Mental Illness Detection at the World Well-Being Project for the CLPsych 2015 Shared Task

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Abstract

This article is a system description and report on the submission of the World Well-Being Project from the University of Pennsylvania in the 'CLPsych 2015' shared task. The goal of the shared task was to automatically determine Twitter users who self-reported having one of two mental illnesses: post traumatic stress disorder (PTSD) and depression. Our system employs user metadata and textual features derived from Twitter posts. To reduce the feature space and avoid data sparsity, we consider several word clustering approaches. We explore the use of linear classifiers based on different feature sets as well as a combination use a linear ensemble. This method is agnostic of illness specific features, such as lists of medicines, thus making it readily applicable in other scenarios. Our approach ranked second in all tasks on average precision and showed best results at .1 false positive rates.

1 Introduction

Mental illnesses are widespread globally (Üstün et al., 2004); for instance, 18.6% of US adults were suffering from a mental illness in 2012 (Abuse and Administration, 2012). Depression and post traumatic stress disorder (PTSD) are some of the most common disorders, reaching up to 6.6% and 3.5% prevalence respectively in a 12 month period in the US (Kessler et al., 2003; Kessler et al., 2005). However, these are often argued to be under-estimates of the true prevalence (Prince et al., 2007). This is in part because those suffering from depression and PTSD do not typically seek help for their symptoms and partially due to imperfect screening methods currently employed. Social media offers us an alternative window into an individual's psyche, allowing us to investigate how changes in posting behaviour may reflect changes in mental state.

The CLPsych 2015 shared task is the first evaluation to address the problem of automatically identifying users with diagnosis of mental illnesses, here PTSD or depression. The competition uses a corpus of users who self-disclosed their mental illness diagnoses on Twitter, a method first introduced in (Coppersmith et al., 2014). The shared task aims to distinguish between: (a) control users and users with depression, (b) control users and users with PTSD and (c) users with depression and users with PTSD.

For our participation in this shared task, we treat the task as binary classification using standard regularised linear classifiers (i.e. Logistic Regression and Linear Support Vector Machines). We use a wide range of automatically derived word clusters to obtain different representations of the topics mentioned by users. We assume the information captured by these clusters is complimentary (e.g. semantic vs. syntactic, local context vs. broader context) and combine them using a linear ensemble to reduce classifier variance and improve accuracy. Our classifier returns for each binary task a score for each user. This enables us to create a ranked list of use in our analysis.

The results are measured on average precision, as we are interested in evaluating the entire ranking. On the official testing data, our best models achieve over .80 average precision (AP) for all three binary tasks, with the best model reaching .869 AP on predicting PTSD from controls in the official evaluation. A complementary qualitative analysis is presented in (Preoţiuc-Pietro et al., 2015).

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2 System Overview

In our approach, we aggregate the word counts in all of a user's posts, irrespective of their timestamp and the word order within (a bag-of-words approach). Each user in the dataset is thus represented by a distribution over words. In addition, we used automatically derived groups of related words (or 'topics') to obtain a lower dimensional distribution for each user. These topics, built using automatic clustering methods from separate large datasets, capture a set of semantic and syntactic relationships (e.g. words reflecting boredom, pronouns). In addition, we use metadata from the Twitter profile of the user, such as number of followers or number of tweets posted. A detailed list is presented in the next section. We trained three standard machine learning binary classifiers using these user features and known labels for Controls, Depressed and PTSD users.

Data

The data used for training consisted of 1,145 Twitter users, labeled as Controls, Depressed and PTSD. This dataset was provided by the shared task organisers (Coppersmith et al., 2015). From training and testing we removed 2 users as they had posted less than 500 words and thus their feature vectors were very sparse and uninformative. Dataset statistics are presented in Table 1. Age and gender were provided by the task organisers and were automatically derived by the method from (Sap et al., 2014).

	Control	**Depressed**	**PTSD**
Number of users	572	327	246
Avg. age	24.4	21.7	27.9
% female	74.3%	69.9%	67.5%
Avg. # followers	1,733	1,448	1,784
Avg. # friends	620	836	1,148
Avg. # times listed	22	17	29
Avg. # favourites	1,195	3,271	5,297
Avg. # statuses	10,772	17,762	16,735
Avg. # unigrams	31,083	32,938	38,337

Table 1: Descriptive statistics for each of the three categories of users.

3 Features and Methods

3.1 Features

We briefly summarise the features used in our prediction task. We divide them into user features and textual features.

Metadata Features (Metadata) The metadata features are derived from the user information available from each tweet that were not anonymised by the organizers. Table 2 introduces the eight features in this category.

m_1	log number of followers
m_2	log number of friends
m_3	follower/friend ratio
m_4	log number of times listed
m_5	no. of favourites the account made
m_6	total number of tweets
m_7	age
m_8	gender

Table 2: Metadata features for a Twitter user.

Unigram Features (Unigram) We use unigrams as features in order to capture a broad range of textual information. First, we tokenised the Twitter posts into unigrams using our tailored version[1] of Chris Potts' emoticon-aware *HappyFunTokenizer*. We use the unigrams mentioned by at least 1% of users in the training set, resulting in a total of 41,687 features.

Brown Clusters (Brown) Using all unigrams may cause different problems in classification. The feature set in this case is an order of magnitude larger than the number of samples ($\sim 40,000 \gg \sim 1000$), which leads to sparse features and may cause overfitting. To alleviate this problem, we use as features different sets of words which are semantically or syntactically related i.e. 'topics'. These are computed on large corpora unrelated to our dataset in order to confer generality to our methods.

The first method is based on Brown clustering (Brown et al., 1992). Brown clustering is a HMM-based algorithm that partitions words hierarchically into clusters, building on the intuition that

[1] Available for download at http://www.wwbp.org/data.html

the probability of a word's occurrence is based on the cluster of word directly preceding it. We use the clusters introduced by Owoputi et al. (2013) which use the method of Liang (2005) to cluster 216,856 tokens into a base set of 1000 clusters using a dataset of 56 million English tweets evenly distributed from 9/10/2008 to 8/14/2012.

NPMI Word Clusters (NPMI) Another set of clusters is determined using the method presented in (Lampos et al., 2014). This uses a word to word similarity matrix computed over a large reference corpus of 400 million tweets collected from 1/2/2011 to 2/28/2011. The word similarity is measured using Normalised Pointwise Mutual Information (NPMI). This information-theoretic measure indicates which words co-occur in the same context (Bouma, 2009) where the context is the entire tweet. To obtain hard clusters of words we use spectral clustering (Shi and Malik, 2000; Ng et al., 2002). This methods was shown to deal well with high-dimensional and non-convex data (von Luxburg, 2007). In our experiments we used 1000 clusters from 54,592 tokens.

Word2Vec Word Clusters (W2V) Neural methods have recently been gaining popularity in order to obtain low-rank word embeddings and obtained state-of-the-art results for a number of semantic tasks (Mikolov et al., 2013b).

These methods, like many recent word embeddings, also allow to capture local context order rather than just 'bag-of-words' relatedness, which leads to also capture syntactic information. We use the skip-gram model with negative sampling (Mikolov et al., 2013a) to learn word embeddings from a corpus of 400 million tweets also used in (Lampos et al., 2014). We use a hidden layer size of 50 with the Gensim implementation.[2] We then apply spectral clustering on these embeddings to obtain hard clusters of words. We create 2000 clusters from 46,245 tokens.

GloVe Word Clusters (GloVe) A different type of word embeddings was introduced by (Pennington et al., 2014). This is uses matrix factorisation on a word-context matrix which preserves word order and claims to significantly outperform previous neural embeddings on semantic tasks. We use the pre-trained Twitter model from the author's website[3] built from 2 billion tweets. In addition to the largest layer size (200), we also use spectral clustering as explained above to create 2000 word clusters from 38,773 tokens.

LDA Word Clusters (LDA) A different type of clustering is obtained by using topic models, most popular of which is Latent Dirichlet Allocation (Blei et al., 2003). LDA models each post as being a mixture of different topics, each topic representing a distribution over words, thus obtaining soft clusters of words. We use the 2000 clusters introduced in (Schwartz et al., 2013), which were computed over a large dataset of posts from 70,000 Facebook users. These soft clusters should have a slight disadvantage in that they were obtained from Facebook data, rather than Twitter as all previously mentioned clusters and our dataset.

LDA ER Word Clusters (ER) We also use a different set of 500 topics. These were obtained by performing LDA on a dataset of $\sim$ 700 Facebook user's posts who reported to the emergency room and opted in a research study.

3.2 Methods

We build binary classifiers to separate users being controls, depressed or having PTSD. As classifiers, we use linear methods as non-linear methods haven't shown improvements over linear methods in our preliminary experiments. We use both logistic regression (**LR**) (Freedman, 2009) with Elastic Net regularisation (Zou and Hastie, 2005) and Support Vector Machines (**LinSVM**) with a linear kernel (Vapnik, 1998). We used the implementations of both classifiers from ScikitLearn (Pedregosa et al., 2011) which use Stochastic Gradient Descent for inference.

A vital role for good performance in both classifiers is parameter tuning. We measure mean average precision on our training set using 10 cross-fold validation and 10 random restarts and optimise parameters using grid search for each feature set individually.

Different feature sets are expected to contribute

[2] https://radimrehurek.com/gensim/

[3] http://nlp.stanford.edu/projects/glove/

Feature type	Features	CvD-LR	CvD-LinSVM	CvP-LR	CvP-LinSVM	DvP-LR	DvP-LinSVM
Metadata	8	.576	.567	.588	.585	.816	.817
Unigram	41687	.838	**.843**	**.850**	.845	.831	.820
Brown	1000	.790	.784	.770	.770	.830	.834
NPMI	1000	.789	.770	.785	.774	.825	.822
W2V	2000	.808	.791	.786	.775	**.850**	.845
GloVe	2000	.788	.784	.780	.761	.844	.839
LDA	2000	.820	.812	.807	.794	.841	.835
LDA ER	500	.785	.787	.740	.736	.850	.834
Ensemble-Avg.	8	.854	.862	.850	**.860**	.856	.839
Ensemble-Lin.	8	.856	**.867**	.856	.840	.862	**.866**

Table 3: Average precision for each individual set of features and both classifiers. The three binary classification tasks are Controls vs. Depressed (CvD), Controls vs. PTSD (CvP) and Depressed vs. PTSD (DvP).

to the general classification results with different insights. A combination of features is thus preferable in order to boost performance and also reduce variance or increase robustness.

We create an ensemble of classifiers, each of which uses the different textual feature sets described in the previous section. The predicted scores for each model are used to train a logistic regression classifier in order to identify the weights assigned to each classifier before their output is combined (**Ensemble-Lin.**). We also experimented with a non-weighted combination of classifiers (**Ensemble-Avg.**).

4 Results

The results of our methods on cross-validation are presented in Table 3. Results using different feature sets show similar values, with all unigram features showing overall best results. However, we expect that each set of features will contribute with distinctive and complimentary information.

The ensemble methods show minor, but consistent improvement over the scores of each individual user set. The linear combination of different classifiers shows better performance compared to the average by appropriately down-weighting less informative sets of features.

Figure 1 shows the three ROC (Receiver Operator Characteristic) curves for our binary classification tasks. These curves are specifically useful for medical practitioners as the classification threshold can be adjusted to obtain an application specific level of false positives.

For example, we highlight that at a false positive rate of 0.1, we reach a true positive rate of 0.8 for separating Controls from users with PTSD and of 0.75 for separating Controls from depressed users. Distinguishing PTSD from depressed users is harder at small false positive rates, with only ~ 0.4 true positive rate.

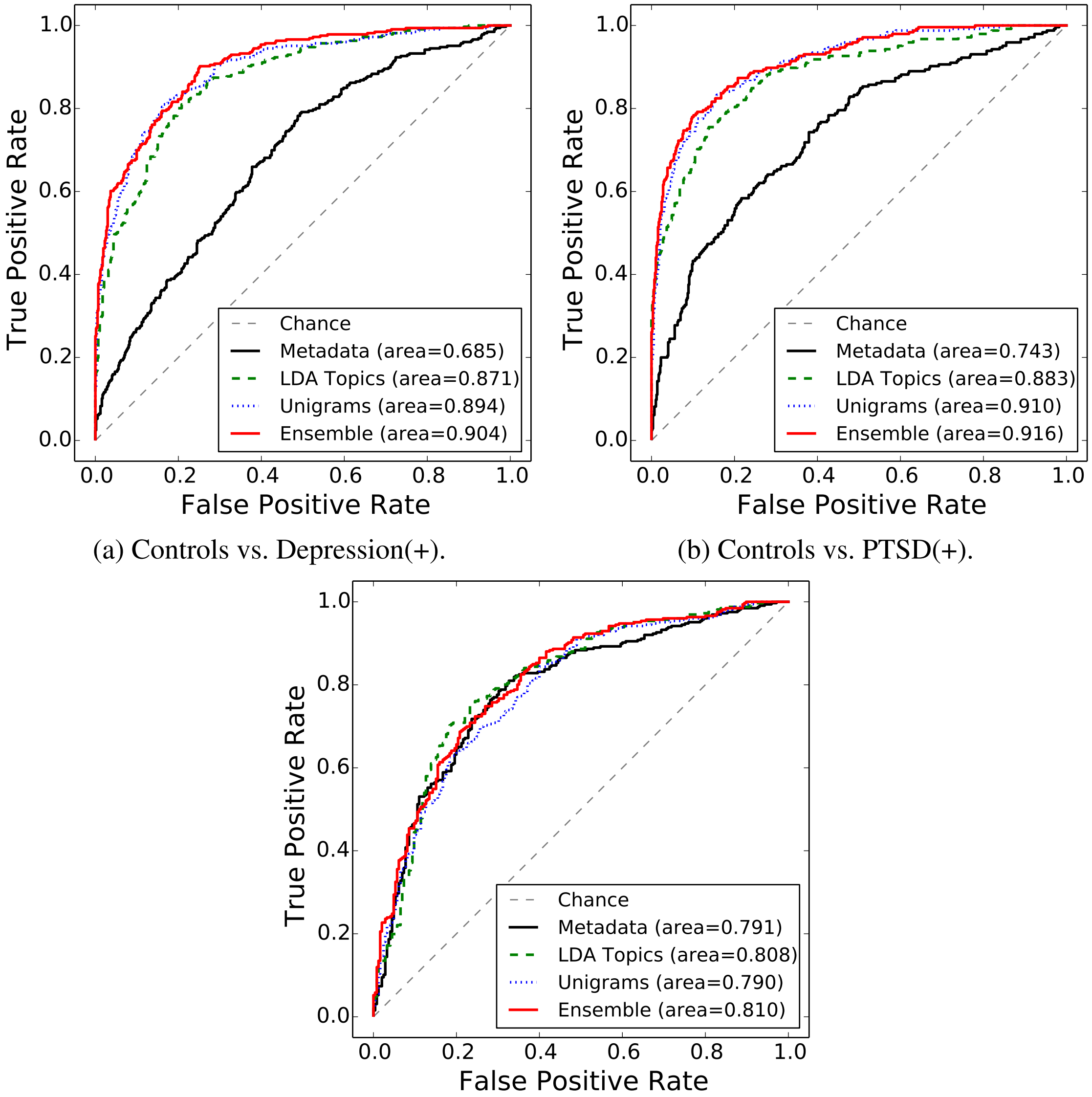
5 Discussion and Conclusions

This paper reported on the participation of the World Well-Being Project in the CLPsych 2015 shared task on identifying users having PTSD or depression.

Our methods were based on combining linear classifiers each using different types of word clusters. The methods we presented were designed to be as task agnostic as possible, aiming not to use medical condition specific keywords or data. We thus expect similar methods to perform well in identifying other illnesses or conditions.

This generalised approach yielded results ranking second in the shared task, scoring above 0.80 on all tasks and reaching up to 0.87 for one of the binary tasks. Further analysis shows that our models perform especially well at small false positive rates (up to 0.8 true positive rate at 0.1 false positive rate) where it ranked first.

Our perspective for future improvements is to use other datasets with similar labels for illnesses in a domain adaptation scenario, as more observations is likely to lead to better prediction quality. Another direction for possible improvement to our methods is to use a ‘learning to rank’ algorithm in place of classifiers.



(a) Controls vs. Depression(+).

(b) Controls vs. PTSD(+).

(c) Depression vs. PTSD(+).

Figure 1: ROC curves and area under the curve for a selected set of features using Linear Support Vector Classification. (+) denotes positive class.

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