

Depressive Moods of Users Portrayed in Twitter

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ABSTRACT

Potential benefits of using online social network data for clinical studies on depression are tremendous. In this paper, we present a preliminary result on building a research framework that utilizes real-time moods of users captured in the Twitter social network and explore the use of language in describing depressive moods. First, we analyzed a random sample of tweets posted by the general Twitter population during a two-month period to explore how depression is talked about in Twitter. A large number of tweets contained detailed information about depressed feelings, status, as well as treatment history. Going forward, we conducted a study on 69 participants to determine whether the use of sentiment words of depressed users differed from a typical user. We found that the use of words related to negative emotions and anger significantly increased among Twitter users with major depressive symptoms compared to those otherwise. However, no difference was found in the use of words related to positive emotions between the two groups. Our work provides several evidences that online social networks provide meaningful data for capturing depressive moods of users.

Categories and Subject Descriptors

H.4 [Information Systems Applications]: Miscellaneous;
J.3 [Life and Medical Sciences]: Health; J.4 [Social and Behavioral Sciences]: Psychology

General Terms

Human Factors

Keywords

Online social network, Twitter, depressive moods, mental health, sentiment analysis

1. INTRODUCTION

Depression is currently the most commonly diagnosed mental disorder in many developed countries, accounting for 75%

of psychiatric admissions and affecting between 9 and 30% of the adult population each year. The costs associated with depression and mental disorder have grown rapidly over recent years and the National Institute of Mental Health reports that in the U.S. major mental disorders cost at least \$193 billion annually in lost earnings alone, which is comparable to that spent for cancer treatment [16]. Despite increasing public knowledge and awareness, many individuals with depression go undetected and untreated, leading to a serious public health problem, because as many as half of undetected depressed patients later meet the criteria for major depression [8].

A number of public programs have been proposed to decrease the prevalence of undiagnosed depression including the National Depression Screening Day (NDSD) and the National Anxiety and Depression Awareness Week. These programs raise awareness of depression and offer free depression screening to the general population [11]. Besides screening depression, they also provide information about treatment and promote public discussion. While these public programs are an important step towards solving depression, their main limitation lies in the selection bias of people they can reach, because the programs are participation-oriented.

In terms of reaching vulnerable individuals, one useful addition to existing screening methods is to use a large amount of content individuals share on online social networks (OSNs). Social networking sites such as Facebook and Twitter are used by hundreds of millions of registered users across a wide age spectrum. With the advent of mobile devices, users can post updates without time and space constraints, thus making OSNs a practical platform for continuously screening the public for depression. Furthermore, selection bias can be avoided and OSN data allows a cost-effective way to study health behaviors from non-clinic-based populations, such as those who may be seeking care but are not yet in treatment [5].

In fact, the data embedded in OSNs have already drawn attention of healthcare providers [7] as well as various other service providers, marketers, and stock market analysts [2]. With new surveillance methods such as mining, aggregating, and analyzing online textual data in real-time becoming available [4], recent research has looked into a wide range of issues related to health using OSN data from the detection of seasonal flu [6] to the community structure of happy people [1]. However, to the best of our knowledge, none of

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HI-KDD '12, August 12, 2012, Beijing, China.

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these works focused on depression or validated the use of OSN data for such research.

We present a preliminary work that attempts to make a new effort towards verifying whether OSN data are reflective of users' clinical depressive symptoms in the offline world. To accomplish this goal, we first explored the expression of depression among the general Twitter population using a random sample of tweets drawn from a large dataset. Then, we examined the usage of language associated with depressive moods of specific individuals in order to determine the extent to which online sentiments match one's offline diagnosis on depression. In particular, we conducted a sentiment analysis of 69 participants to understand how one's depressive states are reflected in daily personal updates.

We find strong evidences that OSN data can be used as valid data for researching depression or depressed feelings of the social network users. Some of the highlights of our findings are as follows. First, a large fraction of updates in Twitter relevant to depression was on '*sharing of depressed feelings*', indicating the possible use of such data for capturing what is known as the 'major depressive episode'. Second, people disclosed not only depressed feelings but also very private and detailed information about themselves such as treatment history. Third, participants who were screened positive for depression exhibited increase in the usage of words related to negative emotions and anger in their tweets. Finally, depressed users were more likely to post tweets about themselves than typical users (i.e., increase in the usage of first person pronoun).

2. RELATED WORK

OSNs integrate various sources of personal information that mirror those found in personal environments, private thoughts, and social behavior, all of which are known to contain valid information about personality. While it is debatable whether one's online personality matches that of his actual self, a study comparing the personal websites of 11 users and their self-judged personalities supports this contention [22]. This finding indicates that Internet data, which can be efficiently collected, have potential for being used in studies on personality and sentiments.

In fact, a number of recent studies used OSN data for sentiment analysis. In Twitter, the association between one's tendency to express emotions (e.g., joy, sadness) was examined against the number of followers in [12]. The study found a positive correlation, indicating that active social support encourages the sharing of emotional content. In terms of depression, researchers in [1] examined the relationship between personal traits (e.g., happy or sad) and social ties. They found that OSNs disproportionately favor connections between individuals with similar traits (i.e., homophily).

In [15], three independent annotators manually coded a sample of public tweets and found 9 representative categories including Information Sharing, Self Promotion, Opinions, Random Thoughts, Me Now, Questions to Others, Presence Maintenance, Anecdotes by Me, and Anecdotes by Others. Among them, Me Now (e.g., "*tired and upset*") and Random Thoughts (e.g., "*I miss NY*"), frequently displayed profile owner's emotions were the two most popular categories.

In order to quantitatively measure depressive symptoms on network level, the authors in [19] conducted a longitudinal study on a person-to-person interconnected social network. They assessed over 12,000 people repeatedly over 32 years to retrieve the results. These previous observations give ample ground for using OSN data in studying depressive signs and depression, with the ultimate goal of building a real-time healthcare system.

3. PILOT STUDY

Before initiating the study, we conducted a pilot test to learn about the feasibility of our study. We wondered whether users would share their depressive feelings on a public broadcast medium like Twitter.

3.1 Sampling

We searched the Twitter Application Programming Interface (API) with the keyword 'depression' and gathered search results over a two-month period of June and July, 2009, in order to find tweets related to depression. To gather data that we could understand, we limited our sample to those tweets written in English and collected from the United States. Geographic location of Twitter users was identified using Google's Geo-location API. In total, we gathered 21,103 tweets that contained the word depression from 14,817 users, which accounted for 0.03% of all tweets based on the total number of tweets (65 million) posted during the same period. A random set of 1,000 tweets (500 tweets from each month) were chosen for content analysis. The selected tweets were posted by 937 users and we manually confirmed that there are no heavy users who might be outreach or social workers who are likely to post information and use the term depression a lot.

3.2 Data Analysis

For data analysis, one of the authors read the tweets and inductively coded them, and the rest of authors confirmed each code through interactive discussions. The generation and refinement of themes were conducted iteratively and continued until a sense of closure was achieved. Also, during this process, the authors continued labeling and setting hierarchical orders between the labels.

First, each tweet was labeled according to its meaning and purpose. At this stage, 12 tweets were excluded because they could not be labeled due to ambiguity and brevity in wording. From the remaining 988 tweets, a total of 1,018 labels were created with some of the tweets having more than one labels about depression. For example, a tweet such as "the use of medication for depression" with an URL was labeled as 'Information about depression medication with URL.' The authors read all the tweets under the labels to confirm that the labeling was appropriate. Among 1,018 labels, 235 labels were excluded because the word depression was used for different meaning such as economic depression, tropical depression, title of other things (dish), and metaphors. The remaining 783 labels (76.92%) were included in the final data analysis. Second, similar labels were grouped, and names were given to identify the groups. For example, tweets about going out and watching funny YouTube videos to overcome depressed feelings were grouped as 'My own remedy for depression.' This process yielded 53 higher-order labels. Through a process of grouping and going back

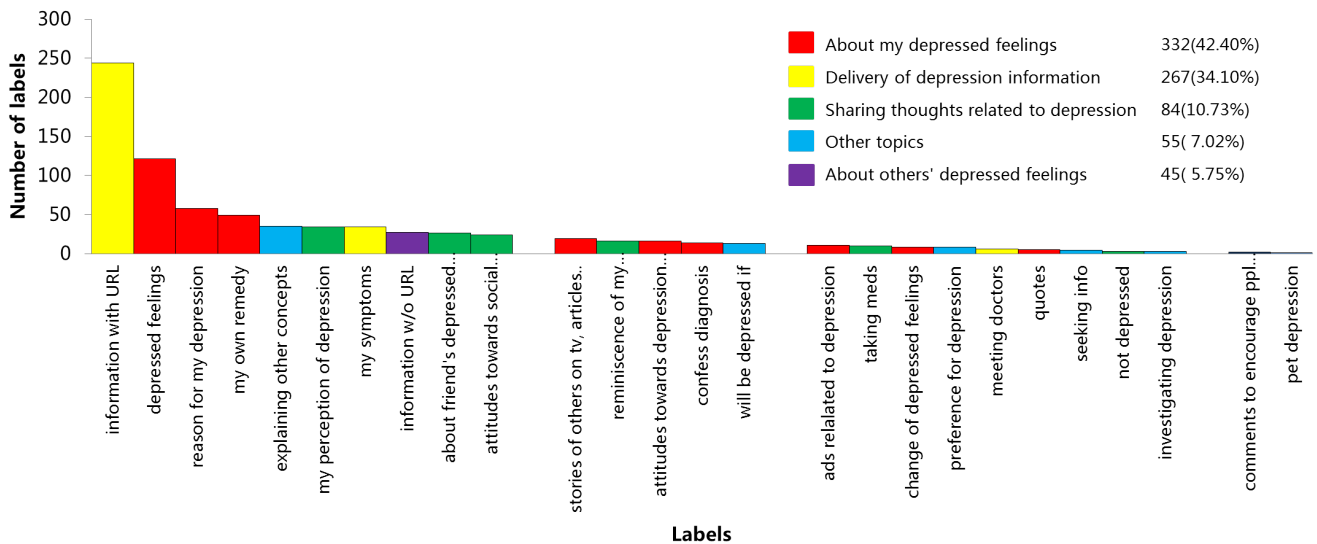


Figure 1: Labeled and categorized language usage in relation to depression

to confirm the groups, and re-grouping, five themes emerged from 53 higher-order labels.

3.3 Results

As described in Figure 1, depression was most frequently mentioned to describe one’s depressed status (42.40% of mental depression tweets). In describing depression, 216 tweets described one’s depressed feelings, 113 tweets contained information on updates on one’s depression treatment, and 3 tweets used the word depression to express that one is not depressed (e.g., “*I am not depressed*”). In describing their depression or depressed feelings, Twitter users provided very detailed information about themselves (e.g., “*My dr. tries to give me birth control for depression, which works for me but i have so many side effects i would rather be moody [with picture]*”, “*Frankly, I don’t like to take medicine for depression. But, I affect other people as well as what I make matter worse if I didn’t take it. What should I do?*”). The reasons for depression, the pattern of depression, and events that make them depressed were identified. In posting updates on their depression, private information such as getting diagnosis, taking medications, meeting doctors, and their own remedies for depression were shared.

The tweets in the second category—delivery of depression information, which appeared 267 times (34.10%)—contained information regarding depression. Among them, most of the tweets (263 tweets) offered information while only four tweets sought depression information. A number of tweets (231 tweets) had a URL link that contained information for depression. Links led to diverse information about depression for fighting depression followed by depression facts such as cause, risk factors, medications, prevalence, policies, etc.

The third category, which had 84 tweets (10.73%), was on sharing thoughts related to depression. Tweets in this category included attitudes toward depression (48 tweets), one’s perception of depression (34 tweets), and comments to encourage others with depression (2 tweets). The fourth cat-

egory, which had 55 tweets (7.02%), included various usage of the word depression such as describing other concepts (35 tweets), ads (11 tweets), quotes (5 tweets), one’s investigation of depression (3 tweets), and pet depression (1 tweets). The fifth category, about others’ depressed feelings, had 45 tweets (5.75%). Tweets in this category included tweets about a friend’s depressed feelings (26 tweets) and stories of others with depression on TV and articles (19 tweets).

3.4 Insights

Our pilot study indicates that an active and diverse conversation related to depression could be found in the short text updates on Twitter. About half of the tweets on depression included information about one’s depressed feelings (42.40%) or others’ depressed feelings (5.75%). About one-third of the tweets shared information about depression (34.10%) and a tenth part of them shared thoughts or opinion about depression (10.73%). The knowledge, opinions and facts that can potentially be extracted from Twitter. In particular, the large fraction of tweets dedicated to sharing of depressed feelings implies that tweets could be used as valid data for researching depression or depressed feelings that could be considered as ‘major depressive episodes’ of the online population. Even though there were some limitations in conducting the pilot test such as the data were collected using only one keyword, we believe that the pilot test met our purpose of providing the basis that people might share their depressed feeling on Twitter. Thus, we conducted a second study of comparing the online and offline expression of depression among Twitter users to identify whether they correlated with each other.

4. METHODS

4.1 Study Design

This study provides a cross-sectional analysis of 69 young adults who completed an Internet-based screening test for depression and allowed us to access their online social network posts. We adopted a mixed method study design, by

utilizing both the survey data and the data gathered from OSNs. The analysis was conducted in three steps: (1) surveying users to identify their self-judged depression level, (2) collecting tweets of the same users, and (3) comparing the depression levels of users with their sentiments and language usage in tweets.

We recruited participants by sending online invitations through Facebook and Twitter. To gather a wide range of samples from both non-depressed and depressed population, we utilized the personal networks of authors and several online communities related to depression.¹ Invitations were sent out twice in September 2011.

Questions in the survey asked for the following information: (i) demographic details—namely age, gender, education, and job, (ii) Twitter ID and permission to gather public tweets of the user, (iii) experience of clinical treatment of depression if any, and (iv) the depression quotient by the Center for Epidemiologic Studies Depression Scale (CES-D), for which we also provided the web link for online assessment. Besides the Twitter ID, no other personal identification information was collected.

The CES-D is a 20-item self-report scale that is designed to measure depressive symptoms in the general population [18]. Its minimum score is zero and a maximum score is 60. Generally depression symptoms are divided into three groups based on the likelihood of having depression: low (0-15), mild to moderate (16-22), and high range (23-60) [9]. Because of high false-positive rates at the cutoff of 16, users with much higher CES-D scores are considered to have a high likelihood of clinical depression. While studies adopt different cutoffs (such as 20, 22, or 27), we chose 22 because it is the most widely used threshold with great improvements in false-positive rates and specificity [8]. A large number of studies have tested this grouping method and confirmed the positive predictive value of the CES-D rating scale across different clinical populations [23].

4.2 Participant Information

A total of 253 users completed our initial research survey. However, not all participants shared their Twitter IDs with us and only 165 participants gave us permission to use their public tweets for this study. Furthermore, not all of them were active on Twitter. In order to ensure that we had enough tweet content for each participant to run sentiment analysis, we screened those users who posted fewer than 50 words during the most recent week from the day the survey was conducted.² After this step, we were left with 69 participants (male=28, female=41). All 69 participants were from a single ethnic group, ensuring that our study controls for the ethnicity factor.

The participants were in an age range of 17–42 (mean=28.2, sd=5.4), and their jobs were diverse. Job description included student, teacher, college lecturer, doctor, nurse, marketer, IT developer, product designer, web designer, exhibition designer, 3D graphic designer, novelist, columnist, ed-

¹We do not disclose the names of these depression related communities to respect participants' privacy.

²The developer of LIWC suggests that at least 50 words are needed to operate the tool properly.

itor, librarian, rock musician, jazz pianist, public servant, accountant, enterpriser, flight crew, barista, housewife, and jobless. Overall 36.2% of the participants were students, 44.9% worked regularly, and the rest were freelancers or jobless. The level of education also varied. More than half of the participants were undergraduates or had received a bachelor's degree (66.7%). The rest were master degree holders (23.2%) and high school graduates (8.7%). Only one of them was a middle school graduate.

As mentioned previously, we used the CES-D cutoff score of 22, which is widely used for offline screening tests, for our online test data. For the 69 participants, we gathered one week worth of tweets prior and up to the date survey was conducted, because the CES-D questionnaires refer to how one felt and behaved during the past one week. The data was collected through the Twitter Application Programming Interface (API). In total, we gathered 5,706 tweets from the participants. The average post rate of the participants was 11.8 tweets per day.

4.3 Sentiment Tool

In order to quantify the level of depressive moods of participants from OSN data, we performed sentiment analysis on the tweet text. We used the LIWC (Linguistic Inquiry and Word Count) sentiment tool, which is a transparent text analysis program that counts words in psychologically meaningful categories [17]. The LIWC tool contains a dictionary of several thousand words, where each word is scaled across the following six criteria: social, affective, cognitive, perceptual, biological processes, and relativity. Each criterion comprises several categories and sub-categories, for which the scores are given. For example, the word "cry" is associated with sadness (sub-category of negative affect) and negative affect (sub-category of affective). Hence, if it is found in the target text, each of these sub-dictionary scale scores will be incremented.

5. RESULTS

Based on the CES-D cutoff score of 22, 41 participants were classified into low or mild depression (CES-D score less than 22) and 28 participants scored positive for depression (CES-D score equal or greater than 22). Among the 28 participants who scored positive for depression, 23 of them confirmed their previous diagnosis history of depression, giving high confidence in the test. For the remaining five participants who had never been diagnosed with depression, we provided information of their CES-D scores and recommended that they seek help from health professionals for ethical consideration of the participants. In the remainder of this section, we call the users who screened negative for depression *normal* group and the users with high probability of depression *depressed* group.

5.1 Normal Group vs Depressed Group

As our first goal, we seek the language determinants of depression and examine the relationship between the CES-D scores and the LIWC scores of tweets of the 69 participants. As mentioned earlier, LIWC scores the relative frequency of a given sentiment category in percentile scale, out of all the words in the input file. LIWC contains many other categories besides the affective process category. The affective

process category typically accounts for 0-10% of the total frequencies [21].

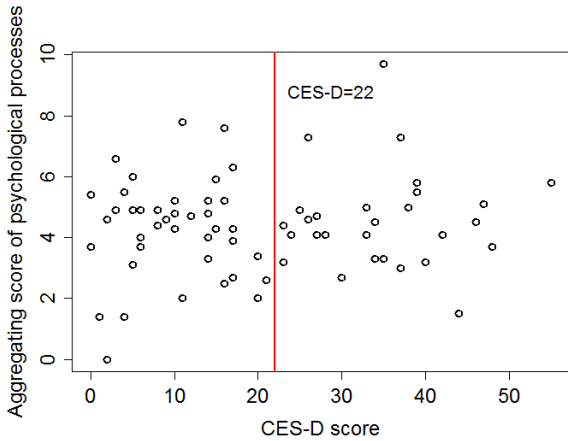


Figure 2: Sentiment scores and CES-D scale of participants

Figure 2 shows the scatter plot of the LIWC score from the affective process category as a function of individuals’ CES-D scores. The normal group and the depressed group had mean CES-D scores of 10.1 and 34.8, respectively. As shown in the figure, users below or above the CES-D cutoff score of 22 did not have any particular difference in the level of affective words they used in tweets. The overall mean LIWC score of 69 participants was 4.41 and the standard deviation was 1.61.

While there was no difference in the total amounts of sentiment expressed in tweets, we found trends in the way different categories of sentiments appeared in tweets. Figure 3 displays the mean scores of the seven major sentiment categories based on the tweets of the users in the two user groups. The positive emotion category is the main category for positive feeling and optimism, meaning that the latter two are sub-categories of positive emotion. Meanwhile, the negative emotion category is the main category for anxiety, anger, and sadness.

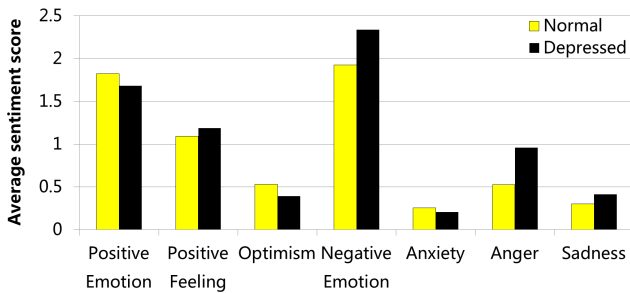


Figure 3: Average positive and negative sentiment scores in tweets depending on the groups classified by CES-D score

Based on two-sample t-test, there was no notable difference in positive emotion, positive feeling, and optimism across the two groups. Users expressed a similar level of these

sentiments, irrespective of their depression level. Negative emotion and anger, however, had a different pattern. Users in the depressed group were more likely to express negative emotions than positive emotions (mean=1.95 and sd=0.55 in normal group, and mean=2.42 and sd=1.15 in depressed group, p-value=0.023 in 95% confidence interval), while this ratio was similar for the normal group. Compared to the normal group, the usage of words related to anger was significantly higher in the depressed group (mean=0.60 and sd=0.52 in normal group, and mean=0.96 and sd=0.92 in depressed group, p-value=0.039 in 95% confidence interval). The usage of words in anxiety and sadness was not substantially different between the two groups.

5.2 Model of Sentiments

In order to understand the statistical correlation between one’s depression status and language usage, we developed a multiple regression model by using all the sentiment categories (a total of 37 categories) and examined how these variables are associated to the CES-D score. However, there was excessively high multicollinearity between LIWC categories (i.e., one category can be explained by some of other categories). Before we conducted regression, therefore, we repeatedly reduced one or more variables that were highly correlated by examining the bivariate correlations between independent variables and condition numbers (CN) of the set of independent variables. Typically, a parameter called CN is used to indicate problems with multicollinearity in regression models [13]. The consensus here is that the degree of collinearity of the model can be in three cut-offs; absent to weak ($CN < 10$), moderate to strong ($10 < CN < 30$), and severe ($CN > 30$).

Following the common approach to examine bivariate correlation in all possible combinations between independent variables, we identified 18 sentiment predictors out of the 37 predictors in the initial categories. The condition number was 8.45, indicating that these variables were reasonable for analysis. Table 1 lists the 18 predictors along with example words for each factor. For instance, the positive feeling predictor includes words such as “love” and “nice”, whereas friends predictors includes words such as “buddy” and “neighbor.”

The CES-D score is predicted to increase by 5.04 times when the “anger” variable rises by one ($p < 0.05$) and decrease by 6.99 times when the “tentative” variable goes up by one. The CES-D score is also predicted to increase with the use of words in the “causation” ($p < 0.05$) and “friends” ($p < 0.01$) categories and decrease with the use of words in the “communication” ($p < 0.05$) category. Then we applied stepwise regression that allows the procedure to select predictor variables to enter the regression equation once more to find the best model for predicting participants’ CES-D scores. As a result, the critical variables in previous model remained in the new model and the model displays similar pattern that depressed people are more likely to use negative words and to refer social words such as words in “friends” category [20].

5.3 Likelihood of Depression by Demographic

Given that we found a meaningful sentiment model for the CES-D depression scores, we also checked to what extent the model is stable across various demographic factors. We ex-

Table 1: Coefficients from regression models predicting the CES-D scores

Predictors	Example words	Coefficients for CES-D score (Multiple regression)		Coefficients for CES-D score (Stepwise variable picking by AIC)	
		Estimate	p-value	Estimate	p-value
Positive Feeling	Love, nice, good	3.38	0.25		
Anxiety	Worried, fearful, nervous	4.02	0.45		
Anger	Hate, kill, annoyed	5.04	< 0.05 *	3.59	< 0.05 *
Sadness	Crying, grief, sad	6.33	0.20	6.09	0.15
Causation	Because, effect, hence	12.1	< 0.05 *	12.2	< 0.01 **
Inhibition	Block, constrain, stop	-4.29	0.11	-3.64	0.11
Tentative	Maybe, perhaps, guess	-6.99	< 0.05 *	-5.63	< 0.05 *
Face	Keep up appearances	5.63	0.14	6.32	0.078
Communication	Tell, speak, claim	-3.54	< 0.05 *	-4.01	< 0.01 **
Social reference	He, she, who	4.98	0.12		
Friends	Buddy, friend, neighbor	15.1	< 0.01 **	12.36	< 0.01 **
Family	Aunt, mother, daughter	6.17	0.19	8.01	0.073
Humans	Adult, baby, boy	2.17	0.55		
School	School, student, class	0.68	0.79		
Work	Job, majors, xerox	-4.79	0.16		
Achievement	Earn, hero, win	-6.47	0.087	-7.24	< 0.05 *
Sleep and dream	Sleep, nap, dream	-0.98	0.66		
Death	Bury, coffin, kill	-11.6	0.10		
		Adjusted R-squared	p-value	Adjusted R-squared	p-value
		0.40	0.0022	0.43	8.94e-05

* Significant level lower than 0.05

** Significant level lower than 0.01

amined the following exogenous variables: (1) gender, (2) age, which was discretely classified after the survey and treated as a binomial variable, (3) occupation, as either regular job or irregular job, and (4) education, which was classified after the survey and analyzed as a binary value divided by college education.

The associations between a high CES-D screening score and demographic characteristics were calculated by determining the percentage of depressed users in each factor category and calculating the odds ratio using a logistic regression on participants' CES-D scores and demographic information. The odds ratio (OR) is a relative measure of risk, which tells in this case how much more likely it is that someone who is exposed to the factor will suffer from depression as compared to someone who is not exposed.

The odds ratio analysis revealed that not all demographic factors had an impact in determining the likelihood of depression for our participants. We did not find any meaningful trend between the male and female participants nor across different age groups, as all of these factors had high $p > .05$ value. However, the other two factors showed a meaningful difference. Participants having a college degree were less likely to have depression than those with lower education ($OR = 0.17, p < .05$), while having a regular job was linked with a significantly reduced likelihood of depression ($OR = 6.28, p < .05$).

While the above analysis did not indicate gender as a significant factor in determining depression, gender indeed has been shown to be a critical factor of depression in previous

works. Women are known to have a higher probability of depression than men [10, 3]. Also, other works suggest a high rate of depression among young adults (up to age of 24 years), whereas we did not find age to be a significant factor for our participants [14]. In order to understand this discrepancy better, we examined the variation of the LIWC sentiment factors across all demographic factors. Figure 4 shows the results for gender.

The figure shows that gender affects the way users post tweets. When controlled for depression probability, female users were on average more expressive than male users. In Figure 4, we can observe this trend in the normal group, where female participants have higher LIWC scores in expressing both positive and negative emotions than the male participants. Within the depressed group, female users also exhibited stronger negative emotion than the male users. We found several other particularities in the use of language across demographic factors. We do not discuss all of them here due to space limitations.

5.4 Qualitative Content Analysis

Finally we assisted the machine based automatic classification of sentiments with qualitative analysis of tweet content. We hired two annotators who investigated 250 randomly chosen tweets each from the normal group and the depressed group, respectively. The chosen tweets were also tagged with demographic information for the annotators to cross check any particularities.

A qualitative content analysis revealed many of the differences across CES-D groups and demographic features that

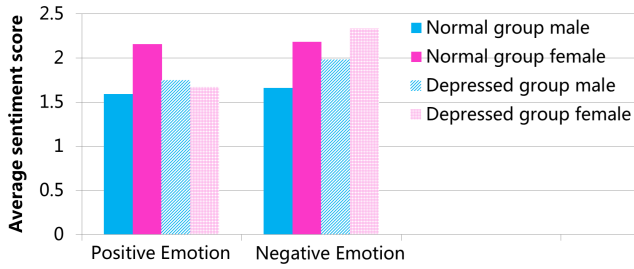


Figure 4: Gender differences in the LIWC category

we could not identify from the regression analysis. First, what was peculiar about the depressed group was that many of their tweets were monologue-like and were written towards an unspecified audience. For example, tweets such as “Berliners live in Berlin. New Yorkers live in New York.” and “I’m a warrior. Let them all come!” do not have a target audience. Similar to existing work, annotators found frequent usage of first person pronoun.

Second, while the odds ratio analysis did not find gender to play a role in predicting the CES-D score, content analysis could identify a clear gender difference. The key difference reported by both of the annotators was that female participants expressed their emotions directly, for example, “My heart was pounding so hard. I got a bouquet! hahaha” and “I feel so ornery and low.” In contrast, male participants revealed their emotion indirectly and often wrote in the style of an objective point of view, for instance, “Huh, my angry energy might be converted into movement...” and “What kind of attitude is that? I’ll face the person who’s giving me trouble.”

Third, job differences were also noticeable in the context and style of tweet posting. Users with regular jobs expressed their negative emotions mostly when they talked about relationships with others, social issues, and their environment, for instance, “the other team was very irritating and mad.” In contrast, users with irregular jobs expressed negative emotions about themselves, for instance, “I dressed wrong today.” or “I have no friend, and I will always be like this. I don’t know what a friend is. I just need to sleep.”

5.5 Insights

While preliminary, the main goal of this research was to explore and determine whether measures of self-judged depression level could be explained reliably (in statistical sense) from users’ posts collected from online social networks. We addressed this goal by conducting regression analysis and content analysis along with users’ demographic information, tweets, and sentiments captured from the tweets. In particular, we found a meaningful difference between the normal and depressed group in their frequency of words conveying negative emotion and anger. The regression model included strong markers of sentiment categories, where the two highest estimates were from “friends” and “causation”, which could reliably predict the CES-D scale of users. We also found that depressed users posted many more monologue-like tweets than the non-depressed users. These findings together indicate the possibility for screening or even continu-

ously monitoring depression through careful examination of such words in tweets.

6. DISCUSSION

6.1 Implications

Here, we provide several additional discussion points regarding the results. First, it is interesting that when people were posting tweets about their depression or depressed feeling, they disclosed very private and detailed information (Section 3). For example, Twitter users posted what was making them depressed or what would make them depressed. Treatment prognosis such as obtaining a medical diagnosis, going to the doctor to change medications, and personal remedies for treating depression or depressed feelings were posted. This indicates that tweets can be used as valid data for researching depression or depressed feelings of online population in a fashion that complements limitations of research conducted in the offline counterpart.

Second, the multiple regression analysis and the qualitative content analysis together suggest that users in the depressed group were more likely to post tweets about themselves than to interact with other users compared to a typical Twitter user (Section 5). Furthermore, in their monologue-like tweet posts, there was a high chance of finding words in certain affect categories such as anger, causation, and friends.

Third, there was an interesting discrepancy between the literature and our finding. While we did not find gender to play a significant role in determining depression, several studies have shown a higher probability of depression for women than men [10, 3]. We may consider several hypotheses to understand this. One is that our samples could be biased. Another is that female social network users are less likely to reveal their depressive moods than males. The public feature of networks like Twitter may hinder depressed females from expressing their negative emotions. Focusing on this line of discrepancy might help us identify unique demographical usage patterns of OSNs.

6.2 Limitations

This study is limited in several manners. One is due to a small number of participants, who were active in Twitter. Because many users often browse others’ tweets but do not post any themselves, it would be interesting to extend our study by additionally considering different types of users (e.g., those who lurk on social media). In the future, we would like to conduct a longitudinal study with a larger number of participants. Another limitation of this work is the sentiment analysis tool. Although the LIWC tool has been used in many studies, language itself is evolving fast and as a result the tool could not parse all the words in Twitter. Emotions and newly-coined words (e.g., LOL) were ignored in this analysis. In order to overcome this limitation, we are currently expanding the existing LIWC dictionary to incorporate popular words used in social media. Finally, we would like to explore the impact of demographic differences like the marital and parent status that may affect the sentiment variables.

7. CONCLUSION

This study demonstrates that it is possible to use online social network data for clinical studies. Based on both quantitative and qualitative analyses, we confirmed a correlation between the depressive state of a user and the tweet sentiment of that user. This leads to the possibility of identifying depression symptoms and episodes from the OSN data. Potential benefits of using OSN data for clinical studies on depression are tremendous, because web environments provide an effective, less-intrusive platform for screening users with depressive symptoms. Such systems allow researchers to track users' everyday circumstances as they interact with other (depressed and non-depressed) users in social networks. Furthermore, because access to web platforms is becoming increasingly ubiquitous with mobile devices, it is possible to build a real-time healthcare system to better understand depression.

Beyond building a screening system, there is great value in utilizing OSN data due to its massive scale and less-intrusive logging capability across time and space. One potential application is to jointly examine the formations of social ties and the gradual changes of users' sentiments for identifying the kinds of social relationships that are beneficial (or harmful) in preventing depression. We expect that the use of online data could assist offline clinical studies of depression, rather than replacing them. Improving mental health and well-being is an important social goal. By building an OSN-based healthcare support system for depression, we hope to better understand the nature of depression and lower the bar in self-screening depression for a larger population.

Acknowledgements Minsu Park and Meeyoung Cha were supported by the Basic Science Research Program through the National Research Foundation, Korea (2011-0030936).

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