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Opinion Paper

A big data analytics framework for detecting user-level depression from social networks

Xingwei Yang[a], Rhonda McEwen[b], Liza Robee Ong[c], Morteza Zihayat[c,*]

[a] Smith School of Business, Queens University, Canada
[b] University of Toronto Mississauga, Canada
[c] Ted Rogers School of Management, Ryerson University, Canada

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ABSTRACT

Depression is one of the most common mental health problems worldwide. The diagnosis of depression is usually done by clinicians based on mental status questionnaires and patient's self-reporting. Not only do these methods highly depend on the current mood of the patient, but also people who experience mental illness are often reluctantly seeking help. Social networks have become a popular platform for people to express their feelings and thoughts with friends and family. With the substantial amount of data in social networks, there is an opportunity to try designing novel frameworks to identify those at risk of depression. Moreover, such frameworks can provide clinicians and hospitals with deeper insights about depressive behavioral patterns, thereby improving diagnostic process. In this paper, we propose a big data analytics framework to detect depression for users of social networks. In addition to syntactic and syntax features, it focuses on pragmatic features toward modeling the intention of users. User intention represents the true motivation behind social network behaviors. Moreover, since the behaviors of user's friends in the network are believed to have an influence on the user, the framework also models the influence of friends on the user's mental states. We evaluate the performance of the proposed framework on a massive real dataset obtained from Facebook and show that the framework outperforms existing methods for diagnosing user-level depression in social networks.

1. Introduction

More than 300 million people are suffering from depression globally (World Health Organization, 2008). According to Government of Canada (2017), one out of three Canadians experience mental illness during their lifetime, with young people aged 15–24 more likely to suffer from mental health disorders, compared to other age groups (CBC News, 2017). Depression is a serious illness and can lead to more serious health conditions, including suicide (World Health Organization, 2008). Although the government provides primary healthcare services for mental illness, a survey in 2016 shows that 40% of respondents agreed that they have experienced feelings of anxiety or depression but never sought medical help (Detels, 2009; The Centre for Addiction & Mental Health, 2019). Traditionally, depression is diagnosed by clinicians through several in-person interviews which is highly relied on self-report questionnaires. Such questionnaires are necessary, but they have several limitations: (1) they rely on patients to recall their moods and activities in the recent past (e.g., generally within a two week period); (2) the answers may be affected by the current mental state of the patient, which may be compromised; and (3) they produce only a single score after a variety of questions are answered. This does not provide sufficient information for clinicians to diagnose depression effectively. With the development of social networks like Facebook, research communities have access to a substantial amount of data offering insight into the feelings and sentiments of users, including studies using semantic analysis on online postings. Several studies show that social network data can be used to predict depression effectively (De Choudhury, Gamon, Counts, & Horvitz, 2013; Islam, Kabir, & Ahmed, 2018; Schwartz et al., 2014). However, most of the existing methods mainly detect depression based on syntactic and syntax features extracted from update statuses of users. Syntactic and syntax features study the grammatical structure and the meaning of the words and sentences. Although such information can help to achieve reasonable assessments, they do not incorporate several important aspects of a user mental state. One of the vital aspects is *user intention* which can provide insights into users' motivation to post a new status in a social network.

* Corresponding author at: Ted Rogers School of Information Technology Management, Ryerson University, Room 2-032, 575 Bay Street, Toronto, ON M5G 2C5, Canada.

E-mail address: mzihayat@ryerson.ca (M. Zihayat).

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This can help understand a user beyond semantic and syntactic features. Another important aspect that existing studies do not consider is the *user's social influence*. Recent psychological studies show that people are affected by mental illness either directly or indirectly through family, friends or colleagues (Government of Canada, 2017). For example, a bad mood can be transferred from one person to another during social interactions (McAnany, 2012; Neumann & Strack, 2000). Such observations imply that in addition to user-level activities (e.g., status update, attending events), the social influence of users should be investigated. To the best of our knowledge, existing studies mainly focus on user-level linguistic features in detecting depression, while the relationship between the social network structure, the influence of users' friends and the risk of experiencing depression remains largely unexplored.

To address the aforementioned research gap, we propose an end-to-end framework to apply machine learning techniques with the aim to detect user-level depression from social networks. In addition to a thorough feature extraction phase, the proposed framework applies novel techniques to infer new features representing two important aspects of a user to detect depression: (i) *User intention*: since the core of our depression analysis is studying what language is associated with user intention, one of the most essential components of our framework is to study the pragmatics of the system. We argue that it is more beneficial to clinicians to provide information based on users' social interactions to supplement existing methods such as assessment questionnaires. We propose a data-driven intention model based on the status updates of users to associate the status updates with user intention, and resultant impact on the user's friendship network. This model offers a better understating of users' mentality in status updates. (ii) *Friends influence*: the main challenge in modeling friendship influence is to measure the influence based on the social network structure and contents posted online. In keeping with the literature, we argue that the closer a friend to a user is, there is a higher chance that the user becomes affected by that friend's mental state. We present two different approaches to calculate the social influence of a user from his friendship network. The first approach calculates the shortest path between the user and his nearest friends with a defined mental status (e.g., depressed or non-depressed). A social influence score is obtained from the user's depressed friends based on their closeness or distance in the friendship network. The second approach finds the similarities of users based on their intention model. A social influence score is calculated from the depressed friends of the user based on the similarity of their intention model. The last challenge is based on the fact that we have to deal with a huge volume of data. Facebook, as one of the most popular social network platforms, had 2.32 billion monthly active users in the fourth quarter of 2018 which is double the number of users from 5 years ago and 20 times more than 20 years ago (Statista Research Department, 2019). The high volume and high velocity of Facebook data makes it challenging to identify complex patterns by traditional statistical analysis. Having an otherwise effective model that struggles with big data might no longer be viable (Gandomi & Haider, 2015). Our proposed framework shows a scalable power to deal with big data. We apply our proposed framework to a dataset of *22 million* records collected from Facebook status updates and demonstrate its effectiveness in identifying depression by comparing to state-of-the-art baselines.

To the best of our knowledge, this study is the first step toward exploring the impact of both user intention and friends' influence on user mental wellness in a unified framework. The ultimate goal of this study is to design a decision support system that can help hospitals and mental health clinics to accelerate the diagnosing process by providing reliable and more comprehensive information regarding a user's mental states. Note that, our objective is to provide another tool in the toolkit of our mental health professionals to support better depression detection and to provide mechanisms using existing datasets to allow for easier follow-up in treatment plans. This framework can never replace the work of qualified mental health professionals, but can offer supplemental data in the treatment of these types of illnesses.

The rest of the paper is organized as follows. In Section 2, we provide a review of relevant prior work. In Section 3, we present the conceptual framework. Sections 4 and 5 describe the process of data-driven feature extraction and our proposed pipelines. In Section 6, we outline the experimental settings and discuss the results. Finally, in Sections 7 and 8, we point out limitations and future research directions, and conclusion the paper.

2. Literature review

Several studies have shown the negative effects that depression can have on language styles. Segrin (2000) analyzed the relationship between depression and social skills indicators, including speech contents. The results showed that people experiencing depression exhibit more negative self-disclosures and negative verbal contents, especially when interacting with a friend. Similarly, Robinson and Alloy (2003) found that the interaction of negative cognitive styles (the likelihood to make negative inferences) and stress-reactive rumination (the likelihood to repetitively think about the negative inferences following stressful events) can be used to predict the onset, number and duration of major depressive episodes. Slonim (2018) also confirmed that the verbal behavior of depressed individuals is more self-focused, as indicated by the use of more first-person pronouns and that their language includes more negative sentiments, as evidenced by the use of more emotionally negative words such as sad, unhappy and etc.

Facebook has been widely used to predict personality. Some significant correlations are found by Sumner, Byers, and Shearing (2011) between users' personalities and their Facebook activities, posts content and emotion. Golbeck, Robles, and Turner (2011) predicted the personality of Facebook users using linguistic features, lists of personal activities or favorite things and social network features. Tadesse, Lin, Xu, and Yang (2018) predicted personality through investigating the social network structure of Facebook, users' social behavior and their language-use habits based on measures of the Big 5 personality model. Personality has also been proved to be associated with depression. Klein, Kotov, and Bufferd (2011) performed a review of existing research that explored the link between depression and personality types. They concluded that depression is related to specific personality traits: neuroticism, extraversion and conscientiousness. While the evidence does not clearly indicate that if personality serves as a precursor or predisposition to depression, they showed that personality traits may help predict and affect the treatment of depression. Hakulinen et al. (2015) studied data from 10 prospective community cohorts with more than 110,000 participants. They concluded that personality is related to the development of depressive symptoms. In turn, depressive symptoms are related to temporary or persistent changes in personality. Although these studies improved our understanding of depression and its related factors, a noticeable limitation is that these studies typically are based on self-reported data from questionnaires and surveys. Moreover, the collection of depression data usually requires recalling past events, and participants dispositions are easily affected by the current mental states which makes it difficult to obtaining high quality of data. As a result, there is increasing interest in using social network data ranging from classifying personality types based on Facebook activities (Laleh & Shahram, 2017) to revealing insights on individuals' psychological states by measuring the emotions features from Twitter posts over time (Chen, Sykora, Jackson, & Elayan, 2018). For example, Kapoor et al. (2018) discussed findings from 132 articles from information system journals on social networks and showed that the research on social networks is widely used as a tool of identifying emotional, social and health concerns. In contrast to the most popular social network platforms such as Facebook and Twitter, Shen and Rudzicz (2017) collected personal narratives from Reddit to study anxiety disorders and classified anxiety-related posts to a binary level of anxiety.

Linguistic features of social network status updates have been used

Table 1
Summary of recent literature work in depression detection.

Authors	Title	Year	Methodology	Algorithm
J. Shen, F. Rudzicz	Detecting anxiety through Reddit	2017	Predict depression with features including, N-gram language modeling, vector embeddings, topic analysis, and emotional norm based on posts from Reddit.	Logistic Regression, a Linear Kernel SVM, Neural Network
A. Reece, C. Danforth	Instagram photos reveal predictive markers of depression	2017	Identify and predict markers of depression from photos posted by Instagram users including features extracted from color analysis, metadata components, and algorithmic face detection.	Bayesian Logistic Regression, Random Forest
A. Laleh, R. Shahram	Analyzing Facebook activities for personality recognition	2017	Predict personality based on Facebook data features selected by LASSO algorithm.	Least Absolute Shrinkage and Selection Operator Regression
B. Primack, A. Shensa, C. Escobar-Viera, E. L. Barrett, J. Sidani, J. B. Colditz	Use of multiple social media platforms and symptoms of depression and anxiety: A nationally-representative study among U.S. young adults	2017	Assess the associations between use of multiple social network platforms and depression/anxiety by controlling demographic and socioeconomic, total time spent on social network	Logistics Regression
M. Islam, M. Kabir, A. Ahmed, M. Islam, M. Kabir, A. Ahmed, M. Islam, M. Kabir, A. Ahmed	Depression detection from social network data using machine learning techniques	2018	Measure and detect depression by using emotional features, linguistics styles in combination of different depressive behaviors based on time from Facebook users' comments	SVM, K-Nearest Neighbors, Decision trees and Ensemble
A. Li, D. Jiao, T. Zhu	Detecting depression stigma on social media: A linguistic analysis	2018	Detect depression stigma expressions from a Chinese social media (Weibo) posts by using linguistics analysis methods in order to design more effective stigma reduction strategies	Simple Logistic Regression, Multilayer Perceptron Neural Networks, SVM and Random Forest
M. Trotzek, S. Koitka, C. Friedrich	Utilizing Neural Networks and Linguistic Metadata for Early Detection of Depression	2018	Detect depression at early stage based on sequences of posts and comments from reddit using machine learning methods.	Neural Networks
X. Chen, M. Sykora, T. Jackson, S. Elayan	What about Mood Swings: Identifying Depression on Twitter with Temporal Measures of Emotions	2018	Identify users with or at risk of depression by detecting eight emotions features from each tweet and LIWC features.	Logistic Regression, SVM, Naïve Bayesian, Decision Trees, Random Forests
A. Husseini Orabi, P. Buddhitha, M. Husseini Orabi, D. Inkpen	Deep learning for depression detection of twitter users	2018	Detect depression by designing a novel approach to optimize word-embedding for classification tasks from twitter users' postings.	SVM, Convolutional Neural Network, Recurrent Neural Network
M. M. Tadesse, H. Lin, B. Xu, L. Yang	Detection of depression-related posts in reddit social media forum	2019	Detect depression related posts from Reddit using NLP, linguistics features such as n-grams, LIWC and LDA, and machine learning techniques.	Logistics Regression, SVM, Random Forest, AdaBoost, Multilayer Perceptron
S. G. Burdisso, M. Errecalde, M. Montes	A Text Classification Framework for Simple and Effective Early Depression Detection Over Social Media Streams	2019	Early depression detection by a novel text classification model, called SS3, whose goal is to provide support for incremental classification, early classification and explainability	Supervised Learning Model SS3
R. Thorstad, P. Wolff,	Predicting future mental illness from social media: A big-data approach	2019	The study shows users' everyday language used on Reddit can be used to predict the future occurrence of several kinds of mental illness including depression. A list of most predictive words for depression are found using machine learning methods	Logistic Regression, Cluster Analysis

to predict depression, however, most of the studies only examine the syntactic and semantic features. These features consider the structure and meaning of words and sentences using linguistics styles classified by Linguistic Inquiry and World Count (2019) including articles, auxiliary verbs, conjunctions, adverbs, personal pronouns, prepositions, functional words, assent, etc. De Choudhury et al. (2013) analyze Twitter status updates of depressed users including the language styles, social engagement and the structure of ego networks to predict the likelihood of depression. Schwartz et al. (2014) believe that the change of seasons is related to the depression by studying Facebook users and the linguistics features (e.g., number of words and ngrams) to find the degree of depression. Li, Jiao, and Zhu (2018) used linguistic features extracted from Chinese social network online postings to improve the ability to automatically detect depression stigma information. Trotzek, Koitka, and Friedrich (2018) try to detect depression as early as possible from social networks using neural network methods based on different word embeddings.

Pragmatics, includes the observation that words can be used to perform an act, also known as "*speech acts*", and is another important linguistics feature set that helps us to understand the information presented by users in social networks. Appling, Briscoe, Hayes, and Mappus (2013) used linguistic features extracted from Facebook status data and create a speech act classifier using Support Vector Machine to determine personality dimensions with speech act types. Although such features are information, the use of speech act is remained unexplored in depression detection. A few past studies consider the ego network structure, betweenness, and the connectivity of social networks to examine depression symptoms and to predict the likelihood of depression using the Center for Epidemiologic Studies Depression Scale (CES-D) questionnaires by studying the adjacent users' influence in the social network structure (De Choudhury et al., 2013; Laleh & Shahram, 2017). Moreover, there are several approaches that measure friends' influence in social networks (Yerasani, Appam, Sarma, & Tiwari, 2019). However, such approaches might not work well when there are few adjacent users with available depression assessments results. For example, in the dataset used in this study, there are 6561 out of 153,727 users for whom assessment results are available and very few of them are direct neighbors of a particular user. Investigations to solve this challenge remain unexplored.

Detecting emotions and opinion using machine learning techniques (Wu, Li, Shen, & He, 2019) in more recent literature are popular in helping to predict the risk of depression using social network data. Islam et al. (2018) showed that constructing decision trees in combination of psychological features is a technique that achieved high prediction performance. Thorstad and Wolff investigated users' posts from the online discussion forum Reddit and found that everyday language can be used to predict future occurrence of different kinds of mental illness including depression using machine learning methods. The cluster analysis in their study showed that depressed users tend to show depressed mood, feelings of worthlessness and recurrent thoughts of death (Thorstad & Wolff, 2019). Burdisso et al. designed a novel text classification framework using a supervised leaning model to address the problem of early depression detection by considering incremental classification, support for early classification and explainability (Burdisso, Errecalde, & Montes-y-Gómez, 2019). Tadesse, Lin, Xu, and Yang (2019) also studies users' post from Reddit to detect depression by employing Natural Language Processing (NLP) and machine learning techniques. They identified words that include preoccupation with themselves, feelings of sadness, anxiety, anger, hostility or suicidal thoughts, with a greater emphasis on the present and future that are common among depressed users. Chen et al. (2018) created a binary classifier for depression detection and achieved a high accuracy in predicting depression using Support Vector Models with Radial Basis Function, and using Random Forests. Husseini Orabi, Buddhitha, Husseini Orabi, and Inkpen (2018) explored a number of neural network architectures to analyze the tweets of 1145 users and optimized their word embedding process to map words from tweets to a vector representation, and showed that convolutional neural network-based models outperforms recurrent neural network models. However, such approaches focus on syntactic and semantic features of users and do not consider other aspects of users.

Table 1 represents a summary of recent work in depression detection. What differentiates our proposed framework from prior methods is that in addition to existing features, it considers other mental aspects of a user such as personality, network structure friendship influences and programmatic linguistics features and user intention into account, thereby providing a more thorough approach to predicting depression risk. Moreover, our prediction framework is flexible in dealing with non-adjacent users and extracts extra information from the hidden network structures. This improves the accuracy of detecting users' risk of depression in social networks.

3. Conceptual framework

The proposed framework in this study is beneficial to clinical services and hospitals to have reliable knowledge to give a more accurate diagnosis and analysis of a patient rather than solely relying on assessment questionnaires. Our framework begins with measuring all the depressive behaviors on a daily basis for each social network user through features deduced from linguistics, personality, network structures. Then, using machine learning techniques, we are able to deal with the increasing volumes and varieties of Facebook activities and find meaningful patterns from the complex data structures.

Fig. 1 shows our proposed framework for depression detection in a

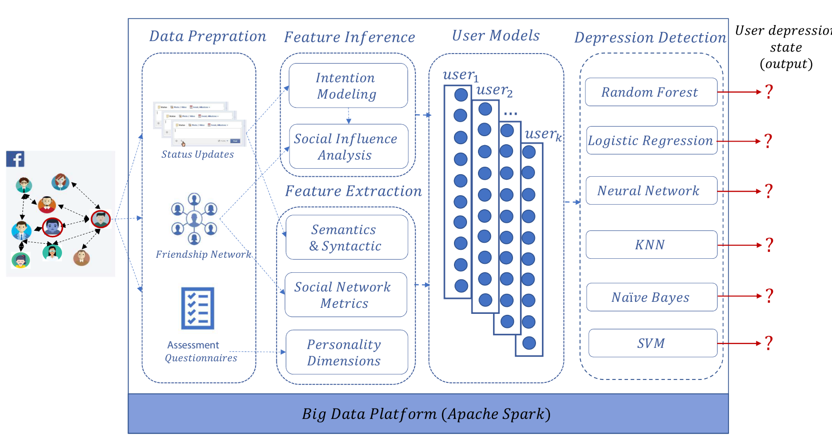


Fig. 1. Conceptual framework for depression detection in social networks.

social network. The proposed framework consists of four main components: (1) *Data preparation*, (2) *Feature extraction*, (3) *Feature inference* and (4) *Depression detection*.

In the first component, we mainly focus on data cleaning and data preparation. Given the status updates and the results of assessment questionnaires, we build a dataset of users whose mental states are estimated. Then, given all the friendship connections, we build a friendship network per user. This network represents how a user is connected to other users whose mental status is known by CES-D depression detection questionnaires. In the second phase, we extract three different types of features: (1) *semantic and syntactic features* which indicate the linguistics characteristics in posts from users; (2) *social network metrics* that show social network structure as well as users' interactions with others in the network; (3) *personality dimensions* which are extracted from personality assessment tests taken by users. The feature inference component develops two models and infers two essential features: we first develop an intention model and create a classifier for an in-depth study to understand the true intention behind an updated status. Moreover, we conduct a social influence analysis to model the social impact of depressed and non-depressed friends in a user's Facebook network. The proposed framework is designed and implemented based on Apache Spark, a popular environment for processing and handling large data sets produced by a social network.

3.1. Data preparation

Our study is conducted based on a dataset, called *myPersonality*, used by Stillwell and Kosinski (2012). The myPersonality is a Facebook application that allows its users to participate in psychological research by filling in questionnaires. It was released in June 2007 and contained more than *6,000,000* responses from users. The use of *myPersonality* led to many top scientific publications, driving progress in our understanding of human psychology, health and behaviors (Bachrach, Graepel, Kohli, Kosinski, & Stillwell, 2014; Michal, Yoram, Pushmeet, David, & Thore, 2013; Rentfrow et al., 2013).

MyPersonality datasets are consist of Facebook users information including users' status updates, users' responses to the International Personality Item Pool (IPIP) version of the NEO Personality Inventory, and to the Center for Epidemiologic Studies Depression Scale (CES-D Scale) questionnaire. In preparation for exploratory data analysis, all datasets were loaded as dataframes in R. These dataframes were then merged together using Facebook generated anonymous ID. From *myPersonality* datasets, we use assessment questionnaires results, Facebook status updates and friendship network measures as our main data sources. We detect and remove all the outlier users from the dataset similar to Anderson, Sweeney, Williams, Freeman, and Shoesmith (2010). For both personality and CESD questionnaires, we consider a respondent as an outlier if the assessment score is more than three standard deviations away from the average scores of all respondents.

Throughout different stages (e.g., data generation, data storage, and data processing) of big data analysis life cycle, the privacy of our data is well protected following the privacy-preserving mechanisms mentioned in Mehmood, Natgunanathan, Xiang, Hua, and Guo (2016). In data generation stage, the access of the data is restricted by the data provider. We signed a non-disclosure agreement and it cannot be used for commercial purposes in data storage stage, after the modeling we do not keep the raw data. And lastly, in data processing stage, all Facebook users' information are anonymous with a machine generated user ID and sensitive attributes are modified or removed so it is unable to uniquely identify a person with information contained in the data. One of the main steps is to identify the mental state of each user. To do so, we use the CES-D (Center for Epidemiologic Studies Depression Scale) screening questionnaire as our primary tool to determine the level of user depression. The CES-D is one of the most common screening tests used by healthcare professionals to measure depression. It consists of a 20-item self-report scale that measures the symptoms of respondents associated with depression (Radloff, 1977). The test asks questions such as, *how often you have restless sleep, poor appetite, feeling lonely in a past period*. Response options range from 0 to 3 for each item (1) Rarely or None of the Time (less than 1 day) = 0; (2) Some or Little of the Time (1–2 days) = 1; (3) Moderately or Much of the time (3–4 days) = 2; (4) Most or Almost All the Time (5–7 days) = 3. The minimum score of a participant is 0 while the maximum is 60, where the higher scores indicate the presence of higher symptomatology of depression. A score of 16 or greater is the commonly used cut-off point to indicate individuals at risk of depression. However, the literature shows that a cut-off of 16 is likely to yield a high number of false-positives (Park, Cha, & Cha, 2012). Thus, several studies utilize higher cut-offs (e.g., 20, 22, or 27). In our study, we chose a score of 23 to be our threshold of a participant to be considered as depressed, as recommended by recent research (Park et al., 2012). As a result, users whose score is higher than or equal to 23 are labeled as *depressed*, and users whose score is lower than 23 are labeled as *non-depressed*.

For all the labeled users, we collect their Facebook status updates posted between February 2011 and July 2012. A total of *22,043,394* status updates from *153,727* users are collected. Every time a user posts an update, a status record for this user is generated. Each record contains rich information about the user and his actions. It consists of information such as user id, date, time, and friendship network that shows the properties and characteristics of the network used to examine the relationship among Facebook users.

4. Depressive behavior feature analysis

In this section, we first present our feature extraction strategies to find features that are likely to detect depression effectively. Then, we propose our feature inference methods to model user intention and friends' influence with respect to depression.

4.1. Depressive behavior feature extraction

In our dataset, each user is represented by several features. However, many of these features are not as effective in detecting depression and can cause performance issues particularly when dealing with large volumes of data. Dimension (or Feature) reduction is one of the most effective approaches to handle big data. To reduce the dimensions (e.g., features) of our dataset and to build a more effective model, we extract features that have the power to discriminate depressive behaviors from non-depressive ones. The linguistics features including syntactic and semantic features are extracted using LIWC (Linguistic Inquiry & World Count, 2019) from Facebook users status updates. LIWC is a computerized text analysis program that outputs the percentage of words in a given text that falls into one or more of over 80 linguistic, psychological and topical categories (Tausczik & Pennebaker, 2010). All the users Facebook status updates are aggregated into a single file and a LIWC analysis of combined status updates is executed for each user. The LIWC software then reports the percentages of the words in each LIWC category out of all of the words used in the combined status updates. We use LIWC category scores to identify an individual's: (1) use of specific types of parts-of-speech, such as articles and pronouns (e.g. we, you, she/he, they); (2) use of words that are associated with psychologically relevant categories, such as positive emotion words and negative emotion words.

4.1.1. Social network metrics

In the second step of our feature extraction, we focus on structural and generalized features existing in our datasets. Below, we present these features and how we extract them:

1 *NumStatus:* given all the status updates of a user, the total number of status updates in the dataset for each user is calculated. This feature represents how active the user is in a social network.

2 *AvgLength:* given all the status updates of a user, AvgLength is the average number of characters used by the user across all their status updates. We use this feature as an indicator of user involvement in a social network.
3 *InsomniaIdx:* literature shows that users with depressive behaviors tend to be more active at night. Hence, we calculate an insomnia index, similar to (De Choudhury et al., 2013), to quantify the posting patterns made by Facebook users during a day. To calculate this metric, we define a *day period* as "6 AM" to "9 PM" and a *night period* as "9 PM" and "6 AM", Eastern time. Then, we aggregate the number of status updates for each user posted during the *day period* and *night period* and define the insomnia index as the difference number of posts between night period and day period.
4 *Betweenness*: in a social network, betweenness represents the number of times a user acts as a bridge within the shortest path between two non-adjacent users. The betweenness of a user is calculated similar to Brandes (2001). The higher the probability of this user is located in a path, the higher the betweenness of the user is.
5 *Density*: this measure is expressed as the number of actual connections a user has divided by the maximum possible number of existing connections in the network. The value of density ranges from 0 to 1. The higher value means that the network is more dense and users in the network are more cohesive.
6 *Transitivity*: transitivity represents the probability of how many of the user's adjacent users are connected.
7 *Brokerage*: the number of friends of a user who are not directly connected to each other.
8 *Network size*: the number of connections (friends) of a user in a social network.

We calculate all the aforementioned features per user. These features are important as they present the structure of a user's network versus the content posted by users. As there are users who do not post update statuses frequently, such features are useful indicators to describe their mental states.

4.1.2. User personality factors

In this study, user personality represents the attitudes and responses of people to external environments. Several psychological studies show that personality features are important in different domains such as marketing (Adamopoulos, Ghose, & Todri, 2018). Moreover, some studies present their association with depression, and therefore, personality factors can be used in depression diagnosis and treatments (Bagby, Quilty, & Ryder, 2008; Klein et al., 2011). In our research, we use the IPIP questionnaire (the International Personality Item Pool) version of the NEO Personality Inventory (Goldberg et al., 2006) to assess Facebook users on the Big Five Factor Model of Personality. *Big Five Factor Model* of Personality is a widely accepted and is the most common used model of personality factor determination in academic psychology. The Big Five Factors are: *openness*, *conscientiousness*, *extraversion*, *agreeableness*, and *neuroticism* (McCrae & Costa, 1990; McCrae & John, 1992). IPIP is a questionnaire measures individuals on the five dimensions of personality defined by the Five-Factor Model of Personality. The test consists of questions that the user must rate on how true they are about themselves on a five-point scale, where 1 = Disagree, 3 = Neutral and 5 = Agree. The higher the score, the more agreeable the personality dimension is to the question. The full description of each trait is shown in Table 2.

As the output of this process, we extract five numerical features representing the personality traits of users.

4.2. Depressive behavior feature inference

In this section, we propose two new approaches to infer important aspects of a user that significantly contribute to identifying depression from social network activities.

Table 3 presents an example that depression can be studied from social networks by considering the content, user intention and the influence of friends' mental health on users'. In this table, we extract fours users and their status update from our real dataset. We also present the intention of the update status as well as the influence score representing how much a user is influenced by his/her depressed friends. According to our labeled data, both U_1 and U_2 are indicated as depressed users. By reading U_1's update status, we can argue that the negative sentiment of the content published by a user might be an indication of the user's mental wellness. On the other hand, even though U_2 is a depressed user, his recent status does not represent any negative sentiment, thus the depression. In our preliminary analysis, we discover that, U_2 might be under the influence of his depressed friends. As shown, the influence score of U_2 is 0.83 which is pretty high. Moreover, U_3 and U_4 are recognized as non-depressed users in this example, they had much smaller influence scores from their network even though their published contents are not necessarily positive (e.g., U_4's post is negative). In this table, we also present user intention in posting a message. The examples also show that the intention of depressed users can be different from non-depressed users.

4.2.1. Intention modeling

A social network is a platform where people express their thoughts and feelings with their friends and family. A large portion of status updates consists of words or sentences written by users in their own language. In addition to the syntax and semantic features extracted from words and sentences, we also propose to obtain pragmatic features to build an *intention model* that helps us better understand the content posted by users in a social network. *Programmatic*, also known as *speech act*, refers to the act of a sentence and it represents an action that indicates the intention of the user.

Several studies analyzed the linguistic content of social networks to detect depression. However, only a few of them focus on classifying the pragmatics of social network content and their impact on depression detection. As mentioned, speech act theory can be applied to study the pragmatics of contents in social networks. There has been extensive research done on speech act classification in computational linguistics, (e.g., Stolcke et al., 2000), however, such methods are not directly applicable to social network content such as status updates in Facebook. The main reason is that the nature of the language used in social network platforms such as Facebook is unconventional. In this section, we build a supervised intention model based on speech-act theory for status updates and use a manually annotated dataset to better understand the meaning of intention behind a status update.

Note that the user intention that we propose in this study is different from the one studied by the information retrieval (IR) community. The

Table 2
The five factor model of personality traits.

Factor	Trait (Low–High)
Neuroticism	Calm–Worrying, Even-tempered–Temperamental, Self-satisfied–Self-pitying, Comfortable–Self-conscious, Unemotional–Emotional, Hardy–Vulnerable
Extraversion	Reserved–Affectionate, Loner–Joiner, Quiet–Talkative, Passive–Active, Sober–Fun-loving, Unfeeling–Passionate
Openness	Down-to-earth–Imaginative, Uncreative–Creative, Conventional–Original, Prefer routine–Prefer variety, Uncurious–Curious, Conservative–Liberal
Agreeableness	Ruthless–Soft-hearted, Suspicious–Trusting, Stingy–Generous, Antagonistic–Acquiescent, Critical–Lenient, Irritable–Good-natured
Conscientiousness	Negligent–Conscientious, Lazy–Hardworking, Disorganized–Well-organized, Late–Punctual, Aimless–Ambitious, Quitting–Persevering

Table 3
Motivation example.

Users	Depression status	Update status	User intention	Influence score
U_1	Depressed	stop making me smile so much its hurting my face	Assertive	0.65
U_2	Depressed	A big Thank you to all the people who wished me on my birthday:)	Expressive	0.83
U_3	Non-depressed	I've decided if I see another person in a movie that looks like me I'm going to try acting.	Commissive	0.42
U_4	Non-depressed	is ready to chill with the relatives tomorrow at grandpa's house:D...still needs to finish my essay:/...absolutely hates that as time goes on, those you were once close to get torn away:(...kinda bummed about that	Commissive	0.33

user intent in IR refers to user modeling which focuses on user interests, preferences and context (Nguyen, Santos, Zhao, & Wang, 2004). The purpose is to capture and represent information on what a user is interested in, how the query can be built, and why the user dwells on a particular search topic. By inferring "what does the user want to do?", a context-aware application is expected to provide appropriate services/responses/search results for users in different domains such as office activities, websearch, medical records retrieval (dos Reis, Bonacin, Jensen, Hornung, & Baranauskas, 2018; Hwang, Kim, & Choi, 2011; Mendoza & Baeza-Yates, 2008). In our study, user intention is based on speech act theory that can be used to study the intention of users with the application of a taxonomy of communicative acts. The user intention in this study refers to *pragmatics* that look beyond the literal meaning of update statuses, and considers how intention contributes to their meaning. From this, one of the most important pragmatics is the intended communicative act of an update status or what the update status was meant to achieve. Our goal is not to model the user based on his/her interactions (e.g., IR approaches), but to have a deeper understanding of content posted by him/her. Note that, in any system that works based on linguistics (our proposed framework), pragmatics are of paramount importance as it considers what language is used for and what we do with language. The speech act theory is one of the most common approaches to study pragmatics as there is a formalized taxonomy of communicative acts. Therefore, our goal is to come up with an annotated dataset to build a classifier to understand the communicative acts behind Facebook posts.

Modeling intention can be defined as a multi-class classification problem in machine learning. Similar to any other classification problem, a large labeled dataset is needed. In order to build the dataset, we select users who are identified as *depressed* by CES-D Scale and who had at least five status updates throughout the whole data collection period. Then, we create a taxonomy of intentions for Facebook by identifying a set of commonly occurring acts. Table 4 shows the acts on which we focused. All the collected status updates are manually annotated by a group of students using the taxonomy presented in Table 4.

The label of "N/A" was assigned to status updates that were not written in the English language, or those that only contained punctuation marks. The distribution of the intentions for the labeled status messages is shown in Fig. 2. Examples of status updates for each speech-act category are listed in Table 5.

Given the annotated dataset, we identify the most important attributes from the content that can help the classifier identify the intention of a status update. After analyzing the content, we use swear words, speech act verbs, punctuations, and number of characters as the input of our classifier to determine the intention of each Facebook status update. These four attributes are highly correlated with respect to speech act types by indicating action of sentences and emotions of users.

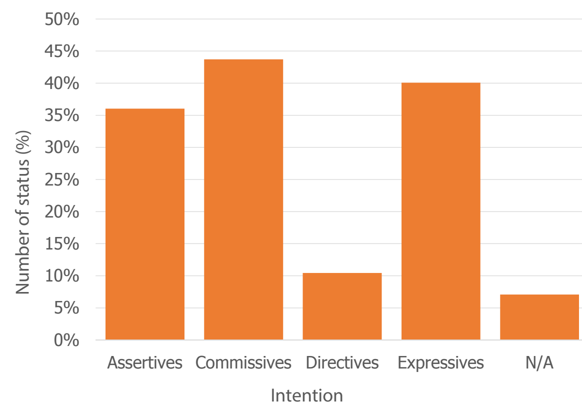


Fig. 2. Distribution of acts in the collected data during user intention modeling.

- *Swear words:* We use an online list of 351 swear words (Austin, 1975) to provide additional indication of emotions expressed in a status update. A binary feature is added to represent whether a vulgar word appeared in a status update or not.
- *Speech act verbs:* We use a collection of 229 English speech act verbs that are identified by Wierzbicka (1987) to represent speech-act types. Binary features are added to represent whether a speech act verb falling under specific categories appeared in a status update or not.
- *Punctuations:* Specific punctuations such as "?" and "!" may indicate certain speech act types. We add binary features to specify the appearance of these punctuation symbols.
- *Number of characters:* The number of characters used in a status update is also used as a feature to indicate a speech act type.

Given all the attributes and the annotated dataset, we train an intention model to determine the speech acts of a status message, which will serve as an additional component to our depression detection framework. Fig. 3 represents the proposed pipeline to detect the intention of a status update posted by a user.

4.2.2. Social influence analysis

Several studies have shown that people are affected by mental

Table 4
Acts taxonomy.

Type	Purpose of the speech act	Examples
Assertives	commit a speaker to the truth of an expressed proposition	statements, descriptions, and predictions, asserting, stating, concluding, boasting, describing, suggesting
Commissives	commit a speaker to some future action	promises, oaths, and bets, promising, pledging, threatening, vowing, offering
Directives	used by a speaker who attempts to get the addressee to carry out an action	orders, requests, and direction giving, requesting, advising, commanding, challenging, inviting, daring, entreating
Expressives	express some sort of psychological state	greetings, congratulations, and thanks, condolences, greeting, thanking, apologizing, complaining, congratulating

Table 5
Examples of status updates for each speech act category.

Speech Act	Example Facebook Status Update
Assertives	is back in Notts and had to put the heating on.
Commissives	is off on vacation in Florida until Tuesday August 10. First, going to a wedding, then exploring Disney World!
Directives	Please vote today:) The pollsters think that only 1 in 3 young people will bother. Prove them wrong and get more attention on youth issues (do you remember those questions about student fees and youth unemployment in the TV debates? Nope. Me neither).
Expressives	Hugs to Liv Lee, Zuzannah, Michal Kosinski, Luning, Iva Cek, Ning and everyone else there this weekend!:o)

illness either directly or indirectly through family, friends or colleague (Government of Canada, 2017). As a result, we argue that the mental state of Facebook users is associated with the friends the users have in their network. A main challenge to studying the network structure and estimating the friendship influence is the fact that among all Facebook users, we usually have access to a small portion of users whose mental status is clearly established as depressed or non-depressed. Among the users who have test results available for analysis, very few of them are direct friends in the network. Some studies only focus on such users and therefore limit the study to the direct friends with a determined mental state, thus use inadequate information. In this work, we expand the analyses to explore connections beyond direct connections of Facebook users by investigating indirect friends in their social network. This gives us a greater chance to take advantage of more available information. We propose two different approaches, *shortest path-based analysis* and *user intention based analysis*, to study the friends' influence by examining the indirect neighbors of a user.

4.2.3. Shortest path-based analysis

As mentioned, closer friends usually have more impact on a user. In this section, we propose an analysis based on the concept of the *shortest path* to estimate friends influence. To explain how this analysis works, we illustrate it by an example. Fig. 4 shows an example of our target user *Tony* who has only Nancy and Jack as his direct friends with available assessment results. According to this network, we also know that Linda and Frank are indirect connections to Tony whose depression statuses are known. We argue that the closer the connection is, the more impact it should have on Tony. Therefore, since Nancy and Linda are direct neighbors to Tony, Tony has a greater chance of being affected by the mental states of Nancy and Linda. If Nancy and Linda are assessed as depressed, then Tony may have a higher chance of being influenced by depression. Moreover, Jack is Tony's friend's friend. They might also have several interests in common, therefore Jack might have an impact on Tony's mental state as well. However, it should not be as strong as Nancy's and Linda's.

To consider different levels of influence for user's neighbors, let j be the jth connection to Tony. For example, we define the distance between Tony and his first neighbors (e.g., Nancy and Linda) to be 1, the distance between Tony and his second level connection (e.g., Jack) to be 2, and the distance between Tony and his third connections (e.g., Frank) to be 3 and so on. Since we argue that the closer a friend is to the user, the higher chance the user is affected by the friend, then Nancy and Linda affect Tony more than Jack, and Jack affects Tony more than

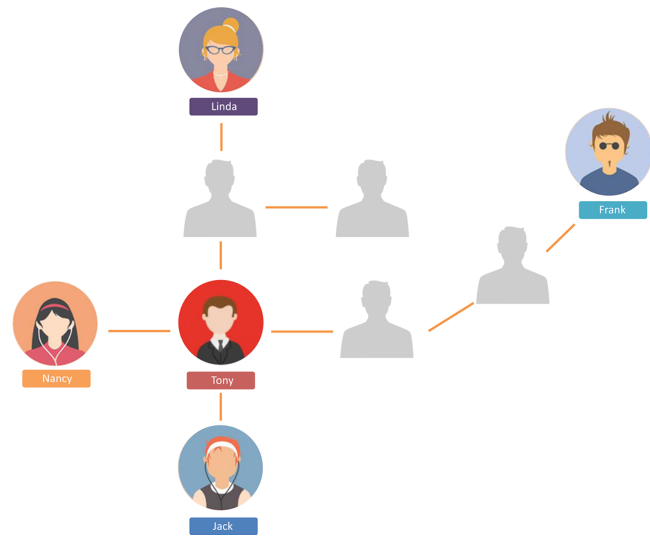


Fig. 4. Friends' influence analysis using the shortest path.

Frank. Assuming we have m levels of Tony's friends, we assign a weight of $m - j + 1$ to the jth level friend for Tony. As a result, we assign a weight of m to Nancy and Linda to indicate the level of influence they have on Tony. Jack who has less influence on Tony is assigned with a weight of $m - 1$. We assign a weight of $m - 2$ to Frank because he has an even lower chance to affect Tony and so on. We define this method as the shortest path approach to calculate the influence score of the nearest possible neighbors.

The proposed approach works as follows. We first run a shortest path estimator for the whole friendship network. We estimate the shortest path between each user and calculate the possibility that the target user is affected by its neighbors. Given user U with k neighbors $[N_1, N_2, \ldots, N_k]$, we define the weight of U and his neighbors as $W_{U,N_i} = m - j + 1$ and a binary variable I that represents the mental state of the neighbor where $I = 0$ means that the user is not depressed and $I = 1$ means that the user is depressed. Then, the possibility of each depressed neighbor affects the target user U is defined as:

$$P(U|N_i) = \frac{W_{U,N_i} \times I}{\sum_{i=1}^{k} W_{U,N_i}} \tag{1}$$

Accordingly, the influence score of user U's depressed neighbors is

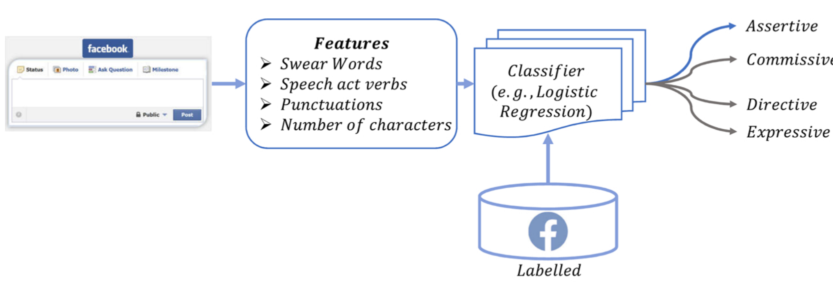


Fig. 3. The proposed intention modeling pipeline.

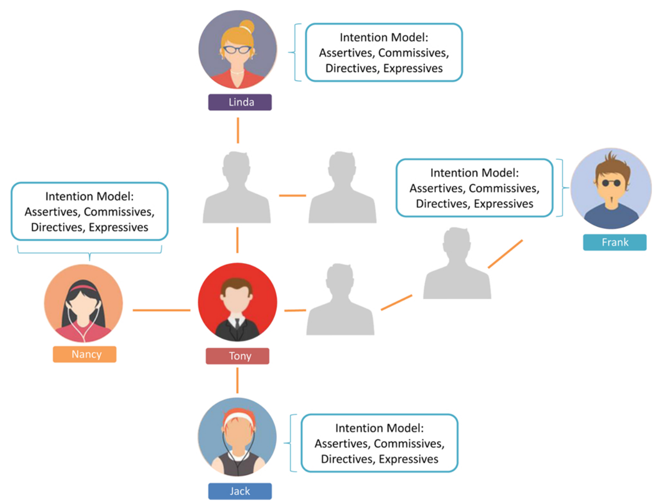


Fig. 5. Friend influence analysis based on user intentions.

denoted and calculated as follows:

$$\text{InfScore}_{\text{SHP}}(U, [N_1, \ldots, N_k]) = \sum_{i=1}^{k} P(U|N_i) \tag{2}$$

4.2.4. User intention based analysis

The second approach is to estimate friends influence based on the intention model. We argue that a negative mood is transferable from one person to another during social interactions. Therefore, the negative status updates and the intention behind them may spread through friendship networks resulting a higher occurrence of similarly negative status updates. Since the proposed intention model represents the true motivation of individuals, the more similar the intention models of two nearby users are, the more likely one user gets affected by the other one. That is, two users with similar intention model understand each other better, therefore they have a higher influence on each other. To estimate friends influence using the intention model, we consider the intention similarity as the second approach to find the level of influence friends may have on a user.

We illustrate this approach by an example. Fig. 5 presents a friendship network of Tony. In this figure, Tony has Nancy, Linda, Jack and Frank as his first, second and third level connections with available assessment test results and user intention models. Given user U, we represent each user as an intention distribution based on five main acts described in Section 4.2 as follows: *IntModel*(U) = $\{f_{1U}, f_{2U}, f_{3U}, f_{4U}\}$, where f_{iU} represents the weight of act i for the user U.

Given the intentions distribution, the target user U and his connection N_i, we calculate the similarity of the target user (e.g., Tony) and his neighbors' based on their *IntModel* vector by using *Euclidean distance*. Since there are four acts, the equation to calculate the similarity of each user-neighbor pair is as follows:

$$d(U, N_i) = \sqrt{\left(f_{1U} - f_{1N_i}\right)^2 + \left(f_{2u} - f_{2N_i}\right)^2 + \left(f_{3u} - f_{3N_i}\right)^2 + \left(f_{4u} - f_{4N_i}\right)^2} \tag{3}$$

To build the friendship network with users whose assessment results are available, we run a shortest path for the whole network and find all the connections with available assessment results to the target user. Similarly, the influence score of user U's depressed neighbors is calculated as:

$$\text{InfScore}_{\text{INT}}(U, [N_1, \ldots, N_k] = \frac{\sum_{i=1}^{k} d(U, N_i) \times I}{\sum_{i=1}^{k} d(U, N_i)} \tag{4}$$

where $\{N_1, \ldots, N_k\}$ are all the connections and I is a binary variable ($I = 0$, user is not depressed; $I = 1$, user is depressed).

Given both scores $InfScore_{SHP}$ and $InfScore_{INT}$, we create two extra features to store the influence score values for each user in our data set using both approaches. The friends' influence features indicate that how much users are influenced by their depressed friends. The values are between 0 to 1.

5. Depression detection

Each user in our social network is modeled as a vector of features. In this section, user models will be the input for different machine learning algorithms to detect depression. In our research, we use different supervised machine learning algorithms to build a model to detect the depression risk of social network users. We mainly used seven machine learning algorithms: (1) *K-Nearest Neighbors (KNN)*, (2) *Logistic Regression (LR)*, (3) *Naive Bayes (NB)*, (4) *Neural Network (NN)*, (5) *Random Forest(RF)*, (6) *Linear Support Vector Machine (SVM)*, and *Classification and Regression Trees(CART)*.

6. Experimental results and discussions

In this section, we evaluate the effectiveness of the proposed framework. Note that, the proposed framework can be implemented based on both single node and cluster. The experimental environment for the cluster consists of one master node and six worker nodes. Each node is equipped with Intel Xeon 2.6 GHz (each 12 core) and 128 GB main memory. All the classification algorithms are implemented based on *Apache Spark 2.3.0*.

6.1. Dataset

As mentioned, we acquire our datasets from the myPersonality dataset (Stillwell & Kosinski, 2012) that include Facebook users information with *22,043,394* Facebook status updates from *153,727* users and their responses to the International Personality Item Pool (*IPIP*) version of the NEO Personality Inventory, and to the Center for Epidemiologic Studies Depression Scale (*CES-D* Scale) questionnaire. From these datasets, we define attributes as shown in our proposed framework, which can be used to characterize depressive behaviors including personality traits scores, social network metrics, social influence and semantic, syntactic, and intention attributes from Facebook user status updates.

6.2. Performance metrics

Several performance metrics are used to evaluate the performance of the proposed framework. The confusion matrix is the most straightforward way to evaluate the effectiveness of the framework. A Confusion matrix for a two-class problem with positive (e.g., depressed users) and negative (e.g., non-depressed users) class values are shown in Table 6.

From this table, we derive the following performance metrics:

1 Accuracy = $\frac{TP + TN}{TP + TN + FP + FN}$
2 Balanced accuracy is defined as the average accuracy obtained on either class $\frac{1}{2}(\frac{TP}{TP + FN} + \frac{TN}{FP + TN})$ in binary classification.
3 Precision = $\frac{TP}{TP + TN + FP + FN}$ is the ratio of number of positive cases correctly classifier to positive class and the total number of elements.

Table 6
Confusion matrix for a binary classifier.

	Prediction positive class	Prediction negative class
Actual positive class	True positive (TP)	False positive (FN)
Actual negative class	False positive (FP)	True negative (TN)

4 Recall = TPR = $\frac{TP}{TP + FN}$ is the rate of positive cases correctly classified to be in positive class
5 F-Score = $2 \times \frac{Precision \cdot Recall}{Precision + Recall}$. It is the harmonic average of the precision and recall, where an F-Score reaches its best value at 1 (perfect precision and recall) and worst at 0.

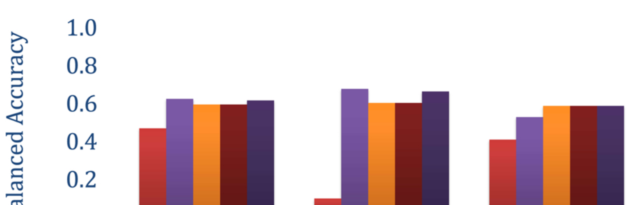
In our study, we also use the *ROC(AUC) curve* and *Kappa* as our predictive performance indicators.

- ROC curve is a probability curve of the true positive rate (TPR) (on the y-axis) versus the false positive rate (FPR) (on the x-axis). It is a commonly used way to visualize the performance of a binary classifier.
- AUC which stands for area under the curve, is used to quantify the performance of a classifier. AUC measures the entire two-dimensional area underneath the entire ROC curve. AUC ranges from 0 to 1 where AUC = 1 means a "perfect" classifier and AUC = 0 means a worst classifier. If AUC = 0.5, the corresponding classification model is worthless, as its predictive ability is no better than random guessing.
- Kappa measures inter-rater agreement for categorical items. It is defined as $1 - \frac{1 - p_0}{1 - p_e}$, where p_0 is the observed agreement and p_e is the expected agreement.

6.3. Intention modeling performance

In this section, we present the performance of our proposed model to detect the user intention. Since a status of user can represent one of the five main intentions, we define the problem as a multiclass classification problem. This also follows recent research on modeling user intention using speech-act (Vosoughi & Roy, 2016). In our dataset, most of the annotated content belongs to three main acts: assertive, directive and expressive. Therefore, we focus on predicting these three acts as they are the most common act types with respect to depressed users in the dataset. We randomly split our dataset by allocating 80% for our training set and 20% for our hold out test set. On the training set, we used 10-fold cross-validation for all methods. We compare the performance of the four classifiers with a baseline classifier. The baseline classifier is designed using the existing text classification techniques. That is, after careful pre-processing such as tokenization and word stemming, we vectorize the statuses based on TF-IDF model (Manning, Raghavan, & Schütze, 2010) and then run a machine learning algorithm (in our case CART) to detect the intention of an update status.

Fig. 6 shows the performance of the methods in detecting user intention. In this figure, all the methods outperform the baseline significantly. Moreover, the proposed model work generally better in predicting expressive act which is the most common act among depressed users. Figs. 7 and 8 show the results of our proposed intention



	Assertives	Directives	Expressives
Baseline	0.4700	0.1000	0.4100
CART	0.6250	0.6774	0.5290
KNN	0.5950	0.6036	0.5877
RF	0.5950	0.6036	0.5877
SVM	0.6165	0.6639	0.5876

Fig. 6. Balanced accuracy for intention modeling.

modeling in terms of precision, recall, and F-Score. As shown, using the proposed model and features, machine learning methods work significantly better than the baseline in detecting user intention.

According to Figs. 6–8, CART has the highest balanced accuracy in *assertive* and *directives* acts, highest precision for all intention types, and highest recall in *directives* and *expressive*.

The results indicate that the CART method performs best for two out of three intention types for all the performance metrics. Based on these results, the CART model is used to detect user intention via the status updates that will be used in the next section for predicting depression risk.

6.4. Depression prediction performance

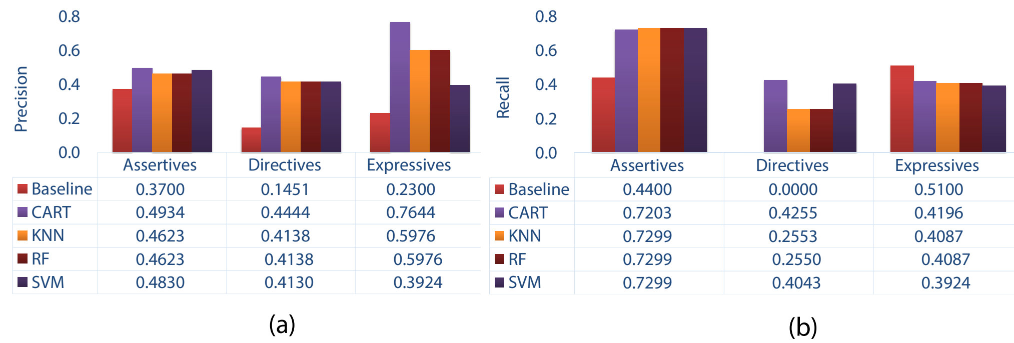
We use the proposed framework to train seven different classifiers on our data to predict depression. We randomly split out dataset including features presented proposed by our framework into 80% of training data and 20% testing data. Then we conduct 10-fold cross-validation for all machine learning techniques. We compare the performance of the classifiers on the test data set in terms of balanced accuracy, accuracy, precision, and recall. The results are presented in Fig. 9. The random forest has the best recall, accuracy and balanced accuracy results among all machine learning methods, except it has a lower precision measure than CART. However, CART has much lower measures in the other three performance metrics. The results indicate that the random forest model yields the best performance with an accuracy of 71.21%, a balanced accuracy of 68.42%, a precision of 70.21% and a recall of 86.84% while logistics regression shows the worst performance with lowest precision, accuracy and balanced accuracy among all other machine learning methods. The results assert that the proposed features can effectively detect depression of a user in Facebook.

6.5. Effectiveness of different feature sets

In this section, we identify the best feature set to detect depression and show the importance of the proposed features in identifying user depression. To do so, we calculate the importance of features using Random Forest. Fig. 10 presents the top 20 important variables and their scores from the most important to the least important with respect to their power to detect depression. Among the top-5 most important features, neuroticism, conscientiousness, and extraversion take 1st, 2nd and 3rd rank. Our feature analysis represents a weight per feature that shows the importance and effectiveness of the feature in detecting depression. These weights can be used balance the user intention and friends influence impacts on the results. Note that, these weights can be changed based on the input dataset. The other approach is to let the learning algorithm assigns the importance weight to the features. In our experiments, the balance between features will be set by the learning algorithms. We also show that important features can change the performance of the algorithms.

We run another set of experiments to explore the features that yield the best prediction performance for our models. For these experiments, we use the random forest method, since it yields the highest balanced accuracy, accuracy, and recall measures. We run the method using different subsets of features. The details of feature subsets are presented in Table 7.

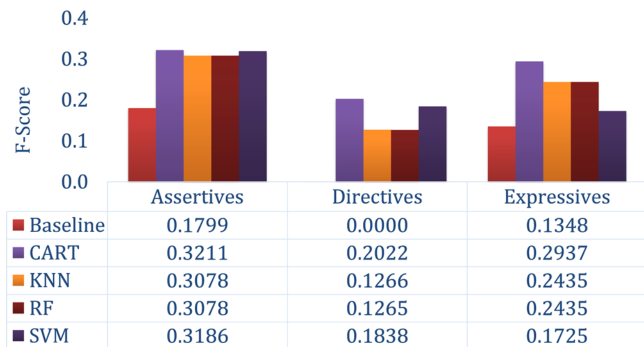
Our goal is to show that different sets of features will return different performance results. We compare the performance metrics precision, recall, F-Score, AUC, accuracy, and Kappa for all eight different feature sets presented in Fig. 11. Fig. 11 shows that the model based on *FS1* with all the features does not necessarily generate the best performances in terms of accuracy, precision, AUC or Kappa. The model based on *FS8* with Top 10 features obtains a higher accuracy, precision and Kappa compared to FS1. This indicates that not all of the features help increase the performance metrics. Compared to model FS2, the



(a) Precision	Assertives	Directives	Expressives
Baseline	0.3700	0.1451	0.2300
CART	0.4934	0.4444	0.7644
KNN	0.4623	0.4138	0.5976
RF	0.4623	0.4138	0.5976
SVM	0.4830	0.4130	0.3924

(b) Recall	Assertives	Directives	Expressives
Baseline	0.4400	0.0000	0.5100
CART	0.7203	0.4255	0.4196
KNN	0.7299	0.2553	0.4087
RF	0.7299	0.2550	0.4087
SVM	0.7299	0.4043	0.3924

Fig. 7. Intention modeling performance in terms of: (a) Precision and (b) Recall.



	Assertives	Directives	Expressives
Baseline	0.1799	0.0000	0.1348
CART	0.3211	0.2022	0.2937
KNN	0.3078	0.1266	0.2435
RF	0.3078	0.1265	0.2435
SVM	0.3186	0.1838	0.1725

Fig. 8. Intention modeling performance in terms of F-Score.

model based on FS7 shows higher precision, F_1, AUC, accuracy and Kappa. This illustrates that data based on users' social network activities provides more beneficial information for observing the depressive behaviors of users. Moreover, the model based on FS3 and FS4, which includes personality and social influence features, produces better results in all performance metrics for predicting depression compared to the model based on FS2 with only linguistics features.

7. Discussions and implications

The literature on depression detection indicates that the use of social network data is an efficient way to overcome the gaps in conventional approaches to diagnosing depression by providing additional data points. In this context, existing methods mainly focus on linguistic features and personality while other related aspects such as social impact or user intention have remained unexplored. The main challenge is how to effectively incorporate new measures of a users activities to represent other related aspects. In this regard, we study the intention of users' activities and users' social influence in detecting depression. Our results show that the proposed framework improves the performance of the existing approaches in depression detection and could be used by clinicians to monitor the depression risks and provide treatment promptly. We also show that our findings are aligned with existing studies in psychology which is an important achievement.

We argue that, identifying the set of features is essential to achieve the best performance for the depression detection model. That is, all available features are not necessarily the best features and there are latent but important features in the data that need to be extracted or inferred. The results of our data-driven feature analysis using random forest are consistent with those from a previous study by Klein et al. (2011). Depression is most often related to the following personality traits: *neuroticism*, *extraversion* and *conscientiousness*. In addition, two

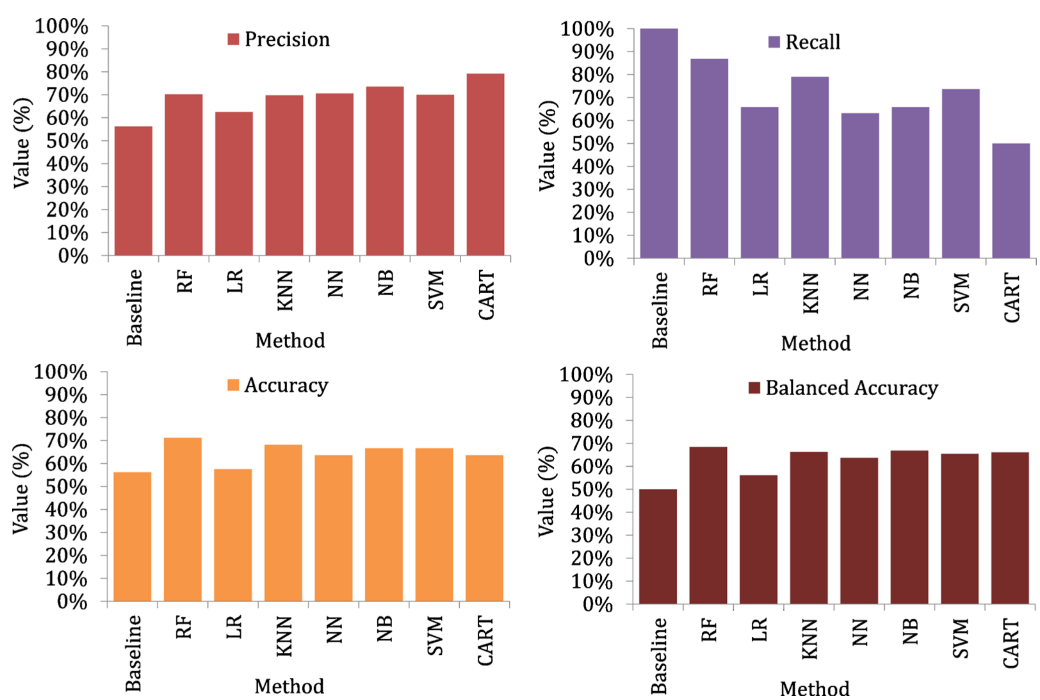


Fig. 9. Depression detection performance for different machine learning methods.

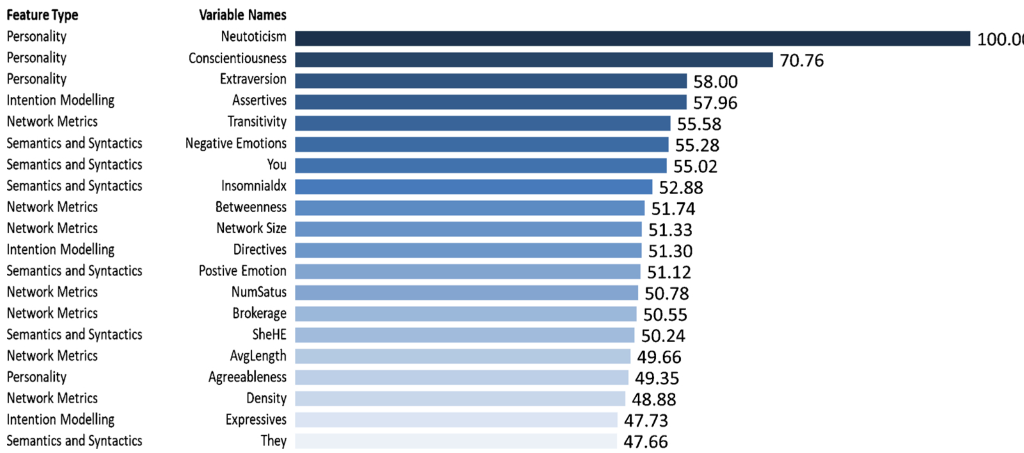


Fig. 10. Top 20 important variables.

speech act types *assertives*, *directives*, and *insomnia index*, which are ranked 4th, 11th, 8th respectively, are the most important ones in detecting depression. Moreover, the *negative emotions* feature is another effective feature which is ranked 6th in our analysis. These findings provide support to the conclusion of Segrin (2000) that negative statements and sadness, which may manifest in assertives and directives types of speech acts, are associated with depression.

We show that a model that includes a subset of features produces better results with respect to the performance metrics. For example, the feature set contains social influence, personality and user intention achieve better performance in different measures such as AUC, accuracy and F-Score. The experimental results confirm that the performance of different machine learning algorithms for detecting depression depends on the input features. Given the same feature set, we found that random forest outperforms other algorithms such CART, SVM, NP in terms of accuracy and balanced accuracy. The proposed framework achieved the average precision of 75%, average recall 85%, average accuracy of 68% and average balanced accuracy of 69%. Note that such performance is achieved by considering both the user intention model and social impact as input features along with syntactic and semantic features. We also evaluated a model that incorporates social influence features (i.e., *FS4*) and showed that social influence achieves highest performance in terms all of the performance metrics compared to models with only linguistics features (i.e., FS2) proposed by Schwartz et al. (2014) and Li et al. (2018). In comparison to the model with personality traits (i.e., FS5) studied in Klein et al. (2011), which examines the relationship between personality traits and depression, the model with the user intention (i.e., FS6) outperforms the model with only personality traits. By comparing the proposed framework with the leading existing frameworks, we assert that although social network activities (e.g., posts) provide insightful information for depression detection, the proposed intention model and the social impact scores are more effective indicators in identifying users' depression state. Overall, the social network provides more information related to users' depressive behaviors and offer opportunities to better determine the personality, true intention behind the status updates, and social impact from the social networks to improve depression detection.

7.1. Research contributions

A key component to diagnosing depression is administering a screening questionnaire, that relies on patient self-report data. Such questionnaires are necessary, but they produce relatively little data at a high cost. Social networks are a potential source of data that can supplement current practices. The availability of such data and advances in machine learning techniques raise an interesting question: Can we model users' behaviors and their mental states in a social network to help clinicians diagnose depression more effectively? Clearly, it is unrealistic to expect to train a general model that works for all users. Moreover, the model should consider individual cognitive aspects of a user (e.g., personality type, activities, etc.) even if they might be in conflict with one another. Although building a framework to model users' mental behaviors and their depression risks is desirable, we are faced with several challenges: (1) Big data, big value, big challenges; (2) Limitations of traditional depression diagnosis methods; (3) Limitations of existing social network based depression detection; (4) Users' social influence on social networks. In order to tackle these challenges, we propose a framework with the use of machine learning techniques that we believe can provide clinicians with supplemental information related to users social interactions to identify depression. In our framework, we advance current literature that uses linguistics and personality schedules for depression prediction by proposing a data-driven user intention model and two different approaches to compute the social influence of a user from his/her friendship network. In order to better understand the content posted by Facebook users, we propose to use pragmatic features, which refers to the act of a sentence, to build

Table 7
Different feature sets.

#	Features description
FS1	All Features include personality scores, social network metrics, social influence, semantic and syntactic, intention model
FS2	Linguistic features include semantic and syntactic features
FS3	Linguistic and Personality include semantic and syntactic features, and user personality traits
FS4	Social influence based on linguistics features include semantic and syntactic features, and social influence measured by the shortest path and the intention model similarity
FS5	Personality features include personality traits scores
FS6	Personality and intentional modeling - include only the personality traits scores and use of the intention model
FS7	Linguistic, Personality, Network Metric and Social Influence based on linguistics features includes semantic and syntactic features, personality traits scores, social network metrics and social influence measured by the shortest path and the intention model similarity
FS8	Top 10 features includes Personality traits: neuroticism, extraversion and conscientiousness; Intention model: assertives; Network Metrics: transitivity, negative emotion, insomnia index, betweenness, network size and semantic and syntactic: you

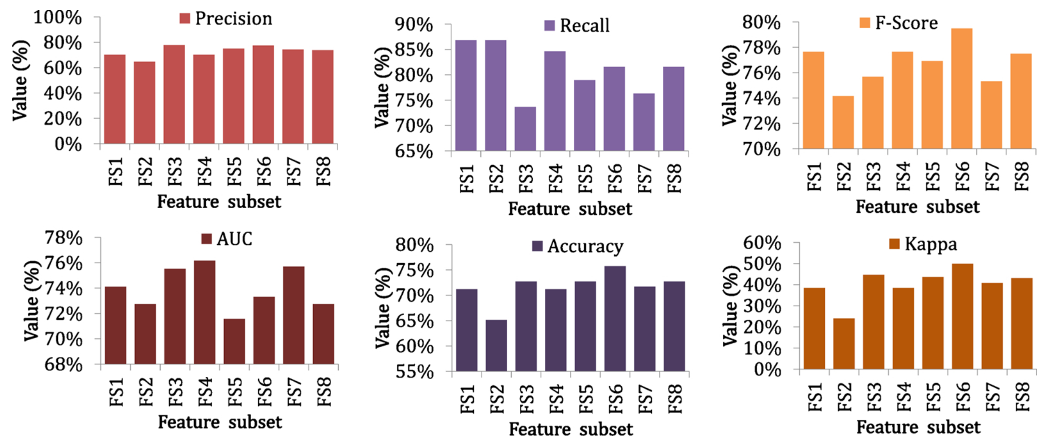


Fig. 11. The prediction power of different feature sets.

an intention model that indicates the intention of the user. To study the influence of friends in a social network, we expand our analyses by not only exploring users' direct connection but also investigating indirect friends in their social network. We obtain social influence scores by proposing a shortest path-based analysis that calculate the closeness based on network structure and intention-based analysis that finds the similarities of users based on their intention model. By taking advantage of big data technologies (e.g., Apache Spark), our framework also shows a scalable power for dealing with large number of users' information.

7.2. Implications for practice

The ability to predict depression risk in early stages via social network data in combination with linguistics features, personality, intention modeling and social influence provides a good opportunity to facilitate platform or system detection for early warning signs. Our framework shows the potential of adding detection into an overall wellness strategy that can provide referrals to individuals who are not aware of their mental states or who are not actively seeking for medical help or access to mental health resources.

Our framework that detects depression behaviors in an early state from the users' past experiences and interactions, has several potential implications for clinical psychological practice. First, our framework in combination with social network information provides accessible knowledge for health care providers to supplement techniques used to identify individuals with depression and development of personalized treatment plan. This method has the potential to become a future clinical tool that combines several sources of individual's language features based on social network and other sources to discover those who may need special mental illness treatment without requiring extra questionnaires or self-reporting responses. Second, the proposed framework provides a scalable platform for a large number of users which supports the possibility of using social network analysis as a remote detection tool to monitor the dynamic depressive states and treatment process of users through artificial intelligence particularly when in-person meetings are difficult. Third, this framework may be used to raise awareness and recognition outside the medical system. There is evidence that depression is becoming a significant issue at work place and in school, thus it is important that there is greater awareness among employers and educators that depression is impacting employees at work place and students on campus. It also raises the concern that skate holders should make efforts to effectively support individuals who are faced with considerable barrier of seeking treatment when symptoms worsen.

In addition to detecting depression, we see the potential of working with medical professionals by applying an adapted version of the framework to support other similar disorders such as stress detection or anxiety detection. Moreover, we believe our framework can also be a useful tool to detect the occurrence of social network platform bullying (Chan, Cheung, & Wong, 2019) by considering social network users' personality, language features and social influence features. Previous research on social network platform bully shows that users with risky social networking practices and certain personality characterizers are more vulnerable to cyberbullying victimization (Peluchette, Karl, Wood, & Williams, 2015). By monitoring social network posts and analyzing users' intention, our framework could be useful in curbing occurrences of cyberbullying victimization.

7.3. Limitations and future research direction

We acknowledge that there are valid concerns raised by critical media scholars about using machine learning to analyze or predict user behavior for mental health purposes. There are instances where the intention of using these types of analytical frameworks build in and upon biases in datasets that can bring additional harm to members of the broader community - especially those in under-represented social groups such as people of color and other minority groups. The concerns raised are a reminder to those of us designing these systems that we must consider a broad range of data and include factors that are otherwise ignored. In this study, we recognize the challenge and try to increase the analytical breath of the framework to mitigate this problem. We reiterate that the framework becomes an additional tool to be used by mental health and medical professionals as they develop an broader treatment and follow-up plan for consenting users.

Our research suggests that there is a high chance that the friends' influence in the network has strong impact on individual's mental state. In particular, what friends post on the online platforms, positive or negative, may affect their neighbors mental states. As future work, we aim to improve our social influence scores by considering the topics a user is posting online. In this way, we can further investigate friends' influence by topic level of each user's status updates and may achieve more accurate social influence scores. Moreover, in this study, we considered one intention category per update status. We will investigate if an update status can be represented as a combination of intention categories. This will bring a new insight about the intention of update statuses posted by a user. As another direction, we plan to build an expert system for clinicians using the proposed framework. This requires to collaborating with medical professionals for additional studies of different age groups, genders and their different risk level of depression.

8. Conclusions

Our study presented a data-driven depression detection framework with the use of machine learning techniques. Our objective is to provide a tool for mental health professionals in monitoring the depressive behaviors of people who are at the risk of depression and providing supplemental information on users' behaviors in social networks. We illustrated that the user intention model based on speech act theory and social influence scores from friendship network have the potential to enhance prediction performance of existing depression detection methods. The proposed framework is designed and implemented based on a big data platform (i.e., Apache Spark) which has scalable power to identify social network users mental state considering both social-level and user-level features without solely relying on questionnaires. It would benefit clinicians to support better depression detection while providing mechanisms using existing datasets to allow for easier follow-up in treatment plans.

Author contributions

Xingwei Yang: Writing – original draft preparation, methodology, visualization

Liza Robee Ong: Investigation, data curation

Morteza Zihayat: Supervision, conceptualization, methodology, software

Rhonda MacEwen: Writing – reviewing and editing, supervision

Appendix

Center for Epidemiologic Studies Depression Scale (CES-D), NIMH

Below is a list of the ways you might have felt or behaved. Please tell me how often you have felt this way during the past week.

	During the Past Week			
	Rarely or none of the time (less than 1 day)	Some or a little of the time (1-2 days)	Occasionally or a moderate amount of time (3-4 days)	Most or all of the time (5-7 days)
1. I was bothered by things that usually don't bother me.	☐	☐	☐	☐
2. I did not feel like eating; my appetite was poor.	☐	☐	☐	☐
3. I felt that I could not shake off the blues even with help from my family or friends.	☐	☐	☐	☐
4. I felt I was just as good as other people.	☐	☐	☐	☐
5. I had trouble keeping my mind on what I was doing.	☐	☐	☐	☐
6. I felt depressed.	☐	☐	☐	☐
7. I felt that everything I did was an effort.	☐	☐	☐	☐
8. I felt hopeful about the future.	☐	☐	☐	☐
9. I thought my life had been a failure.	☐	☐	☐	☐
10. I felt fearful.	☐	☐	☐	☐
11. My sleep was restless.	☐	☐	☐	☐
12. I was happy.	☐	☐	☐	☐
13. I talked less than usual.	☐	☐	☐	☐
14. I felt lonely.	☐	☐	☐	☐
15. People were unfriendly.	☐	☐	☐	☐
16. I enjoyed life.	☐	☐	☐	☐
17. I had crying spells.	☐	☐	☐	☐
18. I felt sad.	☐	☐	☐	☐
19. I felt that people dislike me.	☐	☐	☐	☐
20. I could not get "going."	☐	☐	☐	☐

SCORING: zero for answers in the first column, 1 for answers in the second column, 2 for answers in the third column, 3 for answers in the fourth column. The scoring of positive items is reversed. Possible range of scores is zero to 60, with the higher scores indicating the presence of more symptomatology.

Introduction

This is a personality test, it will help you understand why you act the way that you do and how your personality is structured. Please follow the instructions below, scoring and results are on the next page.

Instructions

In the table below, for each statement 1-50 mark how much you agree with on the scale 1-5, where 1=disagree, 2=slightly disagree, 3=neutral, 4=slightly agree and 5=agree, in the box to the left of it.

Test

Rating	I....	Rating	I.....
	1. Am the life of the party.		26. Have little to say.
	2. Feel little concern for others.		27. Have a soft heart.
	3. Am always prepared.		28. Often forget to put things back in their proper place.
	4. Get stressed out easily.		29. Get upset easily.
	5. Have a rich vocabulary.		30. Do not have a good imagination.
	6. Don't talk a lot.		31. Talk to a lot of different people at parties.
	7. Am interested in people.		32. Am not really interested in others.
	8. Leave my belongings around.		33. Like order.
	9. Am relaxed most of the time.		34. Change my mood a lot.
	10. Have difficulty understanding abstract ideas.		35. Am quick to understand things.
	11. Feel comfortable around people.		36. Don't like to draw attention to myself.
	12. Insult people.		37. Take time out for others.
	13. Pay attention to details.		38. Shirk my duties.
	14. Worry about things.		39. Have frequent mood swings.
	15. Have a vivid imagination.		40. Use difficult words.
	16. Keep in the background.		41. Don't mind being the center of attention.
	17. Sympathize with others' feelings.		42. Feel others' emotions.
	18. Make a mess of things.		43. Follow a schedule.
	19. Seldom feel blue.		44. Get irritated easily.
	20. Am not interested in abstract ideas.		45. Spend time reflecting on things.
	21. Start conversations.		46. Am quiet around strangers.
	22. Am not interested in other people's problems.		47. Make people feel at ease.
	23. Get chores done right away.		48. Am exacting in my work.
	24. Am easily disturbed.		49. Often feel blue.
	25. Have excellent ideas.		50. Am full of ideas.

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Xingwei Yang is a PhD student in Management Analytics at the Smith School of Business at Queen's University. She received her B.Sc. in Mathematics from University of British Columbia. Her research interests are in the area of machine learning, financial mathematics, business analytics and big data.

Rhonda McEwen is Canada Research Chair in Tactile Interfaces, Communication and Cognition and is an Associate Professor of New Media & Communication. Dr. McEwen is the Director of the Institute of Communication, Culture, Information and Technology at the University of Toronto Mississauga. With an MBA in IT from City University in London, England; an MSc in Telecommunications from the University of Colorado; and a PhD in Information from University of Toronto, Dr. McEwen combines communication studies, applied, and behavioral sciences to examine the social and cognitive effects of technologies. Her pioneering approach to using experimental techniques, eye tracking, observations, sensor data, and interviews to investigate Human-Machine Communication involving children and adults across the user spectrum, and including those diagnosed with communication and learning disorders. Dr. McEwen has worked with and researched digital communications media for over 20 years, both in companies providing services, and in management consulting to those companies. Journalists from CBS

newsmagazine 60 Minutes covered McEwen's research in 2012 & 2013, and she has recent publications in Information, Communication & Society, Computers and Education, Learning & Instruction, New Media and Society, and in library and information science journals. Understanding Tablets from Early Childhood to Adulthood is her recently co-authored book.

Liza Robee Ong is a master student in Data Science Program at Ryerson University. Her main research interests are user behavior modeling and big data.

Morteza Zihayat is an assistant professor at Ted Rogers School of Information Technology Management at Ryerson University. Before joining TRSITM, Dr. Zihayat was a Postdoctoral Research Fellow in the Faculty of Information (iSchool) at the University of Toronto. He was also a research fellow in the IBM Spectrum Computing as a member of the BRAIN ALLIANCE – Big Data Research, Analytics, and Information Network. His research concerns machine learning, user modeling and big data analytics. He was recently awarded multiple research grants from government (NSERC and MITACS) and private sectors (IBM Canada). He is a recipient of several institutional awards, including an Outstanding PhD Dissertation Award and Dean's Scholarly Research and Creativity Activity Award. Dr. Zihayat obtained his PhD from York University where he worked on designing scalable frameworks to discover actionable knowledge from Big Data streams and social networks. He has published in various well-respected journals and conferences in data mining, machine learning and information systems such as Decision Support Systems, Information Sciences, ACM SIGKDD, PKDD, SDM SIAM, EDBT.