

A Classification-based Approach for Implicit Feature Identification

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Abstract. In recent years, sentiment analysis and opinion mining has grown to be one of the most active research areas. Most of the existing researches on feature-level opinion mining are dedicated to extract explicitly appeared features and opinion words. However, among the numerous kinds of reviews on the web, there are a significant number of reviews that contain only opinion words which imply some product features. The identification of such implicit features is still one of the most challenge tasks in opinion mining. In this paper, we propose a classification-based approach to deal with the task of implicit feature identification. Firstly, by exploiting the word segmentation, part-of-speech(POS) tagging and dependency parsing, a rule based method to extract the explicit feature-opinion pairs is presented. Secondly, the feature-opinion pairs for each opinion word are clustered and the training documents for each clustered feature-opinion pair are then constructed. Finally, the identification of implicit features is formulated into a classification-based feature selection. Experiments demonstrate that our approach outperforms the existing methods significantly.

Keywords: Opinion Mining, Implicit Feature, Feature Extraction

1 Introduction

Nowadays, an increasing number of people are buying products on the web. Product reviews posted on the web can provide a lot of valuable information for those potential customers. At the same time, the product manufacturers can also obtain useful feedbacks about products from users. However, as the number of reviews that a product receives grows rapidly, sometimes the amount of comments of a product may exceed one thousand or even more, which makes it very hard for a potential customer to read all these reviews to obtain useful information. In order to automatically process and analyze reviews on the web, a lot of research efforts[4, 9, 5] have been done on opinion mining and sentiment analysis from the magnitude of reviews.

Document-level sentiment analysis[12] mainly classifies the whole review's emotional orientation. Sentence-level sentiment analysis determines whether each sentence expressed a positive, negative, or neutral opinion, which is closely related to subjectivity classification[19, 21, 20] that distinguish subjective sentences with opinions from objective sentences. However, both document-level and sentence-level analysis can not discover what exactly people like or do not like, thus simply judging the sentiment orientation of a review unit fails to detect many significant details. In order to extract specific features and opinions from reviews, many researchers began to study the problem of finer-grained opinion mining, which is known as feature-level opinion mining[13, 4, 9, 5].

Example 1. 很漂亮, 功能很多值得购买, 价格有点贵, 很喜欢白色, 送货比较快! (Very beautiful, there are plenty of functions that worth to buy, the price is a little expensive, really like the white color, the delivery is also very fast!)

When people read a customer review, they mostly concern the opinion word and its corresponding aspect or feature. In product review mining, feature is usually the component or attribute of the product. Example 1 is a digital camera review about *Nikon D90*. Explicit features such as “功能” (function), “价格” (price) and “送货” (delivery) can be extracted from the above comment. Except for explicit feature, there is another significant kind of feature that doesn’t directly appear in the review sentences but can be deduced from the opinion word, which is known as implicit feature. In the above example review, the opinion word “漂亮” (beautiful) has implied that the feature which the user talked about is the camera’s “外观” (exterior) although this feature doesn’t explicitly appear in the sentence.

In feature-specific opinion mining, most of the existing researches[1, 24, 7, 23] mainly focused on the problem of extracting product features and opinions that explicitly appeared. However, according to the observation, in our crawled Chinese reviews of five kinds of digit cameras, we statistically discover that at least 28 percent of the sentences are implicit sentences that imply implicit features, which is a considerable proportion.

In this paper, we mainly focus on the problem of implicit feature identification. Our approach is very different from existing research works. The approach that former researches used is based on association rule mining. The core idea of this method is to use mined association rules to identify the implicit feature by finding the mapping of a specific feature for the opinion word. Although the association rule based approach is very useful and effective to identify the implicit feature for some kinds of opinion words that have relatively certain collocated features, for example, the opinion word “便宜” (cheap) is always used to describe the product’s feature “价格” (price). But it fails to deal with many complex situations, for example, the opinion word “好”(good) are often used to describe a lot of features, such as “信号” (signal), “屏幕” (screen) and “摄像头” (camera), by using the mined rules it can only map the opinion word “好” (good) to a specific feature, which is not correct for many other different situations. By considering both the associated relation and the context of the opinion word, our classification-based approach is able to identify different implicit feature for the opinion word with different situations.

The remaining parts of this paper are organized as follows. In section 2, we introduce some related works. The details of our proposed classification-based approach are introduced in section 3. In section 4, the experimental results are evaluated and discussed. our conclusion and future work are presented in section 5.

2 Related Work

Opinion mining has been extensively studied by many researchers in recent years. Most of these researches have focused on two main research directions: one is sentiment classification and the other direction is feature-based information extraction. Research efforts[10, 17, 11, 14] on sentiment classification deal with the task of classifying each customer review as positive, negative or neutral. While feature-based opinion mining[4, 6, 5, 8] focused on the task of extracting opinions consisting of information about features. In contrast to sentiment classification, opinion extraction aims at producing richer information and requires an in-depth analysis of reviews. The most representative researches in feature-level opinion mining are Hu and Liu’s works[4, 5, 9]. The conception of implicit feature was first mentioned in their papers

based on the analysis of English reviews. In contrast to explicit feature that directly appears in review sentences, implicit feature is the feature that does not occur in the comment, but can be deduced from opinion words and contexts based on the understanding of human language.

Semantic association analysis based on Point-wise Mutual Information (PMI) was used to infer the implicit features [15]. They predefined a domain-specific feature set as candidate implicit features, and then take the mutual information approach to map a opinion indicator to a certain feature of the feature set. In [16], a clustering method was proposed to map implicit opinion words to their corresponding explicit features. They clustered product features and opinion words simultaneously and iteratively by fusing both their content information and association relation, and then construct the sentiment association set between the groups of features and opinion words by identifying their strongest n sentiment links.

A co-occurrence association rule mining (coAR) approach was proposed to identify implicit features[3]. They firstly mined a set of association rules of the form [opinion-word, explicit-feature] from review sentences based on the co-occurrence of the opinion-word and explicit-feature. Then they cluster the explicit features to generate more robust rules. When given a new opinion word with no explicit feature, they searched a matched list of rules, among which the rule with the highest frequency weight is fired to map the opinion word to its identified implicit feature. In [18], they proposed a hybrid association rule mining approach for the task of implicit feature identification. Their approach used several complementary algorithms to mine as many association rules as possible. They firstly extract candidate feature indicators and then compute the co-occurrence degree between the candidate feature indicators and the feature words. Each indicator and the corresponding feature word constitute a rule(feature indicator \rightarrow feature word). They used such rules to identify implicit features.

3 Classification-based Approach

In this section, we first illustrate the problem of implicit feature identification and present some definitions we have used in this paper. The framework of our proposed classification-based approach has also been presented. Then we explain the main steps of our approach in detail.

3.1 Problem Statement

In this paper, we focus on the feature-level opinion mining of product reviews. On the online shopping websites, such as Amazon or Taobao Marketplace, each product can receive a large number of customer reviews that have been posted by people who have bought this product. The set of products can be represented as $P = \{P_1, P_2, P_3, \dots, P_n\}$. For each product P_i , there is a set of customer reviews $R_i = \{r_1, r_2, r_3, \dots, r_m\}$. The customer reviews can be regarded as text documents, although some of them may be very short and consisted of just a few sentences, but there are also many long reviews that can be as long as articles. Each review r_j can be represented as a sequence of sentences $r_j = \{s_1, s_2, s_3, \dots, s_l\}$. Each sentence s_k may be consisted of several clauses $s_k = \{c_1, c_2, c_3, \dots, c_h\}$.

Definition 1 *implicit feature*:

A product feature f is defined as the whole product, service or the attribute or component of the product. If a feature f appears in review sentences, then it is defined as *explicit feature*. If f does not appear in review sentences, but it is implied, which means that people who read the review can understand what feature has been talked about, then this feature f is regarded as *implicit feature*.

Definition 2 *implicit sentence*:

Implicit sentence is a sentence in a review that contains at least one implicit feature. *Explicit sentence* is defined similarly, a sentence that contains at least one explicit feature is called *explicit sentence*. It should be noted that a implicit sentence can also be a explicit sentence.

Definition 3 *feature-opinion pair*:

A feature-opinion pair is consisted of a feature and an opinion word, and the opinion word is used to modify the feature. If opinion word and its modified feature co-occur in a sentence, then such feature-opinion pair is defined as the sentence's *explicit feature-opinion pair*. The feature-opinion pair is denoted as $\langle \text{feature}, \text{opinion} \rangle$.

3.2 Overview of the Approach

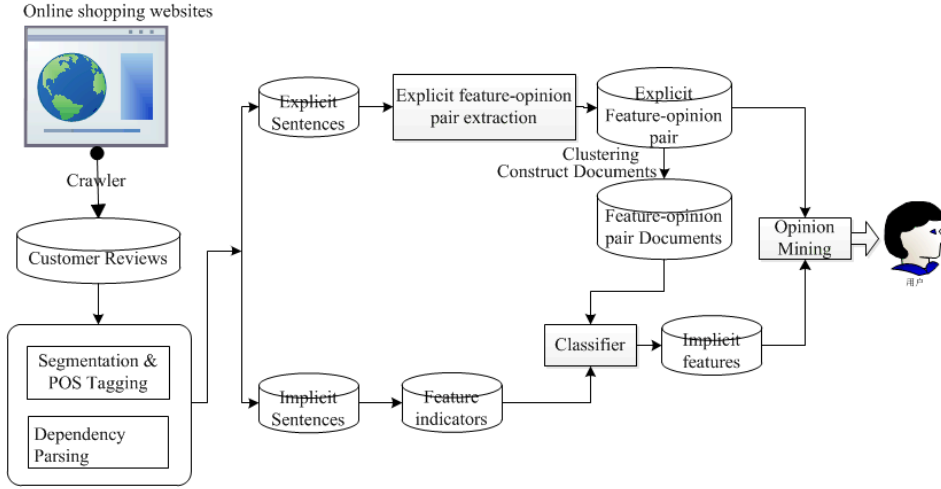


Fig. 1. Framework of Our Approach

In this subsection, we present an overview of our approach, including the flowchart of the approach and the introduction of the main steps, and then explain each step in details. As it has been shown in Fig. 1, it takes the corpus of customer reviews that have been crawled from the online shopping websites as input, and generates the opinion mining summary consisting of both explicit feature-opinion pairs and implicit feature-opinion pairs as the output.

Our approach is consisted of three main steps, including the explicit feature-opinion pair extraction, feature-opinion pair training document construction and implicit feature identification. The detail of each step is described in the following subsections.

3.3 Explicit feature-opinion pair Extraction

There are many existing research works on feature-level opinion mining that are dedicated to extract explicit feature-opinion pairs from customer reviews. Some supervised learning models, such as HMM(Hidden Markov Model) model and CRF(Conditional Random Fields) model, and topic models, such as the MaxEnt-LDA (a Maximum Entropy and LDA combination)[23] hybrid model, are widely used in this task. In this paper, we propose a rule based method to extract feature-opinion pairs from review sentences.

Rule Based Method. This method exploits Chinese dependency grammar to extract feature-opinion pairs. Firstly, we use Chinese dependency grammar to set several rules. Then we make use of these rules to extract candidate feature-opinion pairs. In order to improve the precision of feature-opinion pair extraction, we construct the candidate feature word set \mathcal{CF} and the candidate opinion word set \mathcal{CO} for each product. Since adjectives are quite likely to be opinion words and nouns are likely to feature words, so we extract adjectives and nouns from review sentences, and consider adjectives as candidate opinion words and nouns as candidate feature words. In addition, we use a stopwords list to filter many product-irrelevant adjectives and nouns from the candidate set \mathcal{CO} and \mathcal{CF} . Some frequently used non-adjective opinion words and non-noun feature words are also supplemented.

After analyzing and studying the dependency parsing results of review sentences, we find that most of the discussed features are in subject-predicate(SBV) structure or DE (“的”) structure. Therefore, we mainly exploit the two kind of dependency relation as rules to extract feature-opinion pairs. According to our observation, when the feature word appears before the opinion word, the feature usually satisfy the SBV relation with the opinion word, and when the feature appears after the opinion word, there usually exist a DE structure between the feature and the opinion word. Based on the above observations, Three different rules have been defined to tackle different types of sentence structures to extract the explicit feature-opinion pairs. A summarized representation of these rules is presented in the following paragraphs.

Rule-1: In a dependency relation SBV, the dependency structure is denoted as $sbv(w_1, w_2)$, which means that word w_2 depends on word w_1 through SBV, if word w_2 belongs to the opinion word set \mathcal{CO} and word w_1 belongs to the feature word set \mathcal{CF} , then $\langle w_1, w_2 \rangle$ can be extracted as feature-opinion pair.

Rule-2: In a dependency relation SBV, the dependency structure is denoted as $sbv(w_1, w_2)$, which means that word w_2 depends on word w_1 through SBV, if word w_1 belongs to the feature word set \mathcal{CF} and word w_2 doesn't belong to the opinion word set \mathcal{CO} , and after word w_2 there is a word w_3 that belongs to the opinion word set \mathcal{CO} , then $\langle w_1, w_3 \rangle$ can be extracted as feature-opinion pair.

Rule-3: In a dependency relation DE, if there is a word w_1 that belongs to the opinion word set \mathcal{CO} before the word “的” and a word w_2 belongs to the feature word set \mathcal{CF} after the word “的”, then $\langle w_2, w_1 \rangle$ can be extracted as feature-opinion pair.

The process of the rule based method is described in algorithm 1. We exploit the word segmentation, part-of-speech(POS) tagging and dependency parsing to process the customer reviews. Based on the results of the preprocessing, it can be easy to judge whether a sentence satisfied a rule.

Algorithm 1 Rule based algorithm

Input: Review sentences in the corpus.**Output:** A set of feature-opinion pair.

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1: for each sentence  $s_k$  in corpus do
2:   for each rule  $RL_i$  in the rule set  $\mathbb{R}$  do
3:     if match the rule  $RL_i$  then
4:       extract the feature-opinion pair  $fo = \langle f, o \rangle$ , put  $fo$  into the sentence  $s_k$ 's feature-opinion
         pair set  $FO_k$ 
5:     end if
6:   end for
7: end for
8: return the set of feature-opinion pair.

```

3.4 Feature-opinion pair Training Document Construction

If we regard each explicit sentence as a training text, then the topic or category of this sentence can be labeled as the sentence's feature-opinion pair. For example, for the explicit sentence “送货很快，早上下单下午就送到了！” (Delivering is very fast, order in the morning and have received in the afternoon!), the feature-opinion pair \langle “送货”, “快” \rangle (\langle delivering, fast \rangle) can be viewed as the sentence's labeled topic. If a sentence s_k contains more than one feature-opinion pair (FO_k denotes the sentence s_k 's feature-opinion pair set), then the sentence can be classified into each feature-opinion pair topic of FO_k .

Feature-opinion pair Clustering. For each opinion word, there are usually more one feature-opinion pair that contains the opinion word. For a feature-opinion pair $\langle f, o \rangle$, it means that the opinion word o is used to describe the feature word f . In review sentences, a opinion word generally can be used to describe several different features. For example, the opinion word “好” (good) is often used to describe a lot of product features, such as “手机” (mobile phone), “屏幕” (screen), or “质量” (quality). In product reviews, many different feature words or phrases may be used to express the same feature. For example, features “音质” (vocality quality), “音乐” (music) and “音效” (sound effect) are all related to the same product feature “声音” (vocality). So for each opinion word o , we cluster the feature-opinion pairs $\mathcal{FO}(o) = \{\langle f_1, o \rangle, \langle f_2, o \rangle, \dots, \langle f_n, o \rangle\}$ that contains the opinion word based on the conceptual and semantical relation of these features $\mathcal{F}(o) = \{f_1, f_2, \dots, f_n\}$. Our clustering method is based on [22], we mainly exploit the sharing words and the lexical similarity to cluster features. The size of the feature set $\mathcal{F}(o)$ is relatively small compared with the whole set of features \mathcal{F} , so it is much easier and more effective to the clustering of feature-opinion pairs.

After getting the set of clustered feature-opinion pair, we construct the training document for each clustered feature-opinion pair. For each clustered feature-opinion pair, we collect the sentences that contain the feature-opinion pair into a document, which is labeled by the clustered feature-opinion pair. The document constructing process is presented in algorithm 2.

3.5 Implicit Feature Identification

By constructing the feature-opinion pair training set, the problem of identifying implicit features can be formulated into a text classification problem. Thus many existing text classification approaches can be used to solve this problem. In this step, we mainly deal with the implicit sentences. For each implicit sentence $\mathcal{I}s_k$, the set

Algorithm 2 Document construction**Input:** The set of feature-opinion pair of explicit sentences.**Output:** A set of feature-opinion pair document.

```

1: for each opinion word  $o_i$  in the set of opinion word  $O$  do
2:   get the  $\mathcal{FO}(o) = \{ \langle f_1, o \rangle, \langle f_2, o \rangle, \dots, \langle f_n, o \rangle \}$ 
3:   cluster the feature-opinion pairs
4:   get the clustered feature-opinion pairs  $\mathcal{FO}_c(o_i) = \{ \langle f_{c_1}, o_i \rangle, \langle f_{c_2}, o_i \rangle, \dots, \langle f_{c_m}, o_i \rangle \}$ 
5: end for
6: for each explicit sentence  $s_k$  in corpus do
7:   for each feature-opinion pair  $\langle f_i, o_i \rangle$  in  $FO_k$  do
8:     put the sentence into the document  $d(f_{c_i}, o_i)$  of the clustered feature-opinion pair  $f_{c_i} o_i = \langle f_{c_i}, o_i \rangle$ 
       that includes  $\langle f_i, o_i \rangle$ 
9:   end for
10: end for
11: return the set of clustered feature-opinion pair document  $\mathcal{D}$ .

```

of opinion word can be denoted as $\mathcal{I}o_k = \{o_1, o_2, \dots, o_n\}$. The task of implicit feature identification is to find the implicit feature f_i for each opinion word o_i in $\mathcal{I}o$. The set of clustered feature-opinion pair that contains opinion word o_i can be denoted as $\mathcal{FO}_c(o_i) = \{ \langle f_{c_1}, o_i \rangle, \langle f_{c_2}, o_i \rangle, \dots, \langle f_{c_m}, o_i \rangle \}$. The key issue of this problem is to find the feature f_{c_i} that the opinion word o_i in implicit sentence $\mathcal{I}S_k$ has modified from the feature set $\mathcal{F}_c(o_i) = \{f_{c_1}, f_{c_2}, \dots, f_{c_m}\}$. As the feature-opinion pair can be regarded as the sentence's topic or category, thus the problem of finding the implicit feature f_{c_i} for opinion word o_i in implicit sentence $\mathcal{I}S_k$ has been transformed into a text classification problem.

In order to classify the implicit sentence with a opinion word o_i into the most probable feature-opinion pair $\langle f_i, o_i \rangle$ topic, we design a topic-feature-centroid classifier based on [2]. We modify the centroid construction and classification process to accommodate the situation in this problem.

Topic-feature-centroid construction: Different from the centroid-based approaches in [2] that uses all the words in the corpse to form the lexicon set, we use only a small set of feature-related discriminative words in the training set to construct the lexicon set. For instance, considering the collected training set of feature-opinion pair $\langle \text{“送货”}, \text{“快”} \rangle$ ($\langle \text{delivery}, \text{fast} \rangle$), there are over two hundred different words in this topic, while only a very small number of words contribute to the feature space of this topic, such as word “速度” (speed), “下单” (order) and so on. Many other words, such as “很” (very), “是” (is), “有” (have) and so on, even some of them with a very high frequency, hardly have any discrimination for this topic. Moreover, such irrelevant words could bring on a lot of noise in the representation of the topic. Therefore, in the construction of the lexicon set, we only consider nouns, adjectives and verbs in the training set, and we also construct a filter word set to remove the stop words and irrelevant words. The constructed lexicon set is denoted as $\mathcal{L} = \{wf_1, wf_2, \dots, wf_L\}$, so the centroid for category $\langle f_j, o_j \rangle$ can be represented by a word vector $Centroid_j = \{wf_{1j}, wf_{2j}, \dots, wf_{Lj}\}$, where wf_{kj} ($1 \leq k \leq L$) represents the weight for word wf_k .

In our topic-feature-centroid classifier, we derive a different formulation for the calculation of the weight for word wf_k . The weight for word wf_k of topic $\langle f_j, o_j \rangle$ is calculated as following:

$$wf_{kj} = f_{w_k} \times \log\left(\frac{|C|}{|CF_{w_k}|}\right) \quad (1)$$

where f_{w_k} is the word w_k 's frequency in the training document of feature-opinion pair topic $\langle f_j, o_j \rangle$, $|c|$ is the total number of feature-opinion pair topics for the given opinion word o_j , $|CF_{w_k}|$ is the number of feature-opinion pair topics that contains the word w_k . When a word w_k occurs in every feature-opinion topic, the value of wf_{kj} is 0 because $\log(\frac{|c|}{|CF_{w_k}|})$ becomes 0, which means that word w_k has no discrimination for the topic. Thus our weight calculation method can produce more discriminative features for the feature-opinion topic.

Classification: After the centroid vector of each category is obtained, the implicit sentence is classified by using a denormalized cosine measure:

$$C' = \arg \max_j (\vec{s}_i \bullet \overrightarrow{Centroid_j}) \quad (2)$$

where \vec{s}_i is the word vector representation for the implicit sentence $\mathcal{I}S_k$, since the sentence is usually very short, so we only concern the word's appearance or not. We use the binary representation to denote the word's weight in \vec{s}_i . By using this denormalized cosine measure, it preserves the discriminative capability of feature-opinion pair topic's centroid vector. Since the size of the vector space here is relatively small, so the denormalized measure can be more discriminative for the classification.

The process of implicit feature identification is described in algorithm 3.

Algorithm 3 Implicit feature identification

Input: The set of implicit sentences.

Output: A set of implicit feature-opinion pair.

- 1: **for** each implicit sentence $\mathcal{I}S_k$ **do**
 - 2: **for** each opinion word o_i in $\mathcal{I}o$ **do**
 - 3: apply the topic-feature-centroid classifier for o_i
 - 4: get the implicit feature fc_i
 - 5: **end for**
 - 6: **end for**
 - 7: return the set of implicit feature-opinion pair.
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4 Experiments

In this section, we conducted several experiments and evaluate the performance of our approach. Firstly, we describe the data sets used in our experiments. Then we give the definition of several performance metrics. Lastly, experiment results and corresponding analysis are described. Both the results of explicit feature-opinion pair extraction and implicit feature identification have been evaluated.

4.1 Date Sets and Evaluation Measures

Since there is no standard data set for our experiment, so we crawled the experiment data from the popular Chinese shopping website, Amazon.cn¹, the regional website of Amazon.com in China. Customer reviews are collected from two different domains: cell phone and digital camera. There are totally 4083 reviews and 12760 sentences in our data set. Both the explicit feature-opinion pair and implicit feature-opinion pair of each sentence are manually annotated by two research students in our lab.

¹ <http://www.amazon.cn>

To be fair, those sentences that are annotated inconsistently have been removed and the rest has been confirmed by the author. The details of the data sets are given in Table 1.

Table 1. Experiment Data

| Data Sets | Reviews | Sentences | Explicit features | Implicit features |
|----------------|---------|-----------|-------------------|-------------------|
| Cell Phone | 2694 | 8305 | 4233 | 1449 |
| Digital Camera | 1389 | 4455 | 1817 | 798 |
| Total | 4083 | 12760 | 6050 | 2247 |

The traditional precision (P), and recall (R) and F-measure (F) have been used to evaluate our experiment results of both explicit feature-opinion pair extraction and implicit feature identification. The F-measure is defined as follows:

$$F = \frac{2 * precision * recall}{precision + recall} \quad (3)$$

4.2 Evaluation of explicit feature-opinion pair Extraction

An important step of our approach is to extract the explicit feature-opinion pairs from explicit sentences. The construction of the training document is based on the result of the extracted explicit feature-opinion pairs. In this paper, we use LTP² to accomplish the Chinese word segmentation, part-of-speech(POS) tagging and dependency parsing.

Table 2 shows the result of explicit feature-opinion pair extraction by using our rule based method. As we can see from the table, our rule based method achieves a comparatively satisfactory result in the extraction of feature-opinion pairs. In the construction of the candidate feature word set \mathcal{CF} and the candidate opinion word set \mathcal{CO} for each product, we consider nouns as candidate features and adjectives as candidate opinion words, and also add some verbs to complement the candidate word set. For example, the verb “送货” (deliver) is frequently used as feature and the verb “喜欢” (like) is frequently used as opinion word in customer reviews. A filter word list was constructed to remove many product-irrelevant nouns and adjectives from the candidate set, such as “朋友” (friends), “伤心” (sad) and so on.

Table 2. Result of explicit feature-opinion pair extraction

| Data Sets | Precision | Recall | F-measure |
|----------------|-----------|--------|-----------|
| Cell Phone | 80.21% | 79.99% | 80.10% |
| Digital Camera | 81.95% | 83.43% | 82.68% |

4.3 Evaluation of implicit future Identification

In the end, we give the final experimental results via using our proposed classification-based approach. Our classification-based approach is compare with the rule based approach coAR[3]. We implement the approach coAR proposed in [3]. The best results for each approach is listed in Table 3.

² <http://ir.hit.edu.cn/ltp/>

Table 3. Result of implicit feature identification

| Data Sets | Our Approach | | | CoAR | | |
|----------------|--------------|--------|-----------|-----------|--------|-----------|
| | Precision | Recall | F-measure | Precision | Recall | F-measure |
| Cell Phone | 82.07% | 68.48% | 74.66% | 67.88% | 52.93% | 59.48% |
| Digital Camera | 85.59% | 72.93% | 78.76% | 79.94% | 66.91% | 72.85% |

CoAR mined the association rules of explicit feature-opinion pair based on the co-occurrence of opinion word and feature word, and then used the clustered rules to identify the implicit feature for a given opinion word.

As it can be observed from Table 3, our approach outperforms coAR on all the evaluation metrics for corpora in both cell phone data set and digital camera data set. Co-AR used the mined association rules from the review corpus to identify the implicit feature for the given opinion word by rule matching, which means that their approach always map the opinion word to the same feature word without considering the context of the implicit sentence. While our classification-based approach not only exploit the association relations by extracting explicit feature-opinion pairs, but also take into account the context of the implicit sentence by using the category-feature-centroid classifier to map the opinion word in a specific implicit sentence to the most probable feature word. Thus our approach’s precision is higher than coAR. In addition, our approach’s recall is also higher than the coAR approach. This is because that the rule based coAR approach only adopted the association rules whose weight is greater than the threshold as robust rules. The higher threshold can weed out the lower-frequency association rules and promote the precision, but it would reduce the recall. No matter what threshold is selected, it can not capture a significant number of uncommon association rules. This shortcoming of the rule based approach determines that the recall of coAR is limited to a certain extent.

5 Conclusion and Feature Work

In this paper, we propose a novel classification-based approach to deal with the problem of implicit feature identification. By constructing the document for the clustered feature-opinion pair, the training document that has been labeled by the specific clustered feature-opinion pair can be obtained. Then the problem of implicit feature identification has been formulated into a text classification problem. A rule based method has been proposed to extract explicit feature-opinion pairs from customer reviews. In the phase of implicit feature identification, a topic-feature-centroid classifier has been designed to perform the classification task. It should be pointed out that other feature-opinion pair extraction methods and text classification methods can also be used in our approach. Compared with the rule based approach coAR, our approach overcomes the shortcomings and limitations of the rule based approach and achieves a much better performance on all the measure metrics. However, some undesirable errors still exist in the result of implicit feature identification. Some are caused by the incorrect classification, some are caused by the wrong identification of implicit feature indicators. In our future work, we will explore the performance of approach by using several other text classification approaches in the implicit feature identification step.

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