TUGAS: Exploiting Unlabelled Data for Twitter Sentiment Analysis

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Abstract

This paper describes our participation in the message polarity classification task of SemEval 2014. We focused on exploiting unlabeled data to improve accuracy, combining features leveraging word representations with other, more common features, based on word tokens or lexicons. We analyse the contribution of the different features, concluding that unlabeled data yields significant improvements.

1 Introduction

Research in exploiting social media for measuring public opinion, evaluating popularity of products and brands, anticipating stock-market trends, or predicting elections showed promising results (O’Connor et al., 2010; Mitchell et al., 2013). However, this type of content poses a particularly challenging problem for text analysis systems. Typical messages show heavy use of Internet slang, emoticons and other abbreviations and discourse conventions. The lexical variation introduced by this creative use of language, together with the unconventional spelling and occasional typos, leads to very large vocabularies. On the other hand, messages are very short, and therefore word feature representations tend to become very sparse, degrading the performance of machine learned classifiers.

The growing interest in this problem motivated the creation of a shared task for Twitter Sentiment Analysis in the 2013 edition of SemEval. The Message Polarity Classification task was formalized as follows: Given a message, decide whether the message is of positive, negative, or neutral sentiment. For messages conveying both a positive and negative sentiment, whichever is the stronger sentiment should be chosen (Nakov et al., 2013).

We describe our participation on the 2014 edition of this task, for which a set of manually labelled messages was created. Complying with the Twitter policies for data access, the corpus was distributed as a list of message IDs and each participant was responsible for downloading the actual tweets. Using the provided script, we collected a training set with 8604 tweets. After submission, the 2014 test sets were also made available. Along with the Tweets 2014 test set, evaluation was also performed on a set of tweets with sarcasm, on a set of LiveJournal blog entries, and on sets of tweets and SMS messages from the 2013 edition of the task. Table 1 shows the class distribution for each of these datasets.

|                | Positive | Neutral | Negative |
|----------------|----------|---------|----------|
| Train 2014     | 3230     | 4109    | 1265     |
| Tweets 2013    | 1572     | 1640    | 601      |
| Tweets 2014    | 982      | 669     | 202      |
| SMS 2013       | 492      | 1207    | 394      |
| Tweets Sarcasm | 33       | 13      | 40       |
| LiveJournal 2014 | 427    | 411     | 304      |

Table 1: Number of examples per class in each SemEval dataset. The first row represents all training data; the other rows are sets used for testing.

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character n-grams.

The automatically induced lexicons are a way to use information from unlabeled data to aid in the classification task. In our approach, we take this reasoning further, and focus on the impact of various ways to incorporate knowledge from unlabeled data. This allows us to mimic many real-world scenarios where labeled data is scarce but unlabeled data is plentiful.

2 Word Representations

In text classification it is common to represent documents as bags-of-words, i.e., as unordered collections of words. However, in the case of very short social media texts, these representations become less effective, as they lead to increased data sparseness. We focused our experiments in comparing and complementing these approaches with denser representations, which we now describe.

2.1 Bag-Of-Words and ΔBM25

In a representation based on bags-of-words, each message is represented as a vector \( \mathbf{m} = \{w_1, w_2, ..., w_n\} \in \mathbb{R}^V \), where \( V \) is the size of the vocabulary. In order to have weights that reflect how relevant a word is to each of the classes, we weighted the individual terms according to the ΔBM25 heuristic (Paltoglou and Thelwall, 2010):

\[
\Delta BM25(w_i) = t_{fi} \times \log \frac{(N_n - df_{i,a} + s)(df_{i,n} + s)}{(N_n - df_{i,a} + s)(df_{i,n} + s) + 1},
\]

where \( t_{fi} \) represents the frequency of term \( i \) in the message, \( N_n \) is the size of corpus \( a \), \( df_{i,a} \) is the document frequency of term \( i \) in the corpus \( a \) (i.e., in one of two subsets for the training data, corresponding to either positive or negative messages), and \( s \) is a smoothing constant, which we set to 0.5. This term weighting function was previously shown to be effective for sentiment analysis.

2.2 Brown Clusters

Brown et al. (1992) proposed a greedy agglomerative hierarchical clustering procedure that groups words to maximize the mutual information of bigrams. Clusters are initialized as consisting of a single word each, and are then greedily merged according to a mutual information criterion, to form a lower-dimensional representation of a vocabulary. The hierarchical nature of the clustering allows words to be represented at different levels in the hierarchy. This approach provides a denser representation of the messages, mitigating the feature sparseness problem. We used a publicly available\(^1\) set of 1000 Brown clusters induced from a corpus of 56 million Twitter messages.

We leveraged the word clusters by mapping each word to the corresponding cluster, and we then represented each message as a bag-of-clusters vector in \( \mathbb{R}^K \), where \( K = 1000 \) is the number of clusters. These word cluster features were also weighted with the ΔBM25 scheme.

2.3 Concise Semantic Analysis

Concise Semantic Analysis is a form of term and document representation that assigns, to each term, its weight on each of the classes (Li et al., 2011). These weights, computed from the frequencies of the term on the training data, reflect how associated the term is to each class. The weight of term \( j \) in class \( c \) is given by (Lopez-Monroy et al., 2013):

\[
w_{cj} = \sum_{k \in P_c} \log_2 \left( 1 + \frac{tf_{kj}}{\log(\text{len}(k))} \right),
\]

where \( P_c \) is the set of documents with label \( c \) and \( tf_{kj} \) is the term frequency of term \( j \) in document \( k \). To prevent labels with a higher number of examples, or terms with higher frequencies, to have stronger weights, an additional normalization step is performed to obtain \( nw_{cj} \), the normalized weight of term \( j \) in class \( c \):

\[
nw_{cj} = \frac{w_{cj}}{\sum_{l \in L} w_{lj} \times \sum_{t \in T} w_{ct}}.
\]

In the formula, \( L \) is the set of class labels and \( T \) is the set of terms, making \( w_{lj} \) the weight of term \( j \) for a class \( l \), and \( w_{ct} \) the weight of a term \( t \) in class \( c \). After defining every term as a vector \( t_j = \{nw_{1j}, \ldots, nw_{Cj}\} \in \mathbb{R}^C \), where \( C \) is the number of classes, each message \( m \) is represented by summing each of its terms’ weight vectors:

\[
\mathbf{m}_{\text{csa}} = \sum_{j \in m} \frac{tf_j}{\text{len}(m)} \times \mathbf{t}_j.
\]

In the formula, \( tf_j \) is the frequency of term \( j \) in \( m \).

2.4 Dense Word Vectors

Efficient approaches have recently been introduced to train neural networks capable of producing continuous representations of words (Mikolov

\(^1\)http://www.ark.cs.cmu.edu/TweetNLP/)
Table 2: Number of unigrams, bigrams, and collocation pairs, in the lexicons used in our system.

| Lexicon        | #1-grams | #2-grams | #pairs |
|----------------|----------|----------|--------|
| Bing Liu       | 6789     | -        | -      |
| MPQA           | 8222     | -        | -      |
| SentiStrength  | 2546     | -        | -      |
| NRC EmoLex     | 14177    | -        | -      |
| Sentiment140   | 62468    | 677698   | 480010 |
| NRC HashSent   | 54129    | 316531   | 308808 |

et al., 2013). These approaches allow fast training of projections from a representation based on bags-of-words, where vectors have very high dimension (of the order of $10^4$), but are also very sparse and integer-valued, to vectors of much lower dimensions (of the order of $10^2$), with full density and continuous values.

To induce word embeddings, a corpus of 17 million Twitter messages was collected with the Twitter crawler of Boanjak et al. (2012). Then, using word2vec\(^2\), we induced representations for the word tokens occurring in the messages. All the tokens were represented as vectors $w_j \in \mathbb{R}^n$, with $n = 100$. A message was modeled as the sum of the vector representations of the individual words:

$$m_{vec} = \sum_{j \in m} w_j.$$  

(5)

We also created a polarity class vector $p_c$ for each class $c$, defined as:

$$p_c = \frac{1}{N_c} \sum_{m \in c} m_{vec},$$  

(6)

where $m$ is a message of class $c$ and $N_c$ is the total number of instances in class $c$. These vectors can be interpreted as prototypes of their classes, and are used in the classVec features described below.

3 The TUGAS System

We now describe the TUGAS approach, detailing the considered features and our modeling choices.

3.1 Word Features

To reduce the feature space of the model, messages were lower-cased, Twitter user mentions (@username) were replaced with the token <USER> and URLs were replaced with the <URL> token. We also normalized words to include at most 3 repeated characters (e.g., “helloooooo!” to “hellooo!”). Following Pang et al. (2002), negation was directly integrated into the word representations. All the tokens occurring between a negation word and the next punctuation mark, were suffixed with the _NEG annotation.

We used the following sets of features:

- **bow-uni**: vector of word unigrams
- **bow-bc**: vector of Brown word clusters
- **csa**: Concise Semantic Analysis vector $m_{csa}$
- **wordVec**: word2vec message vector $m_{vec}$
- **classVec**: Euclidean distance between message vector $m_{vec}$ and each class vector $p_c$

3.2 Lexicon Features

The document model was enriched with features that take into account the presence of words with a known prior polarity, such as happy or sad. We included words from manually annotated sentiment lexicons: Bing Liu Opinion Lexicon (Hu and Liu, 2004), MPQA (Wilson et al., 2005) and the NRC Emotion Lexicon (Mohammad and Turney, 2013). We also used the two automatically generated lexicons from Mohammad et al. (2013): the NRC Hashtag Sentiment Lexicon and the Sentiment140 Lexicon. Table 2 summarizes the number of terms of each lexicon.

As Mohammad et al. (2013), we added the following set of lexicon features, for each lexicon, and for each combination of negated/non-negated words and positive/negative polarity.

- The sum of the sentiment scores of all (negated/non-negated) terms with (positive/negative) sentiment
- The largest of those scores
- The sentiment score of the last word in the message that is also present in the lexicon
- The number of terms within the lexicon

Notice that terms can be unigrams, bigrams, and collocations pairs. A group of these features was computed for each of the sentiment lexicons.

3.3 Syntactic Features

We extracted syntactic features aimed at the Twitter domain, such as the use of heavy punctuation, emoticons and character repetition. Concretely, the following features were computed from the original Twitter messages:

- Number of words originally with more than 3 repeated characters
- Number of sequences of exclamation marks and/or question marks
More importantly, we verify that lexicon-based and Brown cluster features have the largest impact on the classification performance.

Table 3: Impact of removing or adding groups of features. The row marked as submitted, in bold, is the one that we submitted to the shared task. The bold column is the official score used to rank participants.

| Features                  | Tweets Test 2013 | Acc | F1 | Official | Tweets Test 2014 | Acc | F1 | Official | SMS 2013 | Acc | F1 | Official | Live Journal 2014 | Acc | F1 | Official | Tweets Sarcasm 2014 | Acc | F1 | Official |
|---------------------------|-----------------|-----|----|----------|------------------|-----|----|----------|----------|-----|----|----------|-------------------|-----|----|----------|-------------------|-----|----|----------|
| bow-uni                   | 65.62           | 59.30| 54.60|          | 69.94           | 66.30| 65.60|          | 68.80    | 62.40| 54.90|          | 60.42             | 58.30| 56.60|          | 57.67             | 43.90| 41.50|
| submitted                 | 69.55           | 67.50| 65.60|          | 71.49           | 69.00| 69.00|          | 70.57    | 67.60| 62.70|          | 68.21             | 68.90| 69.80|          | 53.49             | 50.10| 52.90|
| - lexicons                | 66.90           | 64.30| 61.70|          | 70.37           | 67.00| 66.40|          | 66.46    | 63.30| 58.30|          | 64.27             | 64.20| 65.50|          | 48.84             | 45.10| 47.00|
| - classVec                | 69.37           | 67.30| 65.40|          | 71.83           | 69.30| 69.60|          | 69.14    | 66.60| 62.10|          | 67.51             | 67.50| 69.30|          | 53.49             | 50.10| 52.90|
| - wordVec                 | 69.63           | 67.70| 66.00|          | 70.32           | 67.70| 68.00|          | 66.79    | 64.90| 64.00|          | 68.04             | 68.00| 69.70|          | 53.49             | 50.50| 53.50|
| - bow-bc                  | 68.06           | 66.40| 65.10|          | 67.40           | 64.30| 65.30|          | 67.89    | 65.20| 60.40|          | 68.30             | 68.30| 70.00|          | 52.33             | 49.90| 49.90|
| + syntactic               | 69.58           | 67.60| 65.70|          | 71.24           | 68.30| 68.50|          | 70.38    | 67.40| 62.40|          | 67.95             | 68.00| 69.70|          | 52.33             | 48.80| 50.00|
| + csa                     | 67.45           | 63.70| 60.50|          | 70.10           | 67.30| 67.50|          | 71.48    | 67.60| 62.10|          | 66.11             | 66.00| 68.30|          | 53.49             | 51.30| 50.30|
| + bow-uni                 | 67.69           | 62.50| 58.50|          | 70.64           | 67.30| 66.70|          | 72.77    | 67.10| 60.40|          | 67.60             | 67.20| 67.10|          | 51.16             | 48.00| 43.90|

3.4 Model Training

We used the L2-regularized logistic regression implementation from scikit-learn\(^4\). Given a set of \(m\) instance-label pairs \((x_i, y_i)\), with \(i = 1, \ldots, m\), \(x_i \in \mathbb{R}^n\), and \(y_i \in \{-1, +1\}\), learning the classifier involves solving the following optimization problem, where \(C > 0\) is a penalty parameter.

\[
\min_w \frac{1}{2} w'w + C \sum_{i=1}^{m} \log(1 + e^{-y_i w'x_i}). \tag{7}
\]

In scikit-learn, the problem is solved through a trust region Newton method, using a wrapper over the implementation available in the liblinear\(^5\) package. For multi-class problems, scikit-learn uses the one-vs-the-rest strategy. This particular implementation also supports the introduction of class weights, which we set to be inversely proportional to the class frequency in the training data, thus making each class equally important.

The selection of groups of features to be included in the submitted run, as well as the tuning of the regularization constant, were obtained by cross-validation on the training dataset.

4 Results

We report results using the following metrics:

- **Accuracy**, defined as the percentage of tweets correctly classified.
- **Overall F1**, computed by averaging the F1 score of all three classes.
- **The Official SemEval score**, computed by averaging the F1 scores of the positive and negative classes (Nakov et al., 2013).

\(^3\)http://sentiment.christopherpotts.net/

\(^4\)http://scikit-learn.org/

\(^5\)http://www.csie.ntu.edu.tw/~cjlin/liblinear/

Table 4: Performance comparison using different word representations in isolation.

| Feature group | Acc | F1 | Official |
|---------------|-----|----|----------|
| bow-bc        | 66.33| 63.30| 60.30    |
| wordVec       | 62.34| 60.00| 57.90    |
| bow-uni       | 65.62| 59.30| 54.60    |
| csa           | 61.58| 56.70| 52.90    |
These results indicate that leveraging unlabeled data yields significant improvements.

5 Conclusions

This paper describes the participation of the TUGAS team in the message polarity classification task of SemEval 2014. We showed that there are significant gains in leveraging unlabeled data for the task of classifying the sentiment of Twitter texts. Our score of 69% ranks at fifth place in 42 submissions, roughly 2% points below the top score of 70.96%. We believe that the direction of leveraging unlabeled data is still vastly unexplored and, for future work, we intend to: (a) experiment with semi-supervised learning approaches, further exploiting unlabeled tweets; and (b) make use of domain adaptation strategies to leverage on labelled non-Twitter data.

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