STUDYING DEPRESSION USING LINGUISTIC FEATURES FROM MULTIPLE SOCIAL MEDIA SOURCES

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I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality as a dissertation for the degree of Computer and Information Science.

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Approved for the University of Pennsylvania Committee on Graduate Studies

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Abstract

Depression is one of the major mental health problems of the world. Many cases of depression remain undetected due to restrictive nature of clinical studies and personal or societal stigma associated with this ailment. The scarcity of clinically validated data has made it difficult to achieve reliable machine learning models for depression prediction.

The data of users on social media who self declare symptoms of depression but have not been explicitly screened for depression using a reliable scale is considered to be weakly labelled data (Self-Declared). Though neuroticism is a condition strongly associated with depression, neuroticism data (N7) of users abstracted from generalised personality test surveys which are not specific to depression (MyPersonality Test) is also considered to be a weakly labelled data. On the other hand, the data from Centre for Epidemiological Studies Depression Scale (CES-D), a proven clinical scale for depression, is considered strongly labelled data.

The objective of this thesis was to harness the potential of self-declared data on social media (specifically Twitter) and neuroticism data (N7) from a generalised personality test (MyPersonality Test) to build a model from large-scale weakly labelled data sources to predict depression scores as measured by the clinically validated screening tool: Centre for Epidemiological Studies Depression Scale (CES-D).

Using data from these data sources, two sets of experiments were carried out to evaluate the performance of different datasets along with different linguistic features in predicting depression in a set of Facebook users who also undertook the CES-D screening.

In the first set, machine learning models were trained on different data sources: CES-D, N7 and Self-Declared using Random Forests on three sets of linguistic features, Linguistic Inquiry and Word

Count(LIWC), Latent Dirichlet Allocation(LDA) topic models and Usr2vec. The model was tested against a held-out set of CES-D users. In the second set of experiments, we built unweighted linear ensembles of models built on individual data sources to predict held-out CES-D scores.

A model trained on users from the N7 dataset predicted CES-D scores with an Area Under the Receiver Operating Characteristic Curve (AUC) of 0.64, out-performing the model trained on 70% of the CES-D dataset which predicted the 30% held-out test CES-D scores with an Area Under the Receiver Operating Characteristic Curve (AUC) of 0.59. Improvement in predictions based on the ensemble model was significant as measured by the Wilcoxon Signed Rank test.

This suggests that weakly labelled data which is present in abundance is useful in improving machine learning models for diagnosis of depression.

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Chapter 1

Introduction

1.1 Motivation

Incidence

Depression is one of the major health problems of the world. According to the World Health Organisation [1], depression is an important cause of disability when assessed by the Years Lived with Disability (YLDs). This ailment is the fourth largest contributor to worldwide burden of disease. By the end of this decade, it is estimated that depression would be the second leading cause in Disability Adjusted Life Years (DALY) ranking calculated across all age groups. Middle aged population and women more than men are vulnerable to be afflicted with depression. It is estimated that globally, around 300 million people are suffering from depression. The life time prevalence of depression has been estimated to vary from 3% to 17%.

Symptoms of Depression

According to a study “The Nature of Clinical Depression: Symptoms, Syndromes and Behavior Analysis” by Kanter et al. [2], symptoms of depression can range from low mood, crying episodes, irritability, frustration to anger outbursts etc. The patient tends to lose interest in all activities which were earlier pleasurable. There can be insomnia and loss of appetite. The individual may lack energy and get easily fatigued. These symptoms are generally accompanied by psychomotor retardation i.e. decreased body movements.The affected person may not be able to concentrate and may be forgetful. His confidence level decreases and will often have doubts on himself as to whether he will be successfully accomplishing a simple task. This is generally accompanied by psychosomatic complaints in the form of heaviness in the head, neck or shoulders. Patient may have depressive cognitions in the form of hopelessness, worthlessness and helplessness. There could be frequent thoughts about death ranging from passive death wishes i.e.it would be better that I am dead to actively planning about it to escape from the illness. Neuroticism is a condition closely associated with depression[3].

1.2 Contributions of this Study

Depression is a not only a widespread problem but also largely goes undetected. The various techniques that have been used to diagnose depression include personal interview with healtcare provider, analysis based on scores of CES-D scale(Centre for Epidemological Studies Depression Scale) and computational analysis of data on social media. In the past, several studies (discussed in Chapter 2) have focussed on symptoms associated with mental illness being observable on social media like Twitter, Facebook, and web forums. Detection of depression computationally is a difficult task since it is hard to get validated assessments of depression, and sample size available too is limited due to ethical and privacy concerns. The data of users on social media who self declare symptoms of depression but have not been explicitly screened for depression using a reliable scale is considered to be weakly labelled data. Similarly data of users abstracted from generalised personality test surveys which are not specific to depression (MyPersonality Test) is also considered to be a weakly labelled data. CES-D is a validated scale and provides a reliable measure of depression.

The main contributions of this thesis are:

- Prior Studies have focussed on analysing the individual predictive powers of neuroticism data from MyPersonality Test (N7) and data from social media sources (e.g. Facebook, Twitter etc.) wherein the user explicitly mentions about having a depression condition (Self-Declared data). Since this is a self declared data, this may not necessarily be a valid clinical diagnosis.

To address the challenges in detection of depression and limited sample size of clinically validated data on depression, we used self-declared data from social media sources and neuroticism data (N7) from a general personality evaluation of an individual from MyPersonality Test since the data from these two sources is more easily available. We demonstrated a novel approach of using the predictive power of weak labelled data i.e, neuroticism data from MyPersonality Test (N7) and Self-Declared Data from Twitter on clinically validated Centre for Epidemological Studies Depression Scale (CES-D) using Transfer Learning Techniques.

In studying the predictive powers of the weak labelled data (N7 and Self-Declared) we also analysed the predictive power of various linguistic features (LIWC, Topics and Usr2Vec embeddings).

1.3 Document Structure

The subsequent chapters of this thesis are structured as follows:

Chapter 2 comprises of literature review and goes over the related work in detecting depression and mental illness on social media.

In Chapter 3, we discuss the various sources used to collect data, extraction and description of different features used in our experiment.

Chapter 4 describes the different types of out-of-sample prediction experiments conducted, details of data set combinations used and baseline model.

Chapter 5 evaluates the performance of LIWC, LDA topic models and Usr2vec features and data sources and presents the AUC values ROC curve

Chapter 6 discusses the implication of this work and suggests future research directions.

Chapter 2

Literature Review

2.1 Depression: Clinical Perspective

Depression is known to affect all age groups from children to elderly. This chapter discusses age specific symptoms, diagnostic tools and methodologies used by the clinical fraternity in diagnosis of depression and a review of studies in computational assessment of depression.

Depression symptoms in children and teenagers

Though most of the symptoms of depression in children and teenagers are similar to those of adults, there are certain additional features. These include clinginess, non specific aches and pains, sadness, irritation and reluctance to attend school. There could be weight loss. In the teenagers, apart from above symptoms, extreme sensitivity and features of being misunderstood can be present. Some teenagers may be prone to use recreational drugs and may manifest defiant behaviour [4].

Depression symptoms in elderly

In the middle aged and elderly population, depression may very often remain undiagnosed because of reluctance to report to medical professional. Depression is to be taken seriously in the elderly and should never be dismissed as a part of aging. Symptoms of depression may be different or less obvious in older adults, such as, memory difficulties or personality changes, physical aches or pain, fatigue, often wanting to stay at home rather than going out to socialize or doing new things and suicidal ideation [5].

Cause of Depression

The exact reason why depression takes place is not known. It is integration of genetic causes, environmental factors, life stressors etc. There is generally depletion of Neurotransmitter Serotonin in the brain. Also there is dysregulation in the Hypothalamus-Pituitary-Adrenal axis, rise in the serum cortisol, proinflammatory cytokines and Brain-derived neurotrophic factor (BDNF). Brain areas primarily affected in depression are prefrontal cortex, amygdala and hippocampus [6, 7].

Diagnostic criteria

Major Depressive Disorder (MDD) diagnostic criteria require the occurrence of one or more major depressive episodes. Symptoms of a major depressive episode include the following:

- Depressed mood.
- Anhedonia (diminished interest or pleasure in almost all activities).
- Significant weight or appetite disturbance.
- Sleep disturbance
- Psychomotor agitation or retardation (a speeding or slowing of muscle movement).
- Loss of energy or fatigue.
- Feelings of worthlessness (low self-esteem).
- Diminished thinking ability, concentration and decision making capability.
- Repeated thoughts of suicide or death.
- Longstanding interpersonal rejection ideation (i.e. “Others would be better off without me”; specific suicide plan and suicide attempt [4].

As per Diagnostic and Statistical Manual for mental disorders (DSM- V^{th} Edn), at least five of the above symptoms must be present on most days of the week and for most part of the day in the preceding two weeks [8]. Total number of symptoms and their severity determines whether depression is mild, moderate or severe. In International Statistical Classification of Diseases and Related Health Problems, 10^{th} Revision (ICD-10), the diagnosis is usually based on the ten symptoms of depression and can be classified as:

- Not depressed (fewer than four symptoms)
- Mild depression (four symptoms)
- Moderate depression (five to six symptoms)
- Severe depression (seven or more symptoms, with or without psychotic symptoms)

The symptoms should be present for most of the day and on most days for the preceding two weeks [9].

Management of Depression

The fundamental principles of managing a case of depression are as follows: First and foremost challenge in treating a case of depression is establishing the diagnosis with the help of detailed interview and clinical examination [10]. The diagnosis is straight forward in only a minority of patients. It is not uncommon for a General Physician (GP) to miss the diagnosis. Under the circumstances, certain structured psychometric instruments can be extremely helpful [11]. These instruments are in the form of either questionnaires or inventories. With the help of these instruments, all the symptoms can not only be assessed but also quantified depending on their level of severity.

Centre for Epidemological Studies Depression Scale (CES-D) is one such instrument which has acceptable reliability and validity [12](Figure 3.1). This instrument is helpful as a screening tool for depression in the general population. There are other instruments like Beck Depression Inventory, Hamilton Depression Scale etc. but these are not sensitive screening tools for the general population. General Health Questionnaire (GHQ) can be used as a screening instrument for general population but it lacks specificity for depression [13].

Assessment of personality is also integral to holistic assessment of psychiatric patients for diagnostic as well as therapeutic purposes. Neuroticism has been found to correlate well with depression and can be ascertained with the help of personality inventories like Million Clinical Multiaxial Inventory (MCMI) [14]. However,since conduct and evaluation of these tests require specialised medical training, such tests are best reserved for psychologists and psychiatrists.

It is noteworthy to mention here that depression can result due to a variety of medical disorders, which need exclusion with the help of laboratory tests like blood counts, renal and liver function tests, electro-cardiogram (ECG) and brain scanning with the help of either a CT-Scan or MRI depending on clinician's advice.

Once diagnosis is established, it is essential to assess whether the patient requires an in-patient or an outpatient management depending on his condition and level of severity. If the depression is not severe and functioning is well preserved, he may be treated on an out-patient basis with counselling, antidepressants or combination of both. Psychological interventions involve strengthening of the support system and also various forms of psychotherapies. Cognitive behavioural therapy (CBT) is one such therapy where the patient is made aware of his cognitive distortions. The therapist and the patient have to work together to correct these problems. Selective serotonin reuptake inhibitors (SSRIs) are well established in the treatment of depression and are usually safe even in large doses. Some patients may require hypnotic drugs like benzodiazepines for initial few days to improve sleep and to reduce anxiety. Severe form of depression generally requires inpatient and intensive treatment [15].

2.2 Computational Assessment of Depression

As elaborated above, depression is a not only a widespread problem but also largely goes undetected. In the past, many studies conducted have focussed on symptoms associated with mental illness being observable on social media like Twitter, Facebook, and web forums. Detection of depression computationally is a difficult task since it's hard to get validated assessments of depression, and sample size available too is limited due to ethical and privacy concerns.

2.2.1 Studies based on Surveys

The study by De Choudhury *et al*[16] explored the social media posting activities of depressed users. The users were identified through participants self reporting depression incidents in combination with results obtained for these users from clinically validated tools: Center for Epidemiologic Studies Depression Scale Revised (CES-D) and Becks Depression Inventory (BDI) score. These scores are obtained by scoring the answers chosen by the users in a multiple choice questionnaire which consists of 20 questions, and based on the total score obtained the users are classified in the level of depression they are suffering.

To ensure diversity (age, gender, demography) in the population whose behavioural data was being collected for analysis, they implemented crowdsourcing. The volunteers who self identified themselves as depressed were also required to take the CES-D and BDI test to asses their level of depression and finally were asked to share their public Twitter profile. These profiles were mined for a year and tested against the profiles of not depressed users.

Their social graph, lexicon used, emotions expressed and usage of words referring to popular anti-depressants was taken into account as features to predict depression. This data collected over time per user was then converted to feature vectors and used to train model to predict depression state of a Twitter user. They reported an average accuracy of $\sim 70\%$ and high precision of 0.74, corresponding to the depression class.

Another study by Reece *et al.*[17] aimed at predicting both Depression and Post-Traumatic Stress Disorder in Twitter users. They studied the text and Twitter meta-data that preceded the reported first episode of depression to build predictive model for depression unlike the model described by De Choudhury M *et al* [16] where users were included if they suffered at least two episodes of depression within the year and hence the training data may have contained both types of tweets: (a) posted during a previous depressive episode, (b) tweets posted after users had received a formal diagnosis.

The measured parameters were:

- Total tweets per user,per day, as a measure of user activity.
- Tweet metadata containing number of words in a given tweet was used to assess average word count per tweet.

- If it was a original tweet, re-tweet or a reply.
- Happiness factor was analysed using
  - labMT: a word list of 10221 words, where each word has a happiness score associated with them for sentiment analysis,
  - LIWC 2007 : Linguistic Inquiry and Word Count (LIWC) is a text analysis program that counts words in the text in psychologically meaningful categories and
  - ANEW: Affective Norms for English Words,is a labelled word list, where each word has been scored for valence. Each word in the post is scored based on the ANEW list to obtain a net valence score for the post.

They reported Areas under the Receiver Operating Characteristic curve to be 0.87.

2.2.2 Studies based on self-declared mental health status

Many social media users explicitly mention about their depression episodes, their detection and treatment using statements like "I was diagnosed with depression today". The following studies aimed at building predictive models to identify depression from self-declared data since it is available in abundance and easy to stream.

The 2015 Computational Linguistics and Clinical Psychology(CLPsych) workshop [18] focused on use of computational linguistic technologies which could be used to pick up signals related to mental health in language data and related metadata.

The studies conducted during this workshop collected data according to the procedures of Coppersmith *et al*[19] where users with tweets such as "I was diagnosed with depression(or a mental disease)" were taken into account. They used a human annotator to remove tweets which referred to jokes, quotes etc. Only users with greater than 25 tweets were considered and for such users 3000 public tweets were mined.

In this workshop, University of Maryland treated tweets for 1 week as a single document and performed supervised topic modelling [20]. The World Well Being Project (WWBP) from University of Pennsylvania combined topic modelling with unigram analysis to find which words clustered together and best separated depressed vs non-depressed behaviour[21]. The study from University of

Minnesota, Duluth used N-grams present in Post Traumatic Stress Disorder (PTSD) and depression statuses of all users [22]. The tweets were randomly sampled and the first eight million words of Tweets for each condition were used as the training data. Multiple N-gram combinations were used to create decision list and weigh the occurrence of words in a category. A word with the weight 0 occurred equally in both depressed and not depressed category whereas a word that occurred 400 times in depressed and 100 times in not depressed was weighted at 300. Hence, it's occurrence was indicative of depression. This model presented by University of Minnesota, Duluth outperformed the other models.

The metrics used to evaluate the performance were:

- Average precision: number of correct answer(in this case the number of depressed users) have been encountered up to this point (including current) divided by the total results seen up to this point,
- Precision at 10% false alarms: proportion of retrieved top-10% results that are relevant,
- ROC curve for each method with the highest average precision and
- ROC curves, focused on the low false alarm range (0-10%).

For our study, we analysed the performance of our models by plotting the ROC curve since they are unaffected by the baseline prior probability of positive class (i.e., depressed user).

2.2.3 Studies based on Forum Memberships

Studies by Bagroy *et al.* [23] used data mined from online forums like reddit to understand the depression characteristics and trends in university students from the United States of America. Data that was mined from groups aimed at mental health support discussions was taken as ground truth. They mined another set of Reddit posts, made on generic subreddits unrelated to mental health, to be a control dataset.

Inductive transfer learning approach was used to learn more about depressed users. It incorporated unigram,bigram and trigram and LIWC as linguistic features to identify depression.

Further the study aimed at rating the well being of various universities based on the depression levels of users from these universities in the United States of America.

2.2.4 Studies based on Annotated Tweets

For these studies, a group of annotators were provided with a set of rules to identify posts about depression [24]. These rules are usually set by domain experts and are aimed at filtering out tweets which merely have a mention of the disease and not actual reporting. Linguistic rules are also provided so as to identify and label the tweet with a mood-type. Though these studies provide a very reliable source of labelled data, they are very labour intensive and hence the size of data available is restrictive in nature.

2.3 Transfer Learning

Transfer learning is the process of leveraging the information from other domains (called, source domain) to train a better model for the target domain. In recent years it has found extensive implementation in many learning tasks, such as natural language processing, sentiment prediction and image classification.

Transfer Learning algorithms can be classified into the following:

1. **Inductive Learning:** This is applied in a setting where the number of samples in target domain (M) is very less as compared to the number of samples in source domain (N) $M << N$. The target and source task are different irrespective of whether the source and target domains are similar or not.

2. **Transductive Learning**: This is applied in a setting where the source and target tasks are the same, while the source and target domains are different. In this case no labelled data in the target domain is available while a lot of labelled data is available in the source domain.

3. **Unsupervised Transfer Learning**: Implemented in tasks where both the source and target domain have unlabelled data. This technique focusses on unsupervised learning tasks in the target domain, such as clustering, dimensionality reduction and density estimation.

Transfer Learning and Domain Adaptation for Adapting Personality Model from Facebook to Twitter

Study conducted by Rieman et al.[25] explored adapting personality model from one social media website to another namely Facebook as the source domain and Twitter as the target domain. Their study states that since most of the Tweets can be streamed using APIs and can be accurately mapped geographically a personality model based on Twitter would have proved to be majorly beneficial over using personally identifiable data which is unavailable due to privacy and ethical reasons.

The study talks about vocabulary adaptations from Facebook to Twitter: There exists a vocabulary difference between Twitter and Facebook since Twitter restricts usage to 140 characters on a single post unlike Facebook and words like 'rt' are more common to Twitter than Facebook. They present Target Side Domain Adaptation wherein over-represented words had their frequencies adjusted by normalization. Usage pattern difference was accounted for by implementing the ratio of a word's mean frequency for Facebook users, to the word's mean frequency for Twitter counties.

They reported an increase in the Pearson correlation between Education and Openness from 0.32 to 0.55.

Transfer Learning for Our Study

For our study, we had three different data sources: MyPersonality test, Self-Declared and Clinically validated CES-D. The N7 data from MyPersonality test is from a domain different than CES-D and is aimed at analysing various facets of a human personality, some of which are related to depression. The Self-declared data is from Twitter, thus though from a different domain is present in abundance.

Based on the study of domain adaptation between different social media domains[25], we decided to implement domain adaptation using N7 data from MyPersonality test and Self-declared data from Twitter as the source domain and results from CES-D as target domain. However, we had labelled source and target domain data and hence we decided to leverage the information from both the domains to enhance the predictive power of our model. We implemented the following variations of transfer learning as described by Hal Daume'III and Daniel Marcu [26] which demonstrated baselines that were actually surprisingly difficult to beat:

1. **Single Source Models**: For baseline analysis we trained models from the source domain (i.e. N7, SD and CES-D) using the LIWC, Topics and Usr2Vec features and analysed the predictive power of these models by predicting the CES-D score (i.e., the target domain).

2. **Combined Models** : The predicted CES-D scores from the single source models were used as features to train a second model and the predictive power of these models was analysed by predicting the CES-D score (i.e., the target domain).

Chapter 3

Materials and Methods

The focus of this study was to harness the predictive powers of weak labels (N7 and SD data) to predict strong label (CES-D). Social media (Facebook) posts were mined for those who consented to and volunteered either for the CES-D questionnaire or MyPersonality test (for N7data). Self declared data (SD) was mined from Twitter using regex rules to identify tweets. Based on the literature review of previous studies, LIWC, Topics and Usr2Vec features were used as language features to identify depression.

3.1 Data Sources

1. **CES-D** (Center for Epidemiologic Studies Depression Scale) was created in 1977 by Laurie Radloff [27] and revised in 2004 by William Eaton et al.[28]. It is used to measure self-reported symptoms experienced with depression. The CES-D includes 20 items comprising six scales that reflect the major dimensions of depression: depressed mood, feelings of guilt and worthlessness, feelings of helplessness and hopelessness, psychomotor retardation, loss of appetite and sleep disturbance[29, 30].

   Response categories indicate the frequency of occurrence of each symptom and are scored on a 4 point scale ranging from 0 (rarely or none of the time) to 3 (most or all of the time). This provides a clinically reliable measure of depression.

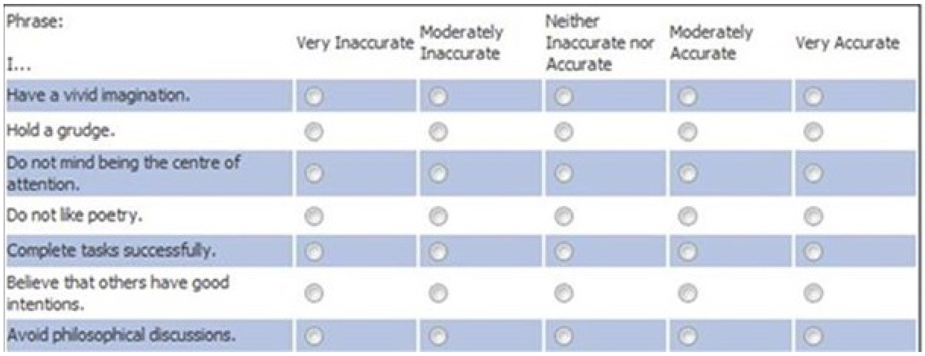
	Rarely or none of the time (less than 1 day)	Some or a little of the time (1-2 days)	Occasionally or a moderate amount of time (3-4 days)	Most or all of the time (5-7 days)
1. I was bothered by things that usually don't bother me.	☐	☐	☐	☐
2. I did not feel like eating; my appetite was poor.	☐	☐	☐	☐
3. 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.	☐	☐	☐	☐

Figure 3.1: Sample Questions from CES-D Questionnaire

2. **N7**: This data was sourced from the MyPersonality dataset. We used the depression facet scores of the "Big 5" item pool.The questionnaire used to populate this dataset has 8 length versions ranging from 20-100 items. Each question in the questionnaire contributes to one of the facets of the personality, namely: Extroversion, Neuroticism, Openness, Agreeableness, Conscientiousness. Based on the answers recorded to questions in the above category N7 depression score was calculated as discussed by Goldberg et al. [31]

   Each response is either positively or negatively related to the trait and are assigned a score from 1 to 5 varying on the option chosen. For responses positively related to the trait, the response "Very Inaccurate" is assigned a value of 1,"Moderately Inaccurate" a value of 2, "Neither Inaccurate nor Accurate" a 3,"Moderately Accurate" a 4, and "Very Accurate" a value of 5.

   For responses negatively related to the trait, the response"Very Inaccurate" is assigned a value of 5, "Moderately Inaccurate" a value of 4, "Neither Inaccurate nor Accurate" a 3, "Moderately Accurate" a 2, and "Very Accurate" a value of 1. [32]



Phrase: I...	Very Inaccurate	Moderately Inaccurate	Neither Inaccurate nor Accurate	Moderately Accurate	Very Accurate
Have a vivid imagination.					
Hold a grudge.					
Do not mind being the centre of attention.					
Do not like poetry.					
Complete tasks successfully.					
Believe that others have good intentions.					
Avoid philosophical discussions.					

Figure 3.2: Sample Questions from MyPersonality Test

3. **Self Declared Data**(SD): This data was collected from 4538 users on Twitter wherein the users identified themselves with having some form of depression. Some statements found were of the form: “I was diagnosed with depression 2 months back.”, “I am feeling depressed after the loss of my wife.”. This data source provides an abundant presence in the form of data streaming using APIs provided by social media sites.

Sample Regex Pattern
1 ....diagnosed with depression on ....
2. Suffering/feel from depression/depressed ···

3.2 Features Used

1. **LIWC** : It is a closed vocabulary analysis wherein categories of words are defined a priori, based on common psychological or linguistic functions determined by researchers[33]. It automatically counts words belonging to around 64 predefined categories, such as positive emotion (e.g., love, nice, sweet), achievement (e.g., earn, hero, win), articles (e.g., the, a), and tentative words (e.g., maybe, perhaps, guess).
   For our experiment we are using the LIWC2015 dataset which is composed of almost 6,400 words, word stems, and selected emoticons. Its creation used data not only from previous LIWC versions-2001 and 2007 but also incorporated language spoken on social media sites like Facebook and Twitter[34] hence making it a good candidate for training a prediction model.

2. **Topics** : It is a data driven lexicon. Weighted Latent Dirichlet allocation (LDA) was used

on around 14 million Facebook statuses to create this feature set. LDA basis itself on the assumption that each document is a mix of various topics and that each word contributes to one of the topics of the document.

Here the aim is to get probability of a topic given the document:

$P(Topic/document) = \Sigma_{word \in Topic}(Topic/word) * P(word/document)$ Here each term has a weight of belonging to a category (which is unlabelled unlike LIWC).

3. **usr2vec**: It is a user embedding feature which aims at understanding the relation between the users and the content that they generate. It aims to estimate the parameters of a user vector $\mathrm{u_j}$, that maximize the conditional probability as described by Silvio *et al.*[36]:

   $P(Posts\ authored\ by\ user\ j/User\ j) =$

   $\Sigma_{post \in Posts\ authored\ by\ user\ j}\Sigma_{words\ that\ make\ up\ the\ post} \log P(word\ in\ post/user\ j)$

   The term $\log P(word\ in\ post/user\ j)$ was minimised using the hinge loss function:

   $= \Sigma_{\bar{w}_k \in\ Vocabulary} max(0, 1 - (each\ word).user\ j + \bar{w}_k.user\ j)$

   where word $\bar{w}_k$ (and associated embedding,$\bar{w}_k$) is a negative sample, i.e. a word not occurring in the sentence under consideration, which was written by user j.

   Creation of this feature was specific to the data source used. For each user there was 100 dimension usr2vec embedding. Hence there were different user embeddings based on survey CESD, N7 and streamed data from social media SD.

Descriptive Statistics

A description containing the population, score statistics of the control and the experimental group is described in the table below.

	N7	CES-D
Min Score	0.8571	0
Max Score	5	53
Number of Depressed Users	8404	347
Number of Not-Depressed Users	8103	371
Average Score	2.61	26.41

Figure 3.3: Descriptive Statistics of users data from MyPersonality Test and CES-D test. Scores were converted into Binary labels 0 and 1 based on Thresholds: CESD: 27, N7: Median Split. For self-declared data from Twitter we collected tweets from 4538 depressed users only.

- **Sample of the Facebook posts collected for users who took the CES-D questionnaire:**

1. Work flow all week and tired ...
2. missing my Girly :(
3. Mood: distraught, confused, uncomfortable, and worried
4. Stupid insomnia why don't you let me sleep, if I could wrap my arms around you I'd hurt you... O well Happy Morning.

- **Sample of the Facebook posts collected for users who took MyPersonality Test:**

1. I want the ablity to make it rain!(weather)
2. " O' what tangled webs we weave when we practice to decive"
3. Summer's almost over, but I'm feeling oddly optimistic about senior year=D bet it's going to be a good one
4. summer was great; had the option of staying up all night just to watch the sun come up in the morning...school ruined this for me...

- **Sample of the Tweets mined using the regex rules are as follows:**

1. When your mind is scattered with thoughts, it's difficult to figure out where the beginning is. #anxiety #depression
2. OK my depression (???) is making me rilly, rilly tired.
3. Sometimes, I just have the urge to curl up up in bed alone and cry for no reason at all. Sometimes, for every reason. #depression
4. I was so excited, knew about it for three weeks, but every time I thought about asking you to come with me, Id get anxious and depressed.

Chapter 4

Experiments

The availability of clinically validated score CES-D is limited due to privacy and ethical laws. Thus, we aimed to explore the predictive power of weak labels such as Facebook data of users who had taken MyPersonality Test (considering their neuroticism facet-N7) and self-declared data from Twitter (users who identify themselves as depressed).

Alongside the aim of identifying the data source(s), with strong predictive powers we also aimed at evaluating the predictive powers of various linguistic features (LIWC, Topics and Usr2Vec) in combination to the data sources.

Hence, for each data source we evaluated the predictive powers of the three linguistic features. To analyse the performance, we plotted the receiver operating characteristic curve, i.e. ROC curve and studied the area under the curve i.e. AUC. The aim for using this was that the classes (depressed vs non-depressed) were imbalanced and AUC-ROC measures the performance of a binary classifier averaged across all possible decision thresholds.

In the first set of experiment (section 4.1), we first tested the predictive powers of each data source along with the three linguistic features using 10 fold cross validation on CES-D (**Single Source Model**), and then created various unweighted linear ensemble of the predicted results from these data sources and evaluated that against the ground truth (**Combined Source Model**).

In the second set of experiment (section 4.2) we held-out 218 users as the testing data and then tested the predictive powers of each data source and their unweighted linear ensembles along with the three linguistic features. The predicted results were evaluated against the 218 held-out users.

4.1 Cross Validation Predictions

CES-D survey data was assigned to 10 stratified-folds and 10 fold Cross validation was performed to report scores.

4.1.1 Single Source

1. CES-D: 718 users who took the CES-D survey were divided into 10 stratified folds. Using cross validation technique, the models based on LIWC, Topics and Usr2Vec features were trained on 9 folds and predicted the 10^{th} fold using a Random Forest Classifier wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37]. The final predicted vector was compared against the ground truth to report the AUC values and draw ROC curve.

2. N7: Three models were trained on 16507 users using LIWC, Topics and Usr2Vec features respectively. The classification algorithm used was Random Forest, wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37]..The predicted vector of 718 CES-D users was found on this trained model. The predicted probabilities were tested against ground truth to get the AUC values and ROC curves.

3. SD: Three models were trained on 4538 users using LIWC, Topics and Usr2Vec features respectively. The classification algorithm used was Random Forest, wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37]..The predicted vector of 718 CES-D users was found on this trained model.The predicted probabilities were tested against ground truth to get the AUC values and ROC curves.

4.1.2 Combined Sources

The following combination of data sources were used to determine the prediction performance on all three features namely LIWC, Topics and Usr2Vec.

1. CES-D and N7: A new feature table was created using:

   - the predicted class probabilities of the entire testing data(718 CES-D users) obtained from the model trained on N7.
   - the predicted class probabilities of 718 users from CES-D, wherein CES-D survey data was assigned to 10 stratified-folds and 10 fold Cross validation was performed to avoid overfitting.

   In the next step a Random Forest Classifier wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37] was trained and tested using the same stratified division of outcomes on these new features and the predicted values were tested against a ground truth to report the AUC values and infer the ROC curve.

2. CES-D and SD: A new feature table was created using:

   - the predicted class probabilities of the entire testing data(718 CES-D users) obtained from the model trained on SD.
   - the predicted class probabilities of 718 users from CES-D, wherein CES-D survey data was assigned to 10 stratified-folds and 10 fold Cross validation was performed to avoid overfitting.

   In the next step a Random Forest Classifier wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37] was trained and tested using the same stratified division of outcomes on these new features and the predicted values were tested against a ground truth to report the AUC values and infer the ROC curve.

3. SD and N7: A new feature table was created using:

- the predicted class probabilities of the entire testing data(718 CES-D users) obtained from the model trained on N7.
- the predicted class probabilities of the entire testing data(718 CES-D users) obtained from the model trained on SD.

In the next step a Random Forest Classifier wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37] was trained and tested using the same stratified division of outcomes on these new features and the predicted values were tested against a ground truth to report the AUC values and infer the ROC curve.

4. CES-D and N7 and SD: A new feature table was created using:

   - the predicted class probabilities of the entire testing data(718 CES-D users) obtained from the model trained on N7.
   - the predicted class probabilities of the entire testing data(718 CES-D users) obtained from the model trained on SD.
   - the predicted class probabilities of 718 users from CES-D, wherein CES-D survey data was assigned to 10 stratified-folds and 10 fold Cross validation was performed to avoid overfitting.

   In the next step a Random Forest Classifier wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37] was trained and tested using the same stratified division of outcomes on these new features and the predicted values were tested against a ground truth to report the AUC values and infer the ROC curve.

4.2 Out-of Sample Predictions

CESD survey data was split into 70% training(500 users) and 30% testing data(218 users).

4.2.1 Single Source

1. CES-D: Three models were trained on 70% training data using LIWC, Topics and Usr2Vec feature respectively. The classification algorithm used was Random Forest wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37]. The predicted class probabilities of the 30% testing data was found on this trained model. The predicted probabilities were tested against ground truth to get the AUC values and ROC curves.

2. N7: Three models were trained on 16507 users using LIWC, Topics and Usr2Vec feature respectively. The classification algorithm used was Random Forest wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37]. The predicted class probabilities of the 30% testing data was found on this trained model. The predicted probabilities were tested against ground truth to get the AUC values and ROC curves.

3. SD: Three models were trained on 4538 users using LIWC, Topics and Usr2Vec feature respectively. The classification algorithm used was Random Forest wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37]. The predicted class probabilities of the 30% testing data was found on this trained model.The predicted probabilities were tested against ground truth to get the AUC values and ROC curves.

4.2.2 Combined Sources

The following combination of data sources were used to determine the prediction performance on all three features namely LIWC, Topics and Usr2Vec.

1. CES-D and N7: A new feature table was created using:

    - the predicted class probabilities of the 30% testing data obtained from the model trained on N7.
    - the predicted class probabilities of the 30% testing data obtained from the model trained on 70% CES-D training data.

In the next step a Random Forest Classifier wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37] was trained on these new features, and the predicted values were tested against a ground truth of the 30% testing data to report the AUC values and infer the ROC curve.

2. CES-D and SD: A new feature table was created using:

   - the predicted class probabilities of the 30% testing data obtained from the model trained on SD.
   - the predicted class probabilities of the 30% testing data obtained from the model trained on 70% CES-D training data.

   In the next step a Random Forest Classifier wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37] was trained on these new features, and the predicted values were tested against a ground truth of the 30% testing data to report the AUC values and infer the ROC curve.

3. SD and N7: A new feature table was created using:

   - the predicted class probabilities of the 30% testing data obtained from the model trained on SD.
   - the predicted class probabilities of the 30% testing data obtained from the model trained on N7.

   In the next step a Random Forest Classifier wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37] was trained on these new features, and the predicted values were tested against a ground truth of the 30% testing data to report the AUC values and infer the ROC curve.

4. CES-D and N7 and SD: A new feature table was created using:

   - the predicted class probabilities of the 30% testing data obtained from the model trained on N7.

- the predicted class probabilities of the 30% testing data obtained from the model trained on SD.
- the predicted class probabilities of the 30% testing data obtained from the model trained on 70% CES-D training data.

In the next step a Random Forest Classifier wherein number of trees was determined using gridsearchCV, all other hyper-parameters were kept as the default values mentioned in sklearn library [37] was trained on these new features, and the predicted values were tested against a ground truth of the 30% testing data to report the AUC values and infer the ROC curve.

The aim for the above set was to determine how do weak labels N7 and SD aid in predicting strong label CES-D (since it is a clinical measure for understanding depression).

Chapter 5

Results and Analysis

5.1 Cross Validation Results

The 10 fold stratified data from CES-D users was predicted on multiple data sources and their linear ensembles using the three linguistic features: LIWC, Topics and Usr2Vec and the AUC-ROC values were recorded (Table 5.1).

Model Trained on	LIWC	Topic	Usr2vec
SD	0.55	0.56	0.57
CESD (718 users)	0.588	0.62	0.60
N7	0.62	0.637	0.55
SD+N7	0.58	0.57	0.58
CESD+SD	0.695	0.70	0.71
CESD+N7+SD	0.698	0.705	0.70
CESD+N7	0.71	0.69	0.74

Table 5.1: Area Under the Curve for Prediction on 718 CES-D users using 10 fold Cross Validation

To establish the statistical significance of the models, Wilcoxon Signed Rank Test was used. The combined model of CESD and N7 and source only model on N7 (which had the highest AUC value) was established to be to be significantly more accurate than the other models. The ROC curves obtained are reported below:

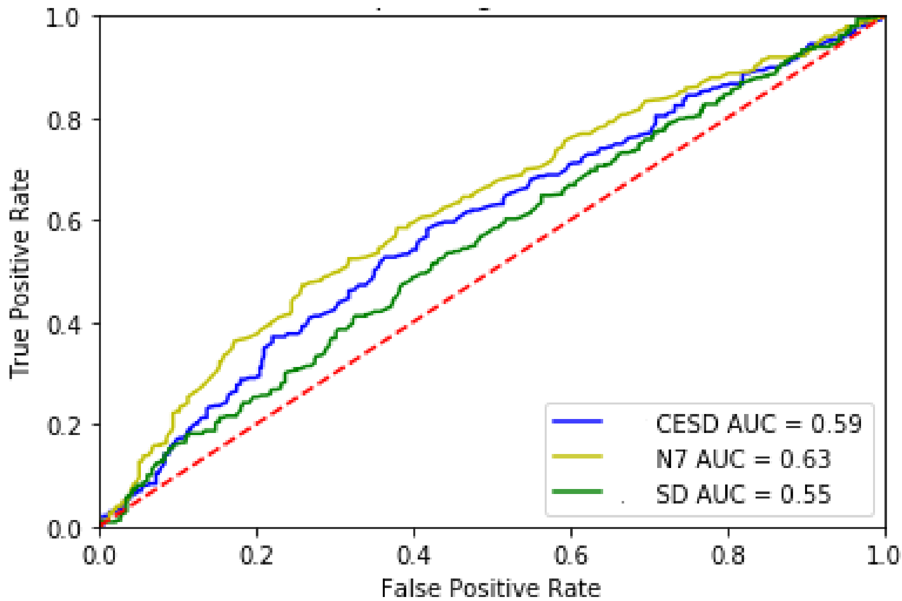


Figure 5.1: ROC curve for 10-fold Cross Validated using Random Forest Classifier for depression sample using LIWC

The 10-fold Cross Validation experiment was conducted using LIWC feature(Figure 5.1). We achieved an AUC of 0.63 with N7 data extracted from MyPersonality Test, CES-D and Self Declared data reported an AUC of 0.59 and 0.55 respectively.

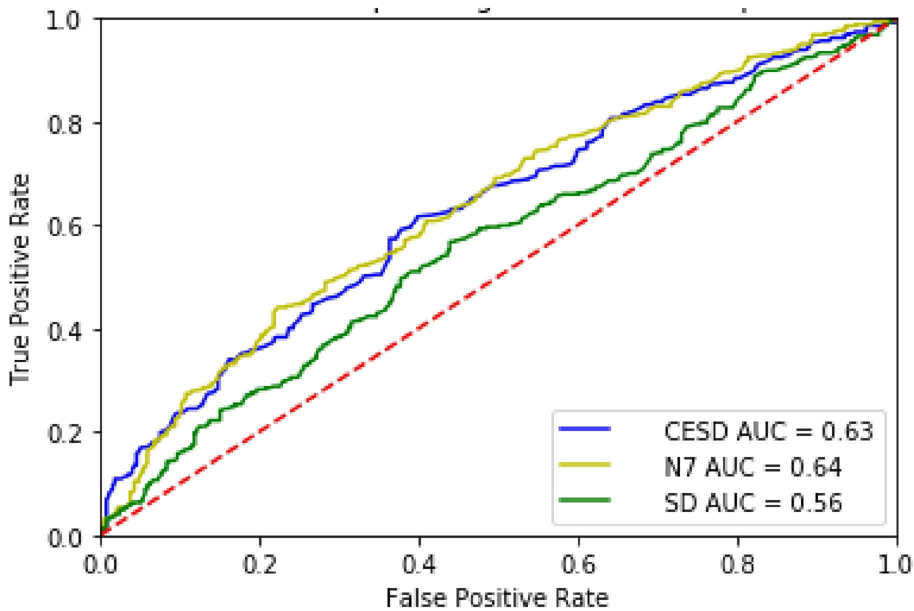


Figure 5.2: ROC curve for 10 fold Cross Validated using Random Forest Classifier for depression sample using Topics

The 10-fold Cross Validation experiment was conducted using Topics feature (Figure 5.2). We achieved an AUC of 0.64 with N7 data extracted from MyPersonality Test, CES-D and Self Declared data reported an AUC of 0.63 and 0.56 respectively.

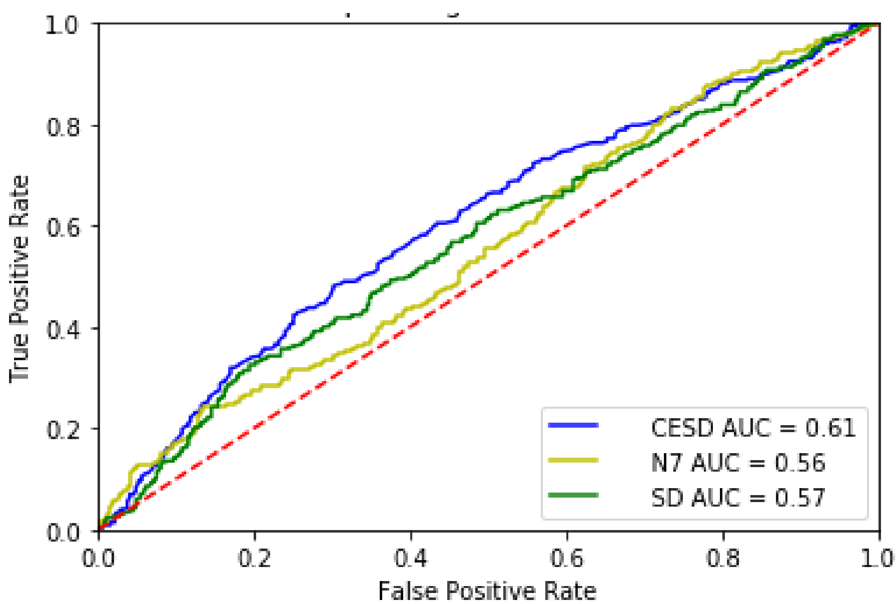


Figure 5.3: ROC curve for 10 fold Cross Validated using Random Forest Classifier for depression sample using Usr2vec

The 10-fold Cross Validation experiment was conducted using Usr2Vec feature (Figure 5.3). We achieved an AUC of 0.61 with models trained on CES-D data, Self Declared and N7 data reported an AUC of 0.57 and 0.56 respectively.

5.2 Out of Sample Predictions

The held-out data from CES-D users (30% of the total data) was predicted on multiple data sources and their linear ensembles using the three linguistic features: LIWC, Topics and Usr2Vec and the AUC-ROC values were recorded (Table 5.2).

Model Trained on	LIWC	Topic	Usr2vec
SD	0.526	0.553	0.562
CESD (500 users)	0.586	0.616	0.628
N7	0.635	0.608	0.509
CESD+SD	0.560	0.592	0.595
SD+N7	0.590	0.601	0.555
CESD+N7+SD	0.601	0.619	0.600
CESD+N7	0.628	0.634	0.603

Table 5.2: Area Under Curve for Out of Sample Prediction on 218 CES-D users:

To establish the statistical significance of the models, Wilcoxon Signed Rank Test was used. The combined model of CESD and N7 and source only model on N7 which had the highest AUC value was established to be significantly more accurate than the other models. The ROC curves obtained are reported below:

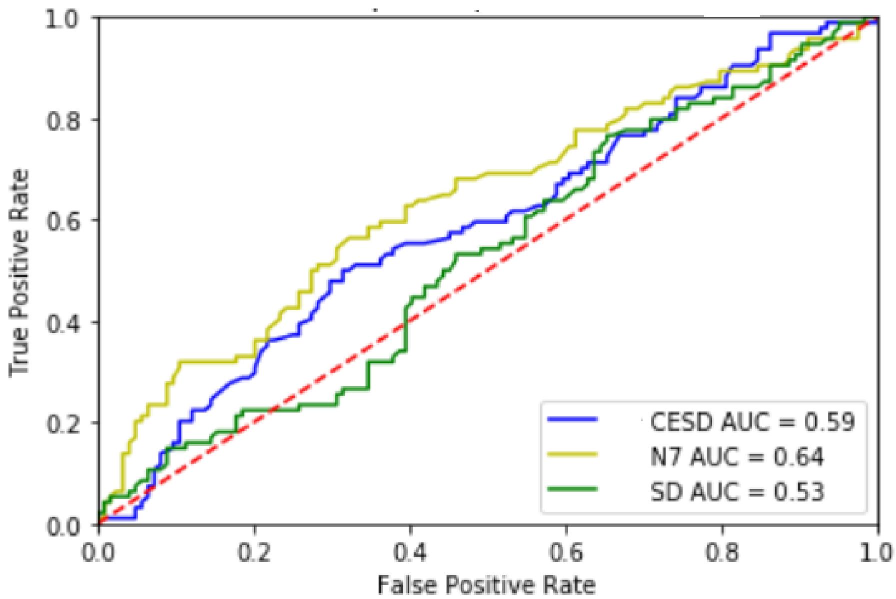


Figure 5.4: ROC curve for held-out dataset using Random Forest Classifier for depression sample using LIWC

The experiment was conducted on the held-out CES-D data using LIWC feature (Figure 5.4). We achieved an AUC of 0.64 with N7 data, CES-D (70% training data) and SD data reported an AUC of 0.59 and 0.53 respectively.

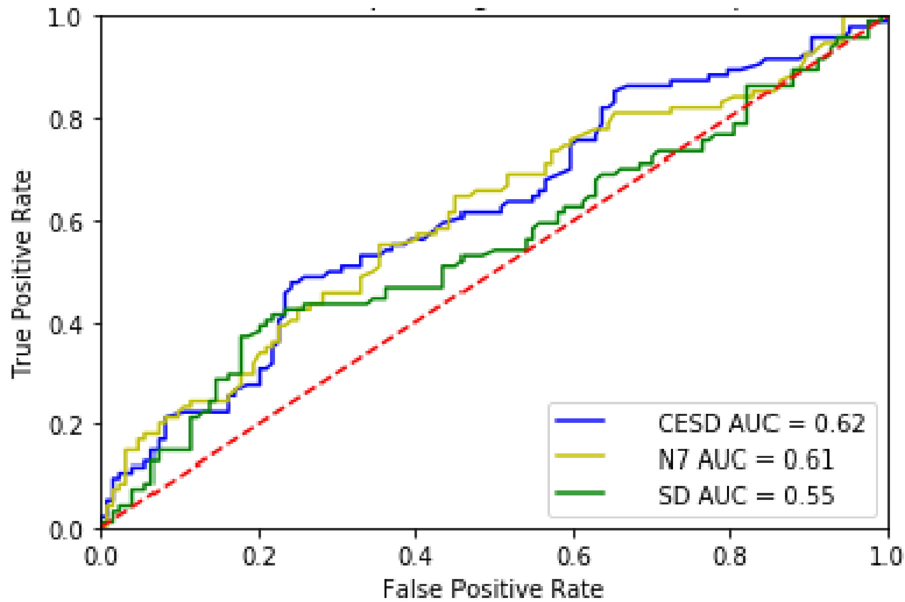


Figure 5.5: ROC curve for held-out dataset using Random Forest Classifier for depression sample using Topics

The experiment was conducted on the held-out CES-D data using Topics feature (Figure 5.5). We achieved an AUC of 0.62 with models trained on CES-D (70% training data), N7 and SD data reported an AUC of 0.61 and 0.55 respectively.

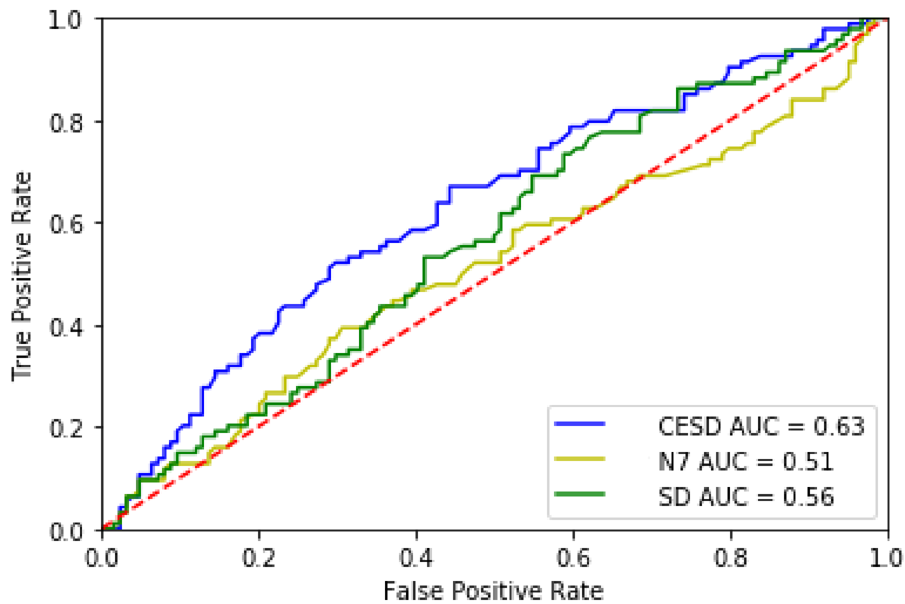


Figure 5.6: ROC curve for held-out dataset using Random Forest Classifier for depression sample using Usr2vec

The experiment was conducted on the held-out CES-D data using Usr2Vec feature (Figure 5.6). We achieved an AUC of 0.63 with models trained on CES-D (70% training data), N7 and SD data reported an AUC of 0.51 and 0.56 respectively.

Table 5.3: Word Clouds likely to be posted by Depressed users Vs Non-depressed users on different data sources

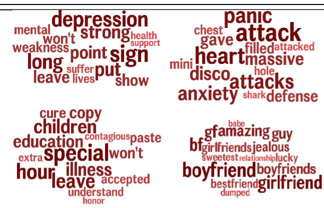
Data Source	Depressed User	Not-Depressed User
CES-D		
SD		
N7		

Table 5.3 presents examples of Topic Wordclouds generated from different data sources to help visualise words that correlated with Depressed and Non-Depressed Users. The wordclouds documented above are aimed at elucidating the different topics that each data source captures.

5.3 Discussion

We mined three forms of data: Self-Declared tweets from Twitter, Facebook Data of users who took the MyPersonality test and Facebook data of users who took the CES-D test. We implemented the transfer learning methods discussed by Hal Daume'III and Daniel Marcu in their study of Domain Adaptation techniques[26] and trained two sets of models - one using the source domain only and the other using the predictions from the source domain as an additional feature to train the data from the target domain.

Two sets of experiments were conducted, one with 10 fold cross validation and the other with the held-out dataset. The best cross validation model (CES-D+N7 using the LIWC feature and CES-D+SD using the Usr2Vec feature) reported an AUC of ~ 0.7 and the best held-out model (N7 using LIWC feature) reported an AUC of ~ 0.63. On comparing these chosen models with the other models using Wilcoxon Signed Rank Test, the p-value reported was < 0.05,thereby concluding the statistical significance of the predictive models.

Chapter 6

Conclusion And Future Work

CES-D is a clinically validated measure of depression but the dataset is limited. N7 and self-declared data are more easily procurable but are considered to be weak features. Hence, the focus of this study was to adapt weak features to predict CES-D scores.

We observed the following:

1. On a held-out dataset, the model trained on data only from N7 to predict CES-D, i.e, with no training data from CES-D shows equal accuracy as that of a model built on training data from CES-D.

2. Wilcoxon Signed Rank Test between the model trained on CES-D and the model trained on N7 reported $p < 0.05$ and hence the null hypothesis (i.e. the difference in AUC values is due to random chance) was rejected, establishing the significant statistical difference between the two models.

3. On comparing the 10 fold Cross Validation results, our model out-performs the current state of art models based on surveys.

4. Due to the difference between the language on Twitter and Facebook, the model trained on self-declared data does not generalize well on Facebook.

For future work, we plan to obtain more clinically validated samples of depressed users from CES-D survey and test the model performances with this increased target domain data. Techniques to generalize language features from Twitter on Facebook should also be explored. We also plan to explore predictive powers of other language features such as n-grams and LabMT to classify depression.

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