Disambiguating word sentiment polarity through Bayesian modeling and opinion-level features

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Abstract. Many opinion words carry different polarity in different context, posing huge challenges to sentiment analysis research. Previous work on contextual polarity disambiguation makes use of term-level context such as word and patterns, and resolves the polarity with pattern-based methods, PMI-based statistical techniques and machine learning methods. The major shortcoming of all such approaches lies in that term-level features are sometimes ineffective in resolving the polarity. In this work, opinion-level features are studied and a Bayesian model is designed to disambiguate word sentiment polarity. Experiments with Opinmine corpus show that the opinion-level Bayesian model achieves significant performance gain in word polarity disambiguation in two domains.
Keywords: word polarity disambiguation, sentiment analysis, opinion mining

1 Introduction

Sentiment analysis research has achieved significant progress in the past decade [**?**]. Many opinion-mining systems have been developed, some of which were even commercialized in fields spanning from multi-modal analysis [1] to intention awareness [2], cyber-issue detection [3], e-health [4], and more. Challenging issues in sentiment analysis are many. A majority of research attention is given to subjectivity detection and sentiment classification. Later on, when corpora are available on product reviews, some research efforts are then made on opinion holder/target extraction.

Turney and Littman (2003) claimed that word polarity ambiguity is an unavoidable challenge [5]. Unfortunately, not much research work is attracted until a relevant task was conducted in SemEval-2010 task on disambiguating sentiment ambiguous adjectives (DSAA) [6]. For the first time, the task organizers provide 2,917 test sentences to 17 participant systems to disambiguate sentiment polarity of 14 Chinese adjectives. Today, sentiment analysis research steps into the era of finely-grained aspect-based opinion mining, in which sentiment word play a vital role as features in machine learning methods [7, 8] or as key elements in rule-based methods [9]. Resolving sentiment polarity of a word now becomes a necessity.

Previous work including systems in SemEval-2010 DSAA task focuses on adjectives in news [6]. Two limitations are worth noting. Firstly, adjectives are just part of the sentiment-ambiguous words. There are many nouns and verbs which give different sentiment polarity in different context. Ignoring these words is fatal to opinion mining systems. Secondly, sentiment-ambiguous words appear much more frequently in reviews created by social media and e-commerce. The major battlefield is reviews. In this work, we conduct research in reviews and address sentiment-ambiguous words of all types.

Similar to the famous word sense disambiguation (WSD) task, word polarity disambiguation (WPD) aims at resolving polarity of the sentiment-ambiguous words in certain context. Given sentiment-ambiguous word w and certain context Ω which is usually a sentence, WPD attempts to predict a deterministic polarity. With a probabilistic model, the process is formalized as:

$$l^* = \text{argmax}_{l \in \{1,-1\}} P(l|w, \Omega) \tag{1}$$

where l denotes a polarity which is usually positive (1) or negative (-1).

Two questions will be answered in this paper:

Q1: *What should be considered as effective context in* Ω?
Q2: *How is the probability* $P(l|w, \Omega)$ *accurately calculated*?

Question Q1 is answered actually by exploring features for word polarity disambiguation while question Q2 is a mathematical problem which calculates the probability that the word is assign a polarity label.

In this work, we make use of the following opinion-level features in word polarity disambiguation: opinion targets, modifying words and opinion indicating N-grams (see more details in Section 3). We adopt Bayesian model, which calculates polarity probability of a given word within a given context based on posterior distributions that are estimated from training/development data. Three contributions are worth noting: First, it is observed in this work that the opinion-level context is effective in resolving polarity ambiguity of sentiment words. Second, the Bayesian model is designed to calculate probability that the given sentiment word carries certain sentiment polarity. Independent assumption is made amongst the features that influence the model. At last, experiments have been conducted which justify usefulness of the features in the opinion-level context and the effectiveness of the Bayesian model.

The rest of this paper is organized as follows. In Section 2 we summarize the related work. In Section 3 we define opinion-level features in our work. In Section 4 we present the Bayesian model that works our polarity probability with these features. We report the experiments as well as discussion in Section 5. The paper is finally concluded in Section 6.

2 Related work

Sentiment analysis research arises from the need to classify opinionated text into positive or negative as an orientation determination problem [10, 11]. Early works aimed to identify a set of opinion polarity keywords [12, 13]. Later, the need for sentiment lexicons was proved necessary and important [14–16]. Sentiment lexicons for other languages then appear, including Chinese [17] and Japanese [18]. Using sentiment lexicon is indispensable in sentiment analysis. Some researches use sentiment words directly as features in machine learning algorithms for sentiment classification. Others use statistics on sentiment words [19]. As many sentiment words present different polarity in different context, further NLP techniques becomes the popular approach for polarity classification.

Turney and Littman (2003) claim that sentiment ambiguous words cannot be avoided easily in a real-world application [5]. In their work, they designed a pointwise mutual information (PMI) based algorithm to calculate sentiment orientation of the sentiment word within review corpus. However unfortunately, word polarity disambiguation has not attracted much research work. Yi et al. (2003) use a lexicon and manually developed patterns to classify contextual polarity [20]. Though the patterns are high-quality and yielding quite high precision over the set of expressions, the recall is rather low. Wilson et al. (2005) propose to recognize contextual polarity of all instances of words from a large lexicon of subjectivity clues that appear in the corpus [21]. Ding et al. (2008) adopt a holistic lexicon-based approach to resolve the ambiguity problem by exploiting external information and evidences in other sentences and other reviews [22]. Qiu et al. (2009) propose to combine lexicon-based methods and corpus-based methods to first determine the sentence polarity [23]. They simply assign the sentence polarity to the polarity of the sentiment-polarity words in the sentence. Wu and Wen (2010) propose a knowledge-based unsupervised method to automatically disambiguate dynamic sentiment ambiguous adjectives with search engine [24].

Difference of this work lies in three aspects: First, we deal with reviews which are rather different from news reports in nature. Second, we explore probabilistic models, which have never been touched in word polarity disambiguation. To train our models, we collect a large volume of raw reviews as development data to address issues caused by the small training data. Third, we built our method on opinion-level. That is, terms in our method are classified into different opinion elements, say opinion target, modifying constituent, etc. We design Bayesian model to count in their contribution in word polarity disambiguation.

3 Opinion-level features

In this work, features for word polarity disambiguation are defined on opinion level. We can safely assume that the opinion elements make different contribution to word polarity disambiguation. To be practical, we observe the elements in the aforementioned 5-tuple one by one to assess their contributions to word polarity disambiguation.

Xia et al. (2008) make use of sentiment units in sentiment analysis [25]. The observation is that in subjective text, a sentiment unit contains sentiment word, modifying word and negation word. We conduct further observation and advance this theory to the concept of opinion unit which is represented with a 6-tuple $< h, t, w, m, n, I >$, in which h represents opinion holder, t opinion target, w sentiment word (i.e., to be disambiguated in terms of polarity), m modifying word(s), n negation word and I a set of indicative words. In this work, we view these elements as candidates of features for word polarity disambiguation. The following opinion elements are found useful: opinion target, modifying word and indicative words.

We exclude opinion holder as our feature in this work. This is because reviews are usually created in social network or e-commerce web sites thus author information is contained (i.e., the registered user name) and the author of a review does not decide the polarity of it . So when one deals with reviews, h is usually ignored. Thus we obtain a revised opinion unit with 5-tuple $< t, w, m, n, I >$. Note social analysis based on user information can be useful to sentiment analysis. But we focus on textual content for word polarity disambiguation in this work. The intra-opinion features are described as follows.

3.1 Opinion target

Study shows that opinion target plays an important role in word polarity disambiguation. We notice that within the reviews , polarity of the sentiment words depend highly on the opinion targets. However, less than 50 percent online reviews contain opinion target. In many reviews, opinion target is missing or out-of-vocabulary. In these cases, we need to define extra features to resolve the polarity ambiguity.

3.2 Modifying word

For presentation convenience, we first define the modifying word. We call a word as modifying word if it syntactically modifies the sentiment word. In practice, we make use of dependency parser to recognize the modifying word. In the cases that the opinion target is not found in reviews, we use the modifying word as feature in this work. In our corpus, we find 178 unique modifying words with the sentiment word 小(*small*). This shows that the modifying words are significant for polarity disambiguation.

3.3 Indicative words

Besides opinion target and modifying word, some words in reviews can also be indicative. We define an indicative word as the word that still helps to resolve polarity ambiguity while it is neither opinion target nor modifying word. We also notice that one single indicative word cannot play very well alone. They must be combined with sentiment word to indicate a positive sentiment. Thus in this work, we consider word N-grams in the word polarity disambiguation method.

4 The Bayesian model

To be general, we safely assume that polarity of a sentiment word can be determined by certain observable context Ω_{w} in the review. In this work, we only consider two opposite polarity values: positive and negative, represented by 1 and -1, respectively. We propose to resolve polarity of w, i.e., ϱ_w ($\varrho_w \in \{1, -1\}$), within context Ω_{w} with a Bayesian model as follows.

$$\varrho_w^* = \underset{\varrho_w \in \{1,-1\}}{\operatorname{argmax}} \; p(\varrho_w|\Omega_{\mathrm{w}}) \tag{2}$$

where $p(\varrho_w|\Omega_{\mathrm{w}})$ is further calculated based on Bayes rule:

$$p(\varrho_w|\Omega_{\mathrm{w}}) = \frac{\mathrm{p}(\varrho_{\mathrm{w}})\mathrm{p}(\Omega_{\mathrm{w}}|\varrho_{\mathrm{w}})}{\mathrm{p}(\Omega_{\mathrm{w}})} \tag{3}$$

As $p(\Omega_{\mathrm{w}})$ is a constant, Equation 2 can be further revised as follows.

$$\varrho_w^* = \underset{\varrho_w \in \{1,-1\}}{\operatorname{argmax}} \; p(\varrho_w)p(\Omega_{\mathrm{w}}|\varrho_{\mathrm{w}}) \tag{4}$$

In what follows, we describe how different context (Ω_{w}) works in word polarity disambiguation.

4.1 The term-based model

The assumption underlying the term-based model is traditional. That is, polarity of the sentiment word can be resolved with term-level context. The typical term-level features are N-grams. Let g_w^i represent one N-gram, $\Omega_{\mathrm{w}} = \{\mathrm{g}_{\mathrm{w}}^1, \mathrm{g}_{\mathrm{w}}^2, ..., \mathrm{g}_{\mathrm{w}}^{\mathrm{K}}\}$ represent the context where K denotes number of features, we revise Equation 4 as follows:

$$\varrho_w^* = \underset{\varrho_w \in \{1,-1\}}{\operatorname{argmax}} \; p(\varrho_w)p(g_w^1, g_w^2, ..., g_w^K|\varrho_w) \tag{5}$$

Applying the independence assumption, we further revise Equation 5 as follows:

$$\varrho_w^* = \underset{\varrho_w \in \{1,-1\}}{\operatorname{argmax}} \; p(\varrho_w)\prod_{i=1}^{K} p(g_w^i|\varrho_w) \tag{6}$$

With a training corpus, we use maximum likelihood estimation (MLE) to estimate $p(\varrho_w)$ and $p(g_w^i|\varrho_w)$.

Two major drawbacks are worth noting in the term-based model. First, Equation 5 indicates that all the N-grams are used as features in word polarity disambiguation. In fact, many of them are not effective. This inevitably noise to the calculation. Second, Equation 6 indicates that the term-level features are deemed independent of each other. This is usually not true in reviews. As we discuss in Section 3, elements of opinion can help resolving word polarity in different manners. Even opinion in the context can influence polarity of the sentiment word. In what follows, we describe the opinion-level model.

4.2 The opinion-based model

We make a new assumption on word polarity disambiguation. That is, polarity of the sentiment word depends highly on opinion-level context. The motivation comes from that polarity is part of an opinion. Thus polarity of a sentiment word should be more precisely resolved with opinion-level context. Again, we start from Equation 4 to incorporate the opinion-level features step by step.

Based on analysis in Section 3, we use opinion target t_w, modifying word m_w and indicative words I_w as the intra-opinion features. We consider opinion-level context $\Omega_\mathrm{w} = \{\mathrm{t_w}, \mathrm{m_w}, \mathrm{I_w}\}$ for sentiment word w. We first design an opinion-level Bayesian model using the intra-opinion features: t_w, m_w and I_w. Equation 4 is revised as follows.

$$\varrho_w^* = \operatorname*{argmax}_{\varrho_w \in \{1,-1\}} \; p(\varrho_w) p(t_w, m_w, I_w | \varrho_w) \tag{7}$$

Applying the independence assumption, we further obtain:

$$\varrho_w^* = \operatorname*{argmax}_{\varrho_w \in \{1,-1\}} \; p(\varrho_w) p(t|\varrho_w) p(m|\varrho_w) p(I|\varrho_w) \tag{8}$$

We model the indicative words with N-grams $I_w = \{g_I^1, g_I^2, ..., g_I^L\}$. Note that N-gram of I_w is different from the term level N-gram as the former considers only opinion indicative words. Now Equation 8 is revised as follows.

$$\varrho_w^* = \operatorname*{argmax}_{\varrho_w \in \{1,-1\}} \; p(\varrho_w) p(t|\varrho_w) p(m|\varrho_w) \prod_{j=1}^{L} p(g_I^j|\varrho_w) \tag{9}$$

In Equation 9, $p(t|\varrho_w)$, $p(m|\varrho_w)$ and $p(g_I^j|\varrho_w)\{j = 1, ..., L\}$ are all estimated with training corpus.

In the cases that some of the opinion-level features are not explicitly given, we set $p(t|\varrho_w) = 1$, $p(m|\varrho_w) = 1$ and $p(I|\varrho_w) = 1$ accordingly. For the extreme case in which all the opinion-level features are missing, Equation 9 becomes:

$$\varrho_w^* = \operatorname*{argmax}_{\varrho_w \in \{1,-1\}} \; p(\varrho_w) \tag{10}$$

which indicates that polarity of the sentiment word in this case is determined randomly by the polarity distribution $p(\varrho_w)$.

In this work, we use Opinmine corpus [26] for parameter estimation. Details of the Opinmine corpus are given in Section 5.1.

5 Evaluation

5.1 Setup

The polarity-ambiguous sentiment words

The sentiment words used in this evaluation are automatically extracted from Opinmine corpus with the following steps in each domain:

1. Sort the sentiment words with count of occurrences of the sentiment words appearing in the Opinmine corpus;
2. Delete the words from the list which are judged as holding a unique polarity in all reviews.
3. Select top 20 sentiment-ambiguous sentiment words for evaluation.

The 20 sentiment words selected from the two domains are presented in Table 1–2. We find most of these words are included in the SemEval-2010 Task on disambiguating sentiment ambiguous adjectives [6].

Table 1. The 20 polarity-ambiguous sentiment words in *mobile phone* domain (POS represents part of speech)

Word	POS	Word	POS	Word	POS	Word	POS
多(*many*)	adj	大(*big*)	adj	提高(*improve*)	verb	少(*decrease*)	verb
突出(*prominent*)	adj	低(*low*)	adj	高(*high*)	adj	敏感(*sensitive*)	adj
快(*quick*)	adj	薄(*thin*)	adj	重(*heavy*)	adj	降低(*decrease*)	verb
小(*small*)	adj	(*light*)	adj	增加(*increase*)	verb	奇(*miracle*)	noun
(*simple*)	adj	害(*serious*)	adj	下降(*drop*)	verb	吃惊(*surprise*)	verb

Table 2. The 20 polarity-ambiguous sentiment words in *digital camera* domain

Word	POS	Word	POS	Word	POS	Word	POS
多(*many*)	adj	大(*big*)	adj	提高(*improve*)	verb	小(*small*)	adj
高(*high*)	adj	低(*low*)	adj	(*light*)	adj	奇(*miracle*)	noun
快(*quick*)	adj	少(*little*)	adj	提升(*improve*)	verb	降低(*decrease*)	verb
少(*decrease*)	verb	突出(*prominent*)	adj	增加(*increase*)	verb	敏感(*sensitive*)	adj
(*simple*)	adj	重(*heavy*)	adj	下降(*drop*)	verb	吃惊(*surprise*)	verb

Note that the occurrence of the words differs in the two domains. So the 20 selected sentiment-ambiguous words are slightly different in the two domains. But the common words are obvious.

Training/Test corpus

We use Opinmine opinion corpus [26] as training/test corpus in this evaluation. Two domains are involved in the 2nd version: *digital camera* and *mobile phone*. Statistics of the Opinmine corpus v2 are given in Table 3.

As this work is focused on polarity disambiguation, we only use reviews that contain the aforementioned sentiment-ambiguous words. We conduct experiments in every domain separately. As opinion annotations are less than 10K in each domain, we adopted the 5-fold cross validation approach in the experiments.

Table 3. Statistics of Opinmine corpus v2.

Domain	# of reviews	# of opinions	# of unique sentiment words
mobile phone	1200	6034	1437
digital camera	1200	9706	1689

The Opinmine corpus contains annotations in two domains. As we do not investigate on the cross-domain method, we conduct experiment in the two domains, separately.

Evaluation metrics
The goal of the proposed method is to determine positive or negative polarity of a sentiment word in a given context. So it is natural that we adopt accuracy in this evaluation. Accuracy is defined as proportion of the correctly determined reviews within all test reviews.

5.2 Experimental results

In this experiment, we intend to compare our Bayesian model based method against the following existing methods for word polarity disambiguation (WPD):

- *Pattern-based method* (PTN): Patterns are finely designed based on words in sentiment lexicon [20] and applied in word polarity disambiguation. In this implementation, we use HowNet sentiment lexicon [27] to handle Chinese reviews.
- *PMI-based statistical method* (PMI): Point-wise mutual information (PMI) is used to calculate sentiment orientation of the sentiment word within review corpus [5]. The starting seeds used in this work are translated to Chinese in order to handle the Chinese WPD task.
- *Machine learning method* (ML): A polarity classifier is trained on Opinmine corpus and then applied to predict polarity of a sentiment word in a context [23].
- *Term-based Bayesian model* (Bayes-TM): Our Bayesian model using term-level features and determining polarity of a sentiment word with Equation 6.
- *Opinion-based Bayesian model* (Bayes-ON): Our method Bayesian model using opinion-level features and determining polarity of a sentiment word with Equation 9.

Experimental results are presented in Table 4.

We can see from Table 4 that Bayes-ON outperforms all the baseline methods significantly in the two domains. Four observations are made. Firstly, PTN performs worse (i.e., -0.081 on average) than Bayes-ON in this experiment. We find this is mainly because of the limited coverage of the hand-compiled patterns and lexicon. Reviews are too flexibly given on social media or e-commerce sites for the patterns to handle. Secondly, PMI is also less effective (i.e., -0.058 on average) than Bayes-ON. Study shows that the PMI equation relies on a much

Table 4. Experimental results of different word polarity disambiguation methods.

Domain	PTN	PMI	ML	Bayes-TM	Bayes-ON
mobile phone	0.749	0.761	0.781	0.728	**0.804**
digital camera	0.733	0.751	0.764	0.705	**0.782**
Average	0.727	0.75	0.768	0.717	**0.793**

bigger corpus to produce reasonable statistics. Thus we believe that a bigger corpus may improve the PMI-based method. Thirdly, ML is inferior to Bayes-ON by 0.040 on average. Similar to the PMI-based method, the ML method relies on more training data, which is rather difficult to obtain. As a comparison, our method achieves around 0.8 on accuracy with the small training corpus. At last, Bayes-ON outperforms Bayes-TM by 0.076 on average. This indicates that the opinion-level features make significant contribution to word polarity disambiguation. We also notice that Bayes-TM is less effective than PTN, PMI or ML. This implies that Bayesian model can not perform well when opinion-level features are not used.

From the encouraging results, we do see a significant performance gain when the opinion-level features are used in the Bayesian model. This justifies the advantage of the Bayesian model and the opinion-level features in word polarity disambiguation.

6 Conclusion and future work

Contextual polarity ambiguity is an important problem in sentiment analysis. In this work, we study this problem with reviews. Different from the previous work which makes use of term-level features, we propose to resolve the polarity ambiguity with opinion-level features including opinion target, modifying word and indicative words. We adopt the Bayesian model and deal with the word polarity disambiguation task in a probabilistic manner. Experiments on Opinmine corpus shows that when using the opinion-level features, the Bayesian model makes significant contribution in word polarity disambiguation in two domains.

This work is still preliminary. The future work is planned as follows. We will further investigate on inter-opinion features for word sentiment polarity disambiguation. Meanwhile, substantial experiments will be conducted in a thorough evaluation.

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