Abstract

This paper describes our system submissions to task 7 in SemEval 2016, i.e., Determining Sentiment Intensity. We participated the first two subtasks in English, which are to predict the sentiment intensity of a word or a phrase in English Twitter and General English domains. To address this task, we present a supervised learning-to-rank system to predict the relevant scores, i.e., the strength associated with positive sentiment, for English words or phrases. Multiple linguistic and sentiment features are adopted, e.g., Sentiment Lexicons, Sentiment Word Vectors, Word Vectors, Linguistic Features, etc. Officially released results showed that our systems rank the 1st among all submissions in English, which proves the effectiveness of the proposed method.

1 Introduction

The study of sentiment analysis is increasingly drawing attention of Natural Language Processing (NLP). Many of the top performing sentiment analysis systems rely on sentiment lexicon (Tan et al., 2008; Na et al., 2009; Mohammad et al., 2013). A sentiment lexicon is a list of words and phrases, such as “excellent”, “awful” and “not bad”, each of them is assigned with a positive or negative score reflecting its sentiment polarity and strength (Tang et al., 2014a). Higher scores indicate stronger sentiment strength. However, many existing manually generated sentiment lexicons consist of lexicons with only sentiment orientation rather than sentiment strength. For example, the words in BL (Ding et al., 2008) are generally divided to two classes, i.e., positive and negative. Although several sentiment lexicons have assigned discrete labels for terms, i.e., strong and weak, for example, MPQA (Wiebe et al., 2005), there is no continuous real-valued scores to indicate the intensity of sentiment so far.

The task of Determining Sentiment Intensity of English and Arabic Phrases intends to automatically create a sentiment lexicon with real-valued scores indicating the intensity of sentiment. The purpose of this task is to test the ability of an automatic system to predict a sentiment intensity score for a word or a phrase. Phrases include negators, modals, intensifiers, and diminishers. Given a list of terms, the participants are required to assign appropriate scores between 0 and 1, to indicate their strength of association with positive sentiment. The task contains three subtasks (the first two are in English and the third is in Arabic) and we participated the first two subtasks in English. The first General English Sentiment Modifiers Set contains phrases formed by a word and a modifier, where a modifier can be a negator, an auxiliary verb, a degree adverb, or even a combination of those above modifiers, e.g., “would be very easy”, “did not harm”, and “would have been nice”. The second English Twitter Mixed Polarity Set contains phrases made up of opposite polarity terms, such as “lazy sundays”, “best winter break”, “couldn’t stop smiling”, etc. The official evaluation measure is Kendall correlation coefficient (Lindskog et al., 2003).

In previous work, the task was treated as a regression problem, the word embedding is used as a feature (Amir et al., 2015). In addition, (Hamdan et al., 2015) adopted unsupervised approach by using
several sentiment lexicons for computing the score for each twitter term and ranked them. In this paper, we treated this task as a ranking problem, and used pair-wise strategy to train the model.

The rest of the paper is organized as follows. Section 2 elaborates the procedure of query reconstruction, data preprocessing, feature engineering and the learning-to-rank model built in our systems. Section 3 describes the data sets and experiments. Finally, Section 4 concludes this work.

2 System Description

The purpose of this task is to predict the sentiment strength of given words or phrases, it is reasonable to regard the value of strength as the relevant score referred to positive polarity. Thus, to address the sentiment strength prediction task, we presented a supervised learning-to-rank system to predict the relevant score which interprets the strength associated with positive sentiment. Figure 1 depicts the architecture of our system, which contains four main modules, i.e., Query Reconstruction, Data Preprocessing, Feature Engineering, and Ranking Model. The diversity of methods for General English and English Twitter domains is located in the different training data.

2.1 Query Reconstruction

Since the sentiment strength task was treated as a ranking problem, we converted the provided training data into appropriate forms as the input of our ranking system in the first stage. In general, several queries were fed into the ranking system served as training data. In consideration of the provided training data is a word list ordered by the strength score associated with positive sentiment, we manually divided the word list into several “queries” and the words in each query were sorted by their corresponding scores. Specifically, the test data would not be processed into Query Reconstruction module, because we considered all records in the test set as a unique query and the Ranking Model was used to predict their relevant scores.

2.2 Data Preprocessing

Due to the characteristic of training data in English Twitter domain, which consists of many informal words, such as “waiiiit”, “#happytweet”, etc., we converted the irregular forms to normal forms. For example, the elongated word “waiiiit” was transformed into “wait”, the hashtag “#happytweet” was converted into “happy tweet”. Then, we used the processed data to perform lemmatization and stemming to extract the further information with the aid of NLTK tool\(^1\).

2.3 Feature Engineering

To address the sentiment strength task, we extracted features summarized as follows: Sentiment Lexicon Features, Sentiment Word Vectors, Word Vectors, and Linguistic Features.

2.3.1 Sentiment Lexicon Features

We employed the following seven sentiment lexicons to extract Sentiment Lexicon Features: Bing Liu lexicon\(^2\), General Inquirer lexicon\(^3\), IMDB\(^4\), M-PQA\(^5\), AFINN\(^6\), NRC Hashtag Sentiment Lexicon\(^7\), and NRC Sentiment140 Lexicon\(^8\). Generally, we

\(^1\)http://www.nltk.org/
\(^2\)http://www.cs.uic.edu/liub/FBS/sentiment-analysis.html#lexicon
\(^3\)http://www.wjh.harvard.edu/inquirer/homecat.htm
\(^4\)http://anthology.aclweb.org/S/S13/S13-2.pdf#page=444
\(^5\)http://mpqa.cs.pitt.edu/
\(^6\)http://www2.imm.dtu.dk/pubdb/views/publication_details.php?id=6010
\(^7\)http://www.umiacs.umd.edu/saif/WebDocs/NRC-Hashtag-Sentiment-Lexicon-v0.1.zip
\(^8\)http://help.sentiment140.com/for-students/
transformed the sentiment orientation of all words in all sentiment lexicons into the range of \(-1\) to \(1\), where the minus sign denotes negative sentiment and the positive number indicates positive sentiment.

We considered each term (consisting of phrases and words) in the provided data as a tuple. If one term contains a single word, the size of this tuple is \(1\). If one term is a phrase, e.g., “happy accident”, the tuple size is the count of words in the phrase (for “happy accident”, it is \(2\)). Then, for each tuple, we concatenated the following sentimental scores extracted from each sentiment lexicon: (1) the maximum sentiment score of words, (2) the minimum sentiment score of words, (3) the sum of sentiment scores of all words. If one word does not exist in a sentiment lexicon, its corresponding score is set to 0. Specifically, if any negator, e.g., “not”, exists in a tuple, we reverse its sentiment orientation.

Considering the diversity of word forms, we also extracted additional sentiment lexicon features about their lemmatization and stemming forms. The final sentiment lexicon representation of the \(i\)-th record \(l_i \in \mathbb{R}^{n_l \times n_s \times 3}\), where \(n_l\) is the number of sentiment lexicons (i.e., \(7\)), \(n_s\) is set as 3 representing the three scores calculated according to the above rules, \(t\) is also set as 3 representing the three forms (i.e., original, lemmatization and stemming forms) of the word in the record.

### 2.3.2 Word Vectors

Word vector is a continuous-valued representation of the word which carries syntactic and semantic information. In this task, we adopted various Word Vectors as features. Since the task data contains phrases made up of more than one word, it is necessary to convert these word vectors into a phrase vector. Unlike previous work which summed up all words vectors to represent the phrase, we first check whether the phrase is present in training data or not. If a phrase is present in training data, we actually treat it as a single token and learn its vector based on the given word vector learning model. If it is a new phrase not existing in training data, we follow previous work and sum up all vectors of words in this phrase as a phrase vector.

In this part, we introduce two types of word vector which are adopted in our method, i.e., Traditional Word Vector and Sentiment Word Vector, which are described as follows:

**Traditional Word Vectors:**

- **GoogleW2V:** We used the publicly available \texttt{word2vec} tool\(^9\) to get word vectors with dimensionality of 300, which were trained on 100 billion words from Google News as \texttt{GoogleW2V} feature.

- **GloveW2V:** The Glove\cite{Pennington2014} rely on different assumptions about the relations between words within a context window. We used the available pre-trained word vector with dimensionality of 100 and trained on 2 billion tweets, which were supplied in \texttt{GloVe}\(^{10}\) as \texttt{GloveW2V} feature.

- **NormalW2V:** We fed \texttt{NRC140 tweet corpus} into \texttt{word2vec} tool to build \texttt{NormalW2V} with dimensionality of 100.

- **NormalW2V\_Multi:** To train specific word vectors (i.e., words and phrases) for this task, we preprocessed the \texttt{NRC140 corpus} by connecting words in the phrase appeared in training data to obtain a single token. The processed data were fed into word vector model to train \texttt{NormalW2V\_Multi} with dimensionality of 100.

**Sentiment Word Vectors:** Since the above word vectors are trained based on the context, they are supposed to contain semantic and syntactic information. However, due to lack of sentiment information, these traditional word vectors may not be quite effective for sentiment analysis tasks. To address this issue, our previous work and other researchers has proposed methods to learn sentiment word vectors.

- **SWV:** In \cite{Zhang2015} we proposed the Combined-Sentiment Word Embedding Model (i.e., \texttt{SVW-C}) to learn sentiment word vectors, which are confirmed to be helpful to settle sentiment analysis task. In this work, we used this model to train the SWV with the aid of \texttt{NRC140 tweet corpus} \cite{Go2009}, where the corpus is made up of 1.6 million positive tweets and 1.6 million negative tweets. The vector size is set as 100.

\(^9\)https://code.google.com/archive/p/word2vec
\(^{10}\)http://nlp.stanford.edu/projects/glove/
- SWV Multi: Similar with NormalW2V Multi, we used the NRC140 corpus as training corpus and reconstructed it to the task specific form. The processed corpus was employed as input of SWV-C model to generate SWV Multi with dimensionality of 100.

- SSWE: The sentiment-specific word embeddings (SSWE) were proposed by (Tang et al., 2014b), which is quite similar to our idea in (Zhang and Lan, 2015) but differs in proposed models. This SSWE sentiment word embeddings were trained by using multi-hidden-layers neural network with vector size of 50.

2.3.3 Linguistic Features
- Negation: The sentiment polarity of word or phrase can be reversed by a modification of negation. Therefore, we collected 29 negations from Internet and we sign 1 or 0 to this binary feature if corresponding negation is present or absent in the pending word or phrase.

- Elongated: This feature represents if word or phrase with one character repeated more than twice, e.g., “lottttt”.

2.4 Ranking Model
Different from the classification or regression methods, which focus on labeling the single record, the ranking method takes the relation between two arbitrary records associated with a query into consideration.

In this module, we used a supervised learning-to-rank approach to perform ranking. Generally, the mentioned approach can be divided into three groups: point-wise, pair-wise, and list-wise. We adopted the second strategy, i.e., pair-wise for our work. In pair-wise strategy, several record1-record2 pairs were constructed with a query and some records which were provided in advance. If record1 is more relevant than record2 in terms of the given query, this pair label will be set as 1, otherwise 0.

3 Experiments and Results
3.1 Datasets
This sentiment strength prediction task was severed as the subtask E of Sentiment Analysis on Tweet in SemEval 2015. Thus, the trial (i.e., 15trial) and test (i.e., 15test) data in SemEval 2015, which contained 200 and 1,315 records separately, are integrated as training data for this task. The organizer provided 200 records as development data set for each domain (i.e., 16trial_twitter and 16trial_general) and the labels are the same as before, where each record is labeled with a decimal in the range of 0 to 1 and the score is the strength associated with positive sentiment.

In consideration of the lack of training data, we expanded it with the Language Assessment by Mechanical Turk lexicon (i.e., LabMT) which automatically labeled by (Dodds et al., 2011). It contains 10,222 words rated on a scale of 1(sad) to 9(happy). Note that the labels in the LabMT are different from the standard data, we converted the score to the scale of 0 to 1 by min-max normalization, i.e., $\frac{x - \min}{\max - \min}$.

3.2 Evaluation Metrics
For this task, Kendall rank correlation coefficient (usually measures the association between two measured quantities) is used as the metric to compare the ranked lists. Besides, the scores for Spearman’s Rank Correlation (a nonparametric measure of statistical dependence between two variables) is provided as well. The Kendall rank correlation coefficient is severed as the final official evaluation criteria.

3.3 Experiment on training data
As we described in 2.1, several operations should be conducted to transform the raw data form to accommodate the ranking system. Considering that the LabMT is a term list that has been automatically labeled, while the provided standard data is more precise, so we constructed each query in LabMT with 200 records. With regard to the provided standard data (i.e., 15trial, 15test), each query was made up of 20 records.

To construct training data for English Twitter domain, the LabMT, 15train and 15test were utilized, whereas the 16trial_twitter was utilized as development data. Several types of features have been proposed in 2.3, in order to conduct feature selection, we adopted hill climbing which is described as: keeping adding one type of feature at a time until no further improvement can be achieved.

The system’s diversity of two domains lies on
Table 1: Results of feature selection experiments for Twitter English and General English domains.

| Feature | English Twitter | General English |
|---------|-----------------|-----------------|
| Traditional W2V | GoogleW2V | ✓ | ✓ |
|           | NormalW2V | ✓ | ✓ |
|           | NormalW2V_Multi | ✓ | ✓ |
|           | GloveW2V | ✓ | ✓ |
| Sentimental W2V | SWV | ✓ | ✓ |
|           | SWV_Multi | ✓ | ✓ |
|           | SSWE | ✓ | ✓ |
| Sentiment Lexicon | SentiLexi | ✓ | ✓ |
| Linguistic | Negation | ✓ | ✓ |
|           | Emphasize | ✓ | ✓ |

Ranking Results (Kendall/Sperman) 59.83%/75.38% 71.67%/86.83%
Regression Results (Kendall/Sperman) 57.80%/73.01% 70.50%/85.26%

the different training data we utilized: all tweet-related data were adopted in English Twitter, while the words and phrases with hashtag(#) or informal forms were removed for General English. Thus, the filtered data of LabMT, 15trial and 15test were severed as training data and the 16trial_General were utilized as development data. The process of feature selection was similar with English Twitter domain except that the Emphasize feature was not used.

Table 1 shows the results of feature selection experiments on the development data, which lists the optimal feature sets of two domains.

From Table 1, it is interesting to find: (1) The Sentiment Lexicon features make a considerable contribution, because that the used sentiment lexicons contain sentiment information to some extent and its sentiment scores in lexicons are closely related to the strength associated with positive sentiment. For example, in BL, the scores of positive words are 1 and the negative words are represented as −1. (2) The Linguistic features (i.e., Negation and Emphasize) also contribute to performance. As for Negation, the possible reason may be that there are plentiful negators existed in training and development data and the emphatic words have similar situation. (3) The NormalW2V and SWV are both effective features for this task. In our further experiments which test the SWV and NormalW2V respectively, we found that SWV performs much better than NormalW2V, which showed that the Combined Sentiment Word Vector Model indeed captured sentiment information from abundant auto-labeled tweets. (4) The ranking based system outperforms the regression method, which indicates that it is convincing to regard this labeling task as a ranking problem. (5) Compared with the results on English Twitter domain, we notice that the performance is much better. Based on the observation on development data of two domains, we found that the phrases on English Twitter domain are made up of opposite polarity terms, e.g., “happy accident”, “couldn’t stop smiling”, while the records in General English domain are much more ordinary. The diversity of data distribution results in the above mentioned gap.

3.4 System Configuration

We built two systems for the two subtasks. In our preliminary experiments, we examined several algorithms with different parameters implemented in RankLib tool\(^{11}\), e.g., Random Forest, RankNet, RankBoost, and ListNet. According to the best performance in our experiments, we adopted Random Forest algorithm with parameters tree = 5, bag = 100 for English Twitter domain and tree = 1, bag = 300 for General English domain for our final submitted systems.

3.5 Results and Analysis

Table 2 lists the performances of our system and the top ranked system provided by organizer on test data.

The results in the Table 2 show that our system indeed performed well on sentiment strength prediction task regardless of domains, where the proposed system ranks 1st above both domains among all submissions. The results of test data are consistent with our experiment on training data, the performance on

\(^{11}\)https://people.cs.umass.edu/ vdang/ranklib.html
English Twitter domain is worse than that on General English domain due to the data distribution.

| Domain | Rank | TeamID | Kendall(%) | Sperman(%) |
|--------|------|--------|------------|------------|
| General | 1    | ECNU   | 70.42      | 86.27      |
|        | 2    | UWB    | 65.91      | 85.36      |
|        | 3    | LSIS   | 34.97      | 50.75      |
| Twitter | 1    | ECNU   | 52.31      | 67.40      |
|        | 2    | LSIS   | 42.16      | 59.06      |
|        | 3    | UWB    | 41.38      | 57.82      |

Table 2: Performances of our systems and the top-ranked system for two domains. General and Twitter stand for General English domain and English Twitter domain respectively.

4 Conclusion

In this paper, we presented a supervised learning-to-rank system to predict the strength of positive sentiment associated with words and phrases. Multiple features, e.g., Sentiment Lexicon, Sentiment Word Vectors, Word Vectors, and Linguistic Features, were presented. We find that the Sentiment Lexicon Features and the Sentiment Word Vectors make contributions to performance improvement. However the phrase vector is not effective as expected and in future work it is interesting to explore more ways to represent phrase.

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