, 2007; Pennebaker et al., 2007; Rude et al., 2004; Pennebaker et al., 2001). Social media's emergence has renewed interest in this topic, though gathering data has been difficult. Deriving measurable signals relevant to mental health via statistical approaches requires large quantities of data that pair a person's mental health status (e.g., diagnosed with PTSD) to their social media feed. Successful approaches towards obtaining these data have relied on three approaches: (1) Crowdsourced surveys: Some mental health conditions have self-assessment questionnaires amenable to administration over the Internet. Combining this with crowdsource platforms like Amazon's Mechanical Turk or Crowdflower, a researcher can administer relevant mental health questionnaires and solicit the user's public social media data for analysis. This technique has been effectively used to examine depression (De Choudhury, 2013; De Choudhury et al., 2013c; De Choudhury et al., 2013b). (2) Facebook: Researchers created an application for Facebook users that administered various personality tests, and as part of the terms of service of the application, granted the researchers access to a user's public status updates. This corpus has been used in a wide range of questions from personality (Schwartz et al., 2013b; Park et al., In press), heart disease (Eichstaedt et al., 2015), depression (Schwartz et al., 2014), and psychological well-being (Schwartz et al., 2013a). (3) Self-Stated Diagnoses: Some social media users discuss their mental health publicly and openly, which allows researchers to create rich corpora of social media data from users who have a wide range of mental health conditions. This has been used previously to examine depression, PTSD, bipolar, and seasonal affective disorder (Coppersmith et al., 2014a; Coppersmith et al., 2 2014b; Hohman et al., 2014). A similar approach has been used to identify new mothers for studying the impact of major life events (De Choudhury et al., 2013a). (4) Affiliation: Some rely on a user's affiliation to indicate a mental health condition, such as using posts from a depression forum as a sample of depression (Nguyen et al., 2014). Other work on mental health and related topics have studied questions that do not rely on an explicit diagnosis, such as measuring the moods of Twitter users (De Choudhury et al., 2011) to measure their affective states (De Choudhury et al., 2012). Outside of social media, research has demonstrated how web search queries can measure population level mental health trends (Yang et al., 2010; Ayers et al., 2013; Althouse et al., 2014).

3 Data

We explain the data collection method briefly here, but any interested reader with further questions about the methodology should contact Coppersmith et al. (2016) for the suicide attempt data and Coppersmith et al. (2014a) for all other conditions. The data for these analyses comes from Facebook posts collected in two ways. The majority of the data comes from users who have openly discussed their mental health issues. These users are frequently referred to as "self-stated diagnosis" users, as they state publicly something like "I was diagnosed with schizophrenia", or "I'm so thankful to have survived my suicide attempt last year". Data from OurDataHelps.org, a data donation site where people provide access to their public posts and fill out a short questionnaire about their mental health history, was used to supplement the data for users who attempted suicide. The data is then deidentified and made available to researchers addressing mental health-related questions. Donors give their permission for their data to be used in research. We use the Meta Graph API to collect a sample of users who used a series of mental health words or phrases in their tweet text (e.g., 'schizophrenia' or 'suicide attempt'). Each post that uses one of these phrases is examined via regular expression to indicate that the user is talking about themselves. Finally, those posts that pass the regular expression are examined by a human to confirm (to the best of our ability) that their self statement of diagnosis appears to be genuine.

This results in a dataset with users that have a self-stated diagnosis of generalized anxiety disorder (n1), an eating disorder (n2), panic attacks (n3), schizophrenia (n4), or someone who would go on to attempt suicide (n5). Some of these users do not exhibit the sort of posting behavior required to create micropatterns (i.e., they rarely post multiple times within a 3 hour time window). We exclude these users from our analysis, which is 5-9We identify a matching control using the subsequent process for each user with a self-reported diagnosis: Create a user pool where the estimated gender matches and the estimated age falls within a 10-year range (the estimated age's advised accuracy). We choose the user whose start and end times of their tweets are the most similar from among the group of users whose ages and genders are matched. The remainder of this study will simply refer to these age-, gender-, and time-matched controls as "matched controls." For most conditions, the population skews female, though for schizophrenia the genders are roughly balanced. The average age tends to be in the early-to-mid 20s.

4 Methods

The purpose of this study was to look at the prevalence of effective micropatterns in social media posts and to identify differences in micropattern occurrence that could be useful in quantifying mental health. We do this primarily by comparing users with anxiety disorders, eating disorders, schizophrenia, and a history of suicide attempts to their matched controls. We use a straightforward and well-understood method for sentiment analysis, VADER. Specifically, we examined trajectories of posted emotional content in three subsequent tweets, no more than three hours from earliest to latest. The same tweet will be counted in more than one overlapping micropattern if more than three tweets occur in the three-hour time window – so if 5 tweets occur in 3 hours, 3 micropatterns will be recorded from those 5 tweets, likewise for 4 tweets, 2 micropatterns will be recorded. The potential overlap exists for both patients and neurotypical users, and subsequent analyses (e.g., classifying users based on proportion of micropatterns) were designed to be robust to this property of overlapping micropattern generation. The number of sequential tweets to examine was chosen to minimize the complexity of the analysis while allowing significant variability to be observed. Critically, we aimed for the resulting dimensions (i.e., number of distinct micropatterns) to be small enough for meaningful interpretation by clinical psychologists.

5 Results

We specifically looked at the trajectories of posted emotional content in three subsequent tweets that were no more than three hours apart from one another. If more than three tweets occur in the three-hour time window, the same tweet will be counted in more than one over89 lapping micropattern - so if five tweets occur in three hours, three micropatterns will be recorded from those five tweets, and four tweets will be counted in two micropatterns. Both patients and neurotypical users have the potential for overlap, and subsequent analyses (e.g., classifying users based on proportion of micropatterns) were designed to be robust to this property of overlapping micropattern generation. The number of sequential tweets examined was chosen to reduce the analysis's complexity while allowing for significant variabile

5.1 Micropatterns are Irregular

Before analyzing the differences in micropattern occurrence between users with mental health conditions and their matched controls, we show that these micropatterns are not randomly distributed and are not an artifact of the different conditions.

Users with mental health issues express negative sentiment more frequently. We observe the distribution of labels for all messages from each condition for each condition. This establishes the baseline rate of occurrence of each label for that condition. Using these base rates, we generate a label at random for each message from each user (i.e., respecting the timestamps of each post but randomly assigning a label rather than what VADER predicted from the text). We then examine the observed micropatterns with these randomly assigned labels for each user. We repeat this procedure 10,000 times, yielding a null distribution of the number and proportion of micropatterns we would expect if the underlying sentiment labels were randomly distributed. The observed z-scores for each micropattern's deviation from normal range from 13.3 to 4859.1, with a median of 125.5. Since the significance for a z-score (at the p ¡ 0.05 level) is 2.96, we can safely assume that the observed population of labels was not likely the result of a random process. This strongly suggests that the differences observed are not attributable merely to random fluctuations and a different base-rate of the underlying labels. Note that the vast majority of the micropatterns observed in all conditions (less than 80percent) are (neutral,neutral,neutral). This is likely an overestimate of the number of neutral messages present, due to the closed-vocabulary nature of our lexicon-based labeling approach. Specifically, VADER depends on a lexicon of words and associated scores, and lexicon-based approaches generally provide higher precision. Some of the observed deviations are consistent with current psychological literature, lending some facevalidity to this approach. To begin, all mental health conditions increase the number of (negative,negative,negative) affect micropatterns. This is consistent with the widely observed phenomenon of those with mental health conditions experiencing more negative affect. This does imply, however, that these are not necessarily randomly distributed negative posts, but rather concentrated and subsequent strings of negative posts. Second, users with schizophrenia were less likely to show affect or affective variability between posts than neurotypicals. This is consistent with research indicating that individuals with schizophrenia have deficits in affective expression, a common negative symptom triggered by both disease pathophysiology and antipsychotic medication use.

5.2 Differenciating Users

We also want to know if micropatterns convey any additional information about mental health and mental health status aside from the labels that make up the micropattern (in this case, positive, negative, and neutral sentiment labels). We would like to investigate how well micropatterns predict meaningful psychological events, but we lack sufficient data to do so more than anecdotally. Instead, we stick with previous research and compare performance on a binary prediction task. The goal is to distinguish users with mental health issues from their matched controls. We created a feature vector for each user, with each entry representing the proportion of micropatterns that a particular micropattern comprised. Similarly, we generated a feature vector for the proportion of sentiment labels assigned to each sentiment label. It displays the accuracy results of a 10-fold cross validation binary classification experiment using a random forest classifier (balanced samples). In every case, the micropatterns outperform the base rate, which is frequently only slightly better than chance. In most cases, combining both signals yields no significant improvement in performance over either one alone. This implies that for the majority of conditions, the majority of the information from the sentiment labels is captured as part of the graph. According to information theory, it may be more appropriate to say how much information is lost.

5.3 Ethics and Privacy

We gave careful thought to the ethics and privacy issues surrounding this work, and we used Benton et al. (2017) ethical guidelines were followed, and social media data donated with consent for use in mental health research from OurDataHelps.Org was used. We strongly encourage researchers interested in working in this area to consider the ethical implications of the research from the start, both for the research itself and for any resulting technology. Mikal et al. (2016) recently conducted focus groups on their perceptions of this line of work, which has greatly informed our work and is highly recommended for informing ethical discussions.

6 Conclusion

We present evidence that quantifiable information relevant to mental health can be found by quickly examining subsequent posts (so-called micropatterns). Furthermore, we show that significant differences in micropatterns can be found between users with mental health conditions and their matched controls even with a simple and straightforward lexicon approach. While some of the observed differences have face validity and correspond to existing psychological literature, others remain unexplained. Furthermore, micropatterns have greater predictive power than the sentiment labels on which they rely, implying that they capture important information that the sentiment of the message alone does not.

Despite its limitations, this study provides promising evidence in support of future research using micropattern analysis to detect progressions in suicide risk and symptoms of psychological disorders. While the current study showed that there are differences in micropatterns between users who have and do not have a specific psychological disorder, no information was gathered on whether specific micropatterns can indicate the severity of a psychological disorder. We also did not test whether micropatterns can differentiate between clinical conditions, which is an obvious next step for future research. The sheer dimensionality of these more complex micropatterns, and how they should be best interpreted for synthesis with the psychological literature, remain challenges. While there is much more work to be done to understand why these micropatterns emerge and what value they have for psychological understanding and intervention, we see this as a promising step and a worthy avenue of future research.

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