EXTRACTING OPINION TARGETS AND OPINION WORDS FROM ONLINE REVIEWS WITH GRAPH CO-RANKING

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Abstract

Extracting opinion targets and opinion words from online reviews are two fundamental tasks in opinion mining. This paper proposes a novel approach to collectively extract them with graph coranking. First, compared to previous methods which solely employed opinion relations among words, our method constructs a heterogeneous graph to model two types of relations, including semantic relations and opinion relations. Next, a co-ranking algorithm is proposed to estimate the confidence of each candidate, and the candidates with higher confidence will be extracted as opinion targets/words. In this way, different relations make cooperative effects on candidates' confidence estimation. Moreover, word preference is captured and incorporated into our coranking algorithm. In this way, our coranking is personalized and each candidate's confidence is only determined by its preferred collocations. It helps to improve the extraction precision. The experimental results on three data sets with different sizes and languages show that our approach achieves better performance than state-of-the-art methods.

1 Introduction

In opinion mining, extracting opinion targets and opinion words are two fundamental subtasks. Opinion targets are objects about which users' opinions are expressed, and opinion words are words which indicate opinions' polarities. Extracting them can provide essential information for obtaining fine-grained analysis on customers' opinions. Thus, it has attracted a lot of attentions (Hu and Liu, 2004b; Liu et al., 2012; Moghaddam and Ester, 2011; Mukherjee and Liu, 2012). To this end, previous work usually employed a collective extraction strategy (Qiu et al., 2009; Hu and Liu, 2004b; Liu et al., 2013b). Their intuition is: opinion words usually co-occur with opinion targets in sentences, and there are strong modification relationship between them (called opinion relation in (Liu et al., 2012)). If a word is an opinion word, other words with which that word having opinion relations will have highly probability to be opinion targets, and vice versa. In this way, extraction is alternatively performed and mutual reinforced between opinion targets and opinion words. Although this strategy has been widely employed by previous approaches, it still has several limitations. 1) Only considering opinion relations is insufficient. Previous methods mainly focused on employing opinion relations among words for opinion target/word co-extraction. They have investigated a series of techniques to enhance opinion relations identification performance, such as nearest neighbor rules (Liu et al., 2005), syntactic patterns (Zhang et al., 2010; Popescu and Etzioni, 2005), word alignment models (Liu et al., 2012; Liu et al., 2013b; Liu et al., 2013a), etc. However, we are curious that whether merely employing opinion relations among words is enough for opinion target/word extraction? We note that there are additional types of relations among words. For example, "LCD" and "LED" both denote the same aspect "screen" in TV set domain, and they are topical related. We call such relations between homogeneous words as semantic relations. If we have known "LCD" to be an opinion target, "LED" is naturally to be an opinion target. Intuitively, besides opinion relations, semantic relations may provide additional rich clues for indicating opinion targets/words. Which kind of relations is more effective for opinion targets/words extraction? Is it beneficial to consider these two types of relations together for the extraction? To our best knowledge

2 Related Work

There are many significant research efforts on opinion targets/words extraction (sentence level and corpus level). In sentence level extraction, previous methods (Wu et al., 2009; Ma and Wan, 2010; Li et al., 2010; Yang and Cardie, 2013) mainly aimed to identify all opinion target/word mentions in sentences. They regarded it as a sequence labelling task, where several classical models were used, such as CRFs (Li et al., 2010) and SVM (Wu et al., 2009). This paper belongs to corpus level extraction, and aims to generate a sentiment lexicon and a target list rather than to identify mentions in sentences. Most of previous corpus-level methods adopted a co-extraction framework, where opinion targets and opinion words reinforce each other according to their opinion relations. Thus, how to improve opinion relations identification performance was their main focus. (Hu and Liu, 2004a) exploited nearest neighbour rules to mine opinion relations among words. (Popescu and Etzioni, 2005) and (Qiu et al., 2011) designed syntactic patterns to perform this task. (Zhang et al., 2010) promoted Qiu's method. They adopted some special designed patterns to increase recall. (Liu et al., 2012; Liu et al., 2013a; Liu et al., 2013b) employed word alignment model to capture opinion relations rather than syntactic parsing. The experimental results showed that these alignment-based methods are more effective than syntax-based approaches for online informal texts. However, all aforementioned methods only employed opinion relations for the extraction, but ignore considering semantic relations among homogeneous candidates. Moreover, they all ignored word preference in the extraction process. In terms of considering semantic relations among words, our method is related with several approaches based on topic model (Zhao et al., 2010; Moghaddam and Ester, 2011; Moghaddam and Ester, 2012a; Moghaddam and Ester, 2012b; Mukherjee and Liu, 2012). The main goals of these methods weren't to extract opinion targets/words, but to categorize all given aspect terms and sentiment words. Although these models could be used for our task according to the associations between candidates and topics, solely employing semantic relations is still one-sided and insufficient to obtain expected performance. Furthermore, there is little work which considered these two types of relations globally (Su et al., 2008; Hai et al., 2012; Bross and Ehrig, 2013). They usually captured different relations using co-occurrence information. That was too coarse to obtain expected results (Liu et al., 2012). In addition, (Hai et al., 2012) extracted opinion targets/words in a bootstrapping process, which had an error propagation problem. In contrast, we perform extraction with a global graph co-ranking process, where error propagation can be effectively alleviated. (Su et al., 2008) used heterogeneous relations to find implicit sentiment associations among words.

3 The Proposed Method

We formulate opinion targets/words extraction as a co-ranking task. All nouns/noun phrases are regarded as opinion target candidates, and all adjectives/verbs are regarded as opinion word candidates, which are widely adopted by pervious methods (Hu and Liu, 2004a; Qiu et al., 2011; Wang and Wang, 2008; Liu et al., 2012). Then each candidate will be assigned a confidence and ranked, and the candidates with higher confidence than a threshold will be extracted as the results. Different from traditional methods, besides opinion relations among words, we additionally capture semantic relations among homogeneous candidates. To this end, a heterogeneous undirected graph G = (V, E) is constructed. V = V t ∪ V o denotes the vertex set, which includes opinion target candidates v t ∈ V t and opinion word candidates v o ∈ V o . E denotes the edge set, where eij ∈ E means that there is a relation between two vertices. Ett ⊂ E represents the semantic relations between two opinion target candidates. Eoo ⊂ E represents the semantic relations between two opinion word candidates. Eto ⊂ E represents the opinion relations between opinion target candidates and opinion word candidates. Based on different relation types, we used three matrices Mtt ∈ R |V t |×|V t | , Moo ∈ R |V o |×|V o | and Mto ∈ R |V t |×|V o | to record the association weights between any two vertices, respectively. Section 3.4 will illustrate how to construct them. 3.1 Only Considering Opinion Relations To estimate the confidence of each candidate, we use a random walk algorithm on our graph to perform co-ranking. Most previous methods (Hu and Liu, 2004a; Qiu et al., 2011; Wang and Wang, 2008; Liu et al., 2012) only considered opinion relations among words. Their basic assumption is as follows.

4 Experiments

4.1 Datasets and Evaluation Metrics Datasets:

To evaluate the proposed method, we used three datasets. The first one is Customer Review Datasets (CRD), used in (Hu and Liu, 2004a), which contains reviews about five products. The second one is COAE2008 dataset22 , which contains Chinese reviews about four products. The third one is Large, also used in (Wang et al., 2011; Liu et al., 2012; Liu et al., 2013a), where two domains are selected (Mp3 and Hotel). As mentioned in (Liu et al., 2012), Large contains 6,000 sentences for each domain. Opinion targets/words are manually annotated, where three annotators were involved. Two annotators were required to annotate out opinion words/targets in reviews. When conflicts occur, the third annotator make final judgement. In total, we respectively obtain 1,112, 1,241 opinion targets and 334, 407 opinion words in Hotel, MP3. Pre-processing: All sentences are tagged to obtain words' part-of-speech tags using Stanford NLP tool3 . And noun phrases are identified using the method in (Zhu et al., 2009) before extraction. Evaluation Metrics: We select precision(P), recall(R) and f-measure(F) as metrics. And a significant test is performed, i.e., a t-test with a default significant level of 0.05.

The Effectiveness of Considering Word Preference

In this section, we try to prove the necessity of considering word preference in Eq.6. Besides the comparison between CR and CR WP performed 321 in the main experiment in Section 4.2, we further incorporate word preference in aforementioned OnlyOA, named as OnlyOA WP, which only employs opinion relations among words and equals to Eq.6 with $\lambda = 0$. Experimental results are shown in Figure 3. Because of space limitation, we only show the results of the same domains in section 4.3, Form results, we observe that CR WP outperforms CR, and OnlyOA WP outperforms OnlyOA in all domains, especially on precision. These observations demonstrate that considering word preference is very important for opinion targets/words extraction. We believe the reason is that exploiting word preference can provide more fine information for opinion target/word candidates' confidence estimation. Thus the performance can be improved.

Parameter Sensitivity

In this subsection, we discuss the variation of extraction performance when changing λ and μ in Eq.6. Due to space limitation, we only show the F-measure of CR WP on four domains. Experimental results are shown in Figure 4 and Figure 5. The left graphs in Figure 4 and 5 present the performance variation of CR WP with varying λ from 0 to 0.9 and fixing $\mu = 0.1$. The right graphs in Figure 4 and 5 present the performance variation of CR WP with varying μ from 0 to 0.6 and fixing $\lambda = 0.4$. In the left graphs in Figure 4 and 5, we observe the best performance is obtained when $\lambda = 0.4$. It indicates that opinion relations and semantic relations are both useful for extracting opinion targets/words. The extraction performance is benefi- cial from their combination. In the right graphs in Figure 4 and 5, the best performance is obtained when μ = 0.1. It indicates prior knowledge is useful for extraction. When μ increases, performance, however, decreases. It demonstrates that incorporating more prior knowledge into our algorithm would restrain other useful clues on estimating candidate confidence, and hurt the performance. 0.0 .1 .2 .3 .4 .5 .6 .7 .8 .9 F-Measure .60 .65 .70 .75 .80 .85 MP3 Hotel Laptop Phone 0.0 .1 .2 .3 .4 .5 .6 F-Measure .65 .70 .75 .80 .85 MP3 Hotel Laptop Phone Figure 4: Opinion targets extraction results 0.0 .1 .2 .3 .4 .5 .6 .7 .8 .9 F-Measure .55 .60 .65 .70 .75 .80 MP3 Hotel Laptop Phone 0.0 .1 .2 .3 .4 .5 .6 F-Measure .50 .55 .60 .65 .70 .75 .80 MP3 Hotel Laptop Phone Figure 5: Opinion words extraction results

5 Conclusions

This paper presents a novel method with graph coranking to co-extract opinion targets/words. We model extracting opinion targets/words as a coranking process, where multiple heterogeneous relations are modelled in a unified model to make cooperative effects on the extraction. In addition, we especially consider word preference in co-ranking process to perform more precise extraction. Compared to the state-of-the-art methods, experimental results prove the effectiveness of our method.

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