Not Every Disability Is Visible - Analysis of Mental Health Disorders Using Twitter

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ABSTRACT

One in 5 adults experiences a mental health condition every year and the numbers are only rising. These illnesses aren't the result of one single event. Research suggests multiple, linking causes. Genetics, environment, and lifestyle influence whether someone develops a mental health condition. In this project, the aim is to narrow down the influence of environment on the mental health illness. We extract the tweets about different mental disorders and analyze them to find if certain locations need more awareness and counselling. It is done in two steps, first by performing sentiment analysis and classifying the disorders based on locations and secondly, by analyzing the places with higher mental illness rates and using the tweet's other features to check if there is awareness about the issue in that location.

Keywords

Mental health illness, sentiment analysis, linear regression, Twitter Analysis.

1. INTRODUCTION

Mental illness is a condition that causes mild to severe disturbances in thought and/or behavior, resulting in an inability to cope with life's ordinary demands and routines. There are more than 200 classified forms of mental illness, some of the more common disorders being depression, bipolar disorder, dementia, schizophrenia, and anxiety disorders.

Mental health research lacks the quantifiable data available to many physical health disciplines. This is partly due to the complexity of the underlying causes of mental illness and partly due to the longstanding societal stigma. Lack of data has hampered mental health research in terms of developing reliable diagnoses and effective treatment for many disorders. Additionally, analysis via traditional methods is time consuming, expensive, and comes with a significant delay.

Social media provides a rich opportunity to utilize the data available to analyze different mental health illnesses to enable a better-informed and better-equipped mental health field. It provides a vast dataset which enables us to consider new directions to solve problems. It has enabled diverse research on a wide range of topics, including political science [1] social science [2], and health at an individual and population level [3].

In this paper, we look at the data from the popular microblogging website called Twitter. The paper *#WhyWeTweetMH: Understanding Why People Use Twitter to Discuss Mental Health Problems* [8], pushes us in the positive direction of using Twitter as a viable dataset for this kind of analysis. One advantage of this data is that the tweets are collected in a streaming fashion and therefore represent a true sample of actual tweets in terms of language use and content.

"Using Twitter to get a fix on mental health cases could be very helpful to health practitioners and governmental officials who need to decide where counseling and other care is needed most," says Dredze, an assistant research professor in the Whiting School of Engineering's Department of Computer Science. "It could point to places where many veterans may be experiencing PTSD, for example, or to towns where people have been traumatized by a shooting spree or widespread tornado damage."

2. RELATED WORK

Johns Hopkins computers scientists, who have already used Twitter posts to track flu cases, say their techniques also show promise as a tool to gather important information about some common mental illnesses. Some of the previous work in this area includes but is not limited to: Predicting the onset of mental illness [4] where computational models were developed to predict the emergence of PTSD and Depression in Twitter users, analyzing the expressions for mental health on Twitter by checking for the magnitude of six mood dimensions [5] and different variations of sentiment analysis.

Most of the work done earlier talks about either the emergence or the existence of the mental health issues using Twitter data. There has been research on the utility of social media for depression, but there have been limited evaluations of other mental health conditions [7] We want to go a step further and predict, based on the location, where help is needed the most.

3. METHOD

3.1 Extracting Data

The data is extracted by querying the Twitter Search API which is a part of the Twitter's REST API. The tweets were extracted by looking up the specific words and hashtags stating these disorders: ADHD, Anxiety, Bipolar Disorder, BPD, Depression, Insomnia, OCD, PTSD, Schizophrenia, Suicide. The data can be extended to Alzheimer's and Parkinson's but they are considered as more of diseases and less of mental disorders. The features being extracted for every tweet are *Author* (username), *Source*, *Location*, *Follower count*, *Retweet count*, *Friends count*, *Created at* (time) and the *Tweet* (Text). These features extracted are more relevant to the aim of the project because environment includes location and surroundings. The tweets extracted were all mapped based on their geographic location. During analysis, we have noticed that a lot of users have not specified their location, or have given an arbitrary location. One of the reasons for this could be to maintain their anonymity.

Fig (1): Mapping of the extracted tweets

3.2 Data Preprocessing

The data extracted has been stored in CSV file format. The csv file with all the features and the tweet's text has been cleaned using the following steps: Using the library string, the tweets are cleaned off punctuations and digits. The text is made lower case and all the retweets are removed from the dataset. Additionally, all the line breaks and spaces are removed to make it a cleaner data set.

3.3 Sentiment Analysis

To assess the severity of the disorder, a sentiment analysis is performed on the tweets. The Python lexicon AFFIN is used to perform sentiment analysis [6]. AFINN is a list of English words rated for valence with an integer between minus five (negative) and plus five (positive). The words have been manually labeled by Finn Årup Nielsen in 2009-2011. Using the lexicon, a final sentiment score is given to the tweets. The more negative the count, the tweet is considered to be more severe. The sentiment score is grouped based on locations and disorder. Further, an aggregation is performed to get a score for each disorder in that location. The different disorders are plotted for the ten locations with the highest negative score.

Fig (2): Location based sentiment analysis

3.4 Multiple Linear Regression

To assess the severity of the mental health illness, sentiment analysis is performed. To assess if there is awareness amongst the twitter users and if help is being provided, we used the features retweet count and favorite count from the extracted tweets and performed regression against the sentiment score to check if the negative scoring tweets had a higher response.

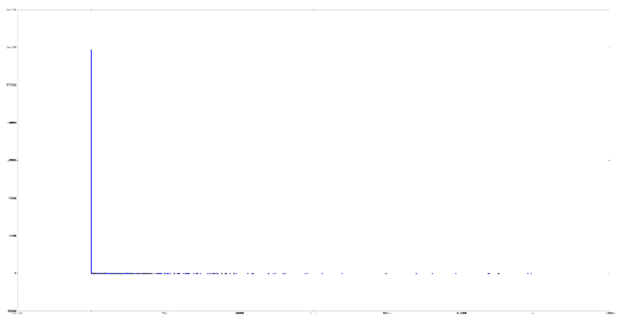

Fig (3): Multiple Linear Regression

In the above graph, we observe that the regression line is directly proportional to the retweet count implying that the favorite count feature is not an appropriate factor to detect the awareness in Twitter. Thus, only retweet count feature from the tweets extracted is used and linear regression is performed between the retweet count and the sentiment score.

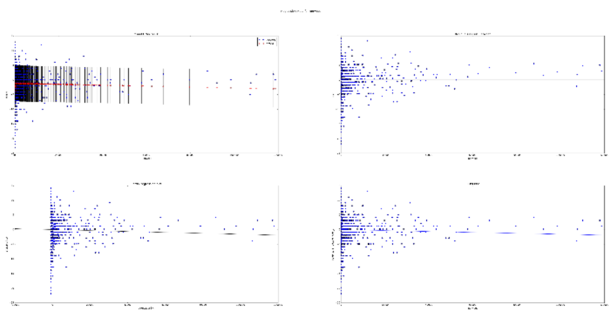

Fig (4): Combined regression Retweet Count Vs Sentiment Score

4. RESULTS

The results from the sentiment analysis which have been visualized above can be written in a tabular format as follows:

	Australia	Canada	France	India	Malaysia	Philippines	UK	USA
ADHD	-4	0	-5	-22	0	2	-25	-97
Anxiety	-41	-301	-122	-94	-92	-24	-224	-1271
Bipolar	-7	-7	45	9	-14	-1	25	-79
BPD	1	1	-12	3	-2	0	-40	-154
Depression	-25	-74	-51	-24	-2	2	-72	-513
Insomnia	-51	-79	-47	-144	-111	-28	-39	-448
OCD	6	-54	18	-6	-28	-2	-79	-84
PTSD	-61	-88	-56	-32	-11	-8	-41	-487
Schizophrenia	-4	-55	-21	3	-5	-3	-2	-153
Suicide	-86	-185	-66	-86	-54	1	-351	-690

Table (1): Sentiment Score for top 10 countries.

Based on the regression analysis performed on the locations with the highest sentiment score, we can see that the tweets with the lower sentiment score have a fairly proportional retweet count.

Since USA and Australia are the countries with the lowest scores for mental disorders, the regression analysis for these locations are specifically performed.

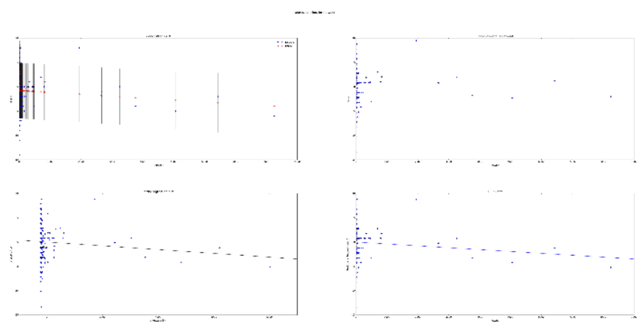

Fig (5): Linear Regression for tweets originating in Australia

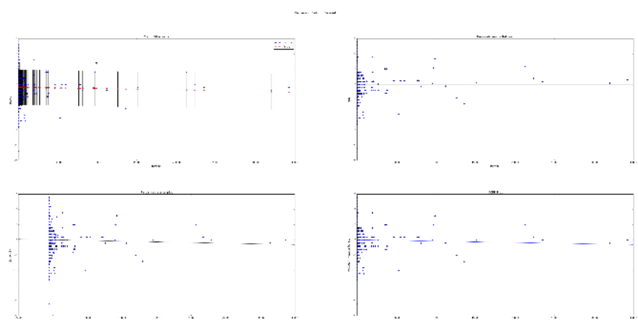

Fig (6): Linear Regression for tweets originating in USA

5. CONCLUSION

From the tweets extracted, we performed sentiment analysis and observed which disorder is prevalent in which region. In this systematic analysis, our results show top 10 regions where mental health illnesses are the highest and for these regions, we performed linear regression to assess the level of response and support that is being provided for these illnesses. Narrowing down the results to the top two countries with the highest mental health disorders, we observed that a significant number of tweets which have higher negative scores also have a healthy response rate. But there are some locations where the response is very low and almost zero. Based on this analysis, the data can be used to not only provide help but also to create more awareness in that location.

6. CONTRIBUTION

The work has been divided accordingly:

- Burde Prerana Kamath: Extracted data from the Twitter API, performed data preprocessing, performed regression on the processed data.
- Janani Muppalla: Extracted data from the Twitter API, performed sentiment analysis and grouped the results based on locations.
- Sri Megha Vujjini: Preprocessed the extracted data, generated visualizations, handled all the documentation.

7. FUTURE WORK

One of the areas where the project can be extended further is why there is such a high percentage of people who have given arbitrary locations or not mentioned locations at all. If it can prove a relationship between mental health disorders and the reason for not specifying where they are from, we can maybe conclude that talking about mental health is a taboo and thus more awareness can be created.

Also, since Twitter does not give access to personal information like gender and age, we are restricted on that front. A more detailed analysis can be performed on what kind of disorders are more prevalent in different age groups and gender.

Furthermore, analysis can also be performed to decode the emoticons being used in the tweet which will further give a better insight into the sentiment analysis.

8. REFERENCES

[1] Amber Boydstun, Rebecca Glazier, Timothy Jurka, and Matthew Pietryka. 2013. Examining debate effects in real time: A report of the 2012 React Labs: Educate study. The Political Communication Report, 23(1), February.

[2] Faiyaz Al Zamal, Wendy Liu, and Derek Ruths. 2012. Homophily and latent attribute inference: Inferring latent attributes of Twitter users from neighbors. In Proceedings of the International AAAI Conference on Weblogs and Social Media (ICWSM).

[3] John W. Ayers, Benjamin M. Althouse, and Mark Dredze. 2014. Could behavioral medicine lead the web data revolution? Journal of the American Medical Association (JAMA), February 27

[4] Glen Coppersmith, Mark Dredze, Craig Harman 2014. Quantifying Mental Health Signals in Twitter. Conference: Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality, January 2014.

[5] Michael Billot 2011. Analysis of Mental Health Expression on Twitter. Summer 2011 NSF NEU.

[6] https://finnaarupnielsen.wordpress.com/2011/06/20/simplest-sentiment-analysis-in-python-with-af/

[7] Johnsen, K.J., Rosenvinge, H.J., & Gammon, D. (2002). Online group interaction and mental health: An analysis of three online discussion forums. Scandinavian Journal of Psychology, 43(5), 445-449.

[8] Natalie Berry, Fiona Lobban, Maksim Belousov, Richard Emsley, Goran Nenadic, Sandra Bucci. #WhyWeTweetMH: Understanding Why People Use Twitter to Discuss Mental Health Problems. JMIR Vol 19 (2017).