Improve Polarity Detection of Online Reviews with Bag-of-Sentimental-Concepts

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Abstract. In this paper, we present our system that participates in the Polarity Detection task, which is the elementary task in the ESWC-14 Challenge on Concept-Level Sentiment Analysis. In addition to traditional Bag-of-Words features, we also employ state-of-the-art Sentic API to extract concepts from documents to generate Bag-of-Sentimental-Concepts features. Our previous work SentiConceptNet is served as the reference concept-based sentiment knowledge base for concept-level sentiment analysis. Experimental results show that adding Bag-of-Sentimental-Concepts can improve the accuracy by 1.18%, indicating the effectiveness of concept-level sentiment analysis. Our demo website is located at http://140.115.51.136:5000.

1 Introduction

The growth in social media use has altered the role of users from information receivers to information providers. As snowballing numbers of people share their ideas, experiences, and opinions on the Web, sentiment analysis has become a overwhelming topic for those who wish to understand public opinion from online data.

A fundamental task in sentiment analysis [1] is classifying the polarity of a given text at the document level — whether the expressed opinion in a document is positive, negative, or neutral. Early work in that area includes Turney [2] and Pang [3] who applied different methods for detecting the polarity of product reviews and movie reviews respectively. Such existing approaches primarily rely on parts of text in which opinions and sentiments are explicitly expressed such as polarity terms and their co-occurrence frequencies. However, sentiments are often carried implicitly through underlying semantics, which make purely syntactical approaches ineffective [4]. To this end, concept-level sentiment analysis is developed to go beyond a traditional word-level analysis of text. By relying on large semantic knowledge bases, concept-level sentiment analysis steps away from blind use of keywords and word co-occurrence count, but rather relies on the implicit features associated with natural language concepts.

In this paper, we present our system that participates in the Polarity Detection task, which is the elementary task in the ESWC-14 Challenge on Concept-Level Sentiment Analysis. In addition to traditional Bag-of-Words features, we also extract concepts from documents to generate Bag-of-Sentimental-Concepts features. Our paper is organized as follows: Section 2 describes the system overview and our method. Section 3 presents the experimental results. Section 4 gives the conclusion remarks.

2 Method

2.1 Formulation and term weighting schemes

In this paper, polarity detection is formulated as a classification problem. Each document is transformed to a feature vector and then classified as either positive or negative. We adopt the support vector machines (SVM) as our classification model because its efficacy has been demonstrated for binary classification tasks and allows non-binary value in feature vectors.

Following the classical Bag-of-Words feature representation, a document d is represented as a term vector $\mathbf{v}$, in which each dimension v_i corresponds to a term t_i. v_i is calculated by a term-weighting function. In this task, we use t_i's term frequency (TF) in d as v_i's value.

2.2 SentiConceptNet

SentiConceptNet [5] is a concept-level sentiment dictionary is built through a two-step method combining iterative regression and random walk with in-link normalization using ConceptNet 5 [6]. ANEW [7] and SenticNet 2 [8] are exploited for propagating sentiment values based on the assumption that semantically related concepts share common sentiment. Currently, SentiConceptNet contains 265,353 concepts with sentiment values, ranging from -1 to 1

2.2 Bag of Sentimental Concept Features

In addition to Bag-of-Words features introduced in Section 2.1, we also explore the sentimental concepts contained in review texts. We adopt the graph-based approach proposed by Rajagopal et al. [9] for extracting concepts from the review articles and represent each review as a bag of concepts (Bag-of-Sentimental-Concepts). The reference sentiment dictionary is SentiConceptNet. Each dimension v_i corresponds to a concept c_i. v_i is calculated by a term-weighting function. In this task, we use c_i's term frequency (TF) in d or TF(c_i)*Sentiment_value(c_i) as v_i's value.

3 Experiments

In this experiment, we use the Blitzer review dataset. It contains several files. We use reviews in the positive.review file or negative.review file to compile our development set. The all.review file is used to train the final model for online testing. The statistics of these three files are shown in Table 1.

Table 1. Statistics of the used files in the Blitzer dataset.

File Name	# of reviews
positive.review	21,972
negative.review	16,576
all.review	148,718

Our system is evaluated in terms of precision (P), recall (R), F-measure (F), and accuracy (ACC). We perform 10-fold cross-validation on the development set with three configurations of our polarity detection system: Bag-of-Words and Bag-of-Words+Bag-of-Sentimental-Concepts (TF) and Bag-of-Words + Bag-of-Sentimental-Concepts (TF(c_i)*Sentiment_value(c_i)). As shown in Table 2, adding Bag-of-Sentimental-Concepts features achieves greater accuracy than Bag-of-Words features due to their larger vocabulary size and higher sentiment unit level (word-level v.s. concept-level). When a concept's term frequency multiplied by its sentiment value, the performance can be further improved. Our demo website is located at http://140.115.51.136:5000.

Table 2. Performance comparison.

Configuration	P	R	F	ACC
Bag-of-Words	86.97%	86.71%	86.84%	85.02%
Bag-of-Words + Bag-of-Sentimental-Concepts	87.57%	87.12%	87.34%	85.61%
Bag-of-Words + Bag-of-Sentimental-Concepts (TF(c_i)*Sentiment_value(c_i))	87.12%	88.95%	88.02%	86.20%

4 Conclusion

In this paper, we present our system that participates in the Polarity Detection task, which is the elementary task in the ESWC-14 Challenge on Concept-Level Sentiment Analysis. In addition to traditional Bag-of-Words features, we also employ state-of-the-art Sentic API to extract sentimental concepts from documents to generate Bag-of-Sentimental-Concepts features. Our previous work SentiConceptNet is served as the reference concept-based sentiment knowledge base for concept-level sentiment analysis. Experimental results show that adding Bag-of-Sentimental-Concepts can improve the accuracy by 1.18%, indicating the effectiveness of concept-level sentiment analysis.

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