Understanding and Quantifying patterns of mental health issues in Bangladesh

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1 Abstract

Major public health concerns include suicide and mental illness. Around 800,000 people attempt and 16 million actually commit suicide each year, according to statistics (World Health Organization, 2013). Similar to other major problems, mental illness affects almost one in four people globally over the course of their lifetime (World Health Organization, 2013). Suicide and mental illness have a negative impact on quality of life, with the latter accounting for the fourth-highest share of years lived with a disability (Vigo et al., 2016). In addition, five of the top twenty causes of disease burden worldwide were mental illnesses (Vigo et al., 2016). Over the past fifty years, there hasn't been much improvement in these numbers (Franklin et al., 2016). Scalability and long-term efficacy metrics are challenges for current care delivery systems.

2 Introduction

As stated in the second preface, Both suicide and mental illness are serious problems in terms of public health. About 800,000 people take their own lives each year, and another 16 million have seriously considered doing the same (World Health Organization, 2013). Nearly one-quarter of the world's population will experience mental illness at some point in their lives (World Health Organization, 2013). Disability-adjusted life years lost due to mental illness (including suicide) rank fourth overall (Vigo et al., 2016). Five of the leading twenty causes of death and disability worldwide are related to mental disease (Vigo et al., 2016). Over the past fifty years, little has changed to improve these numbers (Franklin et al., 2016). Challenges in scaling and measuring long-term effectiveness plague today's healthcare systems. Many think a technological and scientific revolution in mental health is feasible in light of recent successes in other fields.

2.1 Why Social Media?

When it comes to digital pheno-typing, language is a particularly interesting and fruitful data source. The ability to understand, measure, and eventually enhance mental health is greatly aided by the lens of language, which provides insight into a person's perception, cognition, and other psychological processes. For computational linguists, social media provides a veritable gold mine of linguistic data. Additionally, the user-authored time stamp is included, which is essential for this task. Therefore, social media is one source of data that can identify precursors to mental health issues and suicide. Micropatterns in social media data may reveal dynamic variations in internal situational elements, such as short sequences of emotion, cognition, behavior, and symptoms related to distinct psychological states. Lots of people provide enough details about themselves on their public social media profiles for researchers to be able to track momentary alterations in their behaviors, thoughts, feelings, and other symptoms linked with various mental health conditions. One month before a suicide death, researchers noticed a seesaw impact between social media posts about a maladaptive coping behavior and a negative mindset, and this negative association grew stronger in the week leading up to the suicide. To complement this effort, we automate labeling and explore micropatterns outside of any larger system. No previous studies have looked at micropatterns in the content of social media posts for mental diseases other than suicidality. The importance of temporal information in the assessment of psychological symptoms provides a broad impetus for exploring micropatterns and data on the timescale of minutes and hours. The diagnosis of a mental disease, as well as assessments of treatment efficacy and relapse, can be guided by knowledge of symptom cooccurrence throughout defined time periods.

2.2 Related Work

There is a plethora of research on how language affects mental health (Tausczik and Pennebaker, 2010; Ramirez-Esparza et al., 2008; Chung and Pen- nebaker, 2007; Pennebaker et al., 2007; Rude et al., 2004; Pennebaker et al., 2001). The resurgence of curiosity about this topic due to the rise of social media has made it more challenging than ever to collect the necessary information. Large amounts of data that link an individual's mental health condition (say, diagnosed with PTSD) to their social media feed are necessary for statistical techniques to derive quantitative signals related to men- tal health. Three methods have been used successfully to collect this information: (1) Surveys using crowdsourcing: Self-report questionnaires for several mental health issues can be administered electronically. A researcher can combine this with crowdsourcing services like Amazon's Mechanical Turk or Crowdflower to distribute appropriate mental health questionnaires and collect the user's public social media data for analysis. The study of depression with this method has proven to be quite fruitful (De Choudhury, 2013; De Choud- hury et al., 2013c; De Choudhury et al., 2013b). (2) Facebook: Scientists developed a Facebook app that gave users personality assessments based on their public status updates, as part of the platform's terms of service. Personality (Schwartz et al., 2013b; Park et al., In press), cardiovascular illness (Eichstaedt et al., 2015), depressive disorder (Schwartz et al., 2014), and mental health are only few of the areas where this corpus has been applied (Schwartz et al., 2013a). Thirdly, self-diagnosed disorders are discussed openly by some social media users, allowing researchers to amass large amounts of data from people with a variety of mental health issues. Depression, post-traumatic stress disorder, bipolar disorder, and seasonal affective disorder have all been studied using this method (Cop- persmith et al., 2014a; Coppersmith et al., 2 2014b; Hohman et al., 2014). New moms have been tracked in a similar fashion so that the effects of significant life changes can be studied (De Choudhury et al., 2013a). Some people use a user's affiliation as a proxy for their mental health, such as when they take threads from a depression forum as evidence that depression is widespread on the internet (Nguyen et al., 2014). Measures of Twitter users' affective states (De Choudhury et al., 2011) are just one example of non-diagnostic work in the field of mental health and related themes (De Choudhury et al., 2012). Excluding the influence of social media, studies have shown that questions asked via Google can be used to gauge societal shifts in mental health (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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8 References

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