

Identifying Depression-Related Tweets from Twitter for Public Health Monitoring

Danielle Mowery*1, Hilary A. Smith², Tyler Cheney², Craig Bryan² and Michael Conway¹

¹Biomedical Informatics, University of Utah, Salt Lake City, UT, USA; ²Psychology, University of Utah, Salt Lake City, UT, USA

Objective

We aim to develop an annotation scheme and corpus of depressionrelated tweets to serve as a test-bed for the development of natural language processing algorithms capable of automatically identifying depression-related symptoms from Twitter feeds.

Introduction

Major depressive disorder has a lifetime prevalence of 16.6% in the United States. Social media platforms – e.g. Twitter, Facebook, Reddit – are potential resources for better understanding and monitoring population-level mental health status over time. Based on DSM-5 [1] diagnostic criteria, our research aims to develop a natural language processing-based system for monitoring major depressive disorder at the population-level using public social media data.

Methods

In this pilot study, three annotators - two psychology undergraduates (A1, A2) and a postdoctoral biomedical informatics researcher (A3) - annotated 900 tweets using a linguistic annotation scheme based on DSM-5 depression criteria (e.g. *anhedonia* – "*I don't enjoy singing anymore*") [2]. We report agreement between annotator pairs computing F-score, a surrogate for kappa. Finally, we trained and tested three machine learning classifiers – *support vector machine, naïve bayes,* and *decision tree* – for predicting two depression-related classes: 1) whether a tweet represents **clinical evidence of depression** or **not** and 2) if the tweet is depression-related, whether it is classed as *low mood, fatigue or loss of energy,* or *problems with social environment.* We trained and tested each classifier using the Weka toolkit (v.3.6.8) with 10-fold cross validation using unigram features, and then reported classifier performance compared against 884 adjudicated tweets with sensitivity and positive predictive value.

Results

We observed high agreement between annotator pairs: A1/A2: 81%, A1/A3: 76%, and A2/A3: 78%. Of the 884 adjudicated tweets, the majority of tweets represented no clinical evidence of depression (n=635; 72%) then clinical evidence of depression (n=249; 28%). The skewed distribution of the most frequent 3 clinical evidence of depression symptoms/stressors ranged from low mood (n=114; 13%), fatigue or loss of energy (n=51; 6%), and problems with social environment (n=36; 4%). Overall, we observed comparable sensitivities and positive predictive values among classifiers for discerning whether a tweet represented clinical evidence of depression or not (Table 1). No clinical evidence of depression and fatigue or loss of energy can be more accurately identified than low mood, problems with social environment, and other types of clinical evidence of depression by all three classifiers. No one classifier performs with both superior sensitivity and positive predictive value for any one symptom/stressor, suggesting that different approaches may be necessary for reliable classification.

Conclusions

Automatically identifying depression-tweets with a moderate degree of accuracy is feasible. We are actively improving our training models leveraging a corpus of ~10,000 tweets, expanding symptoms/

stressors being detected, and experimenting with richer features for symptom/stressor detection (e.g. gender, age).

Table 1. Classification performance using unigrams. SVM=Support Vector Machine; NB=Naïve Bayes; DT=Decision Tree; Sens=sensitivity; PPV=positive predictive value

| | SVM | | NB | | DT | |
|--|------|-----|------|-----|------|-----|
| | Sens | PPV | Sens | PPV | Sens | PPV |
| clinical evidence of depression or not | 75 | 74 | 75 | 75 | 75 | 73 |
| no clinical evidence of depression | 84 | 81 | 83 | 83 | 90 | 78 |
| clinical evidence of depression | 51 | 56 | 56 | 56 | 37 | 60 |
| low mood | 33 | 41 | 37 | 36 | 23 | 50 |
| fatigue or loss of energy | 88 | 73 | 84 | 84 | 90 | 69 |
| problems with social environment | 6 | 17 | 14 | 8 | 0 | 0 |

Keywords

social media; mental health; Twitter; public health; natural language processing

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*Danielle Mowery E-mail: danielle.mowery@utah.edu



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