Simultaneously Identifying Opinion Targets and Opinion-bearing Words Based on Multi-Features in Chinese Micro-Blog Texts

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Abstract: *We propose to simultaneously identify opinion targets and opinion-bearing words based on multi-features in Chinese micro-blog texts, i.e., to identify opinion-bearing words by means of opinion-bearing words dictionary and to identify opinion targets by considering multi-features between opinion targets and opinion-bearing words, and then we take a future step to optimize forwarding-based opinion target identification. We decompose our task into four phases: 1) construct opinion-bearing words dictionary and identify opinion-bearing word in a sentence from Chinese micro-blog; 2) design multiple features related to opinion target identification, containing token, Part-Of-Speech (POS), Word Distance (WD), Direct Dependency Relation (DDR) and SRL; 3) design three kinds of different feature templates to identify feature-opinion pairs <opinion target, opinion-bearing word> in Chinese micro-blog texts; 4) combining forwarding relation between individual micro-blogs, we solve the problem of identifying opinion target in short micro-blog. The experiments with Natural Language Processing (NLP) and Chinese Computing (CC) 2012 and 2013's labeled data show that our approach provides better performance than the baselines and most systems reported at NLP and CC 2012 and 2013.*

Keywords: *Opinion mining, opinion target identification, micro-blog, feature-opinion pairs, sentiment polarity.*

1. Introduction

In recent years, sentiment analysis, which mines opinions from information sources such as news, product reviews and twitter, has drawn much attention in the Natural Language Processing (NLP) field, such as [2, 3, 7, 10, 13, 16], especially the micro-blog opinion mining. Micro-blog today has become a very popular communication tool among internet users in China. According to the reports[1], the number of micro-blog users has increased from 63,110,000 by the end of 2010 to 274,000,000 in June 2012, and the number is still constantly growing. So many micro-blog users share opinions on different aspects of life everyday and express their various emotion and sentiment, such as joy, anger, grief, praise, criticism and so on, which makes people's opinion information expanded rapidly. As a result, it is very difficult to rely on the artificial method to mine opinions in micro-blog texts, there is an urgent requirement to help user analyse the massive information using computer.

Liu *et al.* [11] Introduced Chinese micro-blog and concluded that it mainly has three characteristics as following:

1. Due to the short text message, micro-blog has terms' sparsity, so it is not suitable for opinion mining only based on terms.

2. There exist many homophonic words, abbreviated words, internet slang in micro-blog, such as "杯具" (Bei Ju) standing for "悲剧" (tragedy), "3Q" standing for "谢谢" (thanks), "屌丝" (Diao Si) standing for "无奈与自嘲的年轻人" (young people who has no height, no wealth and no appearance) and so on.

3. There are a variety of relations between individual micro-blogs, including forwarding, commenting and sharing. It is very convenient for micro-blog users to express their opinions and sentiment.

The above characteristics of micro-blogs make it tough to extract opinion targets and opinion-bearing words. In order to further analyse opinions of micro-blogs, we propose a novel algorithm based on multi-features to simultaneously identify feature-opinion pairs <opinion target, opinion-bearing word>. The remainder of this paper is structured as follows. In section 2, we briefly summarize related works. Section 3 gives an overview for constructing opinion-bearing words dictionary and describing multiple features. The proposed approach is described in section 4, followed by the optimization algorithm in section 5. Experimental results are reported in section 6. Lastly, we conclude in section 7.

2. Related Works

Although document-level/sentence-level sentiment analysis can provide the overall polarity of the whole

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text/sentence, it fails to detect the targets of the sentiment in texts/sentences.

For opinion mining of product reviews, properly identifying opinion targets and opinion-bearing words can construct domain-related entity thesaurus and sentiment vocabulary, as [6, 8, 14] have described. In addition, if correctly identify the correspondence relation between opinion target and opinion-bearing word, we can generate visual product reviews. [4] proposed opinion targets are often nouns or noun phrases frequently mentioned, and only consider adjectives as candidate of opinion-bearing words. After extracting opinion targets, they first locate all the sentences containing opinion targets, and then take the adjectives modifying opinion targets as opinion-bearing words. However, the algorithm is further improved by Popescu and Etzioni [13], they filter out noun phrases not belonging to opinion targets and define ten kinds of syntactic relations, and then use them in the syntactic tree to extract opinion-bearing words.

Through linguistics and semantic analysis of review articles, Kamal *et al.* [7] designed the rules to extract feature-opinion pairs <opinion target, opinion-bearing word> for product reviews. Jin *et al.* [5] also proposed supervised learning algorithm to extract opinion targets and opinion-bearing words. They take this as a sequence labeling task, and use HMM to obtain the most likely tag sequence. Although the algorithm consider ordinal relation between sentences, it isn't good for fusion multi-features because HMM is a generative model.

Xu *et al.* [15] proposed a novel two-stage framework for mining opinion targets and opinion-bearing words, their method achieves superior performance over unsupervised methods. But they only considered adjectives as opinion-bearing words and ignored other type of word such as verbs or nouns. Lu [12] proposed to separately identify opinion holders and targets with dependency parser in Chinese news texts. Their proposed approach shows better performance on opinion holder/target identification with the traditional Chinese test data, such as Chinese news.

However, in this paper we focus on the simultaneous identification of opinion targets and opinion-bearing words, and make full use of multi-features, combining with discriminative model Conditional Random Field (CRF), to simultaneously extract opinion target and opinion-bearing word in a sentence. We apply the algorithm into Chinese micro-blog post, and take a future step to optimize forwarding-based opinion target identification. The input is a collection of micro-blogs containing forwarding relations and the output is feature-opinion pairs <opinion target, opinion-bearing word>. Our approach shows encouraging performance on simultaneous identification of opinion targets and opinion-bearing words, and the results are much better

than the baseline results and most results reported in conference on natural language (CCF) processing and Chinese Computing (CC) 2012 and 2013 (NLP and CC 2012 and 2013).

3. Feature Extractions And Selection

3.1. Data Preprocessing

In our approach, rich features representations are used to simultaneously identify opinion targets and opinion-bearing words in Chinese micro-blog texts. In order to generate such features, much NLP work has to be done beforehand, such as micro-blogs normalization, word segmentation, Part-Of-Speech (POS) tagging and so on.

In our experiment, 600 subjective micro-blog sentences labeled with "opinionated=Y" are extracted from NLP and CC 2012 and 2013. In order to conveniently obtain rich features, we design a three-step approach for data preprocessing in this paper:

1. We build a simple rule-based model for micro-blog normalization which can correct simple spelling errors into normal form, such as "!!!!!" to "!" and " 。。。。。 " To " 。 ".
2. The URL and the parentheses enclosing only English words or numbers are all removed in sentences, and the emoticons are also deleted, such as ":-)", ":-(", ":D" and so on.
4. To enhance the precision of word segmentation in micro-blog texts, internet slang expressing opinions is first recognized with a new Chinese word segmentation tool ICTCLAS2013[1].

3.2. Opinion-Bearing Words Dictionary

Opinion-bearing Word, a key indicator of an opinion, is the words or phrases containing polarity (i.e., positive or negative). Micro-blog users usually express their sentiment polarity towards opinion target with opinion-bearing words. According to the characteristics of micro-blog, the opinion-bearing words dictionary would be made up of two portions. One of them is provided by HowNet[1] and National Taiwan University Sentiment Dictionary (NTUSD)[2]. After removal of duplicated and unusual words, finally, we obtain 11,036 negative and 7, 019 positive opinion-bearing words.

The other is internet slang appeared in social network. In order to obtain more abundant

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opinion-bearing words, especially for Chinese micro-blog, two persons from our lab would label internet slang used to express users' opinions in micro-blog texts. After the removal of some internet slang rarely being used and without explicit opinions, which come from National Language Resource Monitoring and Research Center (Network Media) [3], finally, we achieve 848 opinion-bearing words with polarity, 791 of which have emotion tagging consistency. The data labeled by two persons is shown in Table 1. "+1" is positive opinion, while "-1" is negative.

Table 1. The distribution of opinion-bearing words with polarity.

		Person 1		
		+1	-1	
Person 2	+1	459 (a)	36 (b)	495 (a+b)
	-1	21 (c)	332 (d)	353 (c+d)
		480 (a+c)	368 (b+d)	848 (N)

Where $N = a+b+c+d$, and the meaning of each character is described as follows:

- a represents the quantities that two persons have the same emotion tagging labeled "+1";
- b represents the quantities that person 1 labels "-1" but person 2 labels "+1";
- c represents the quantities that person 1 labels "+1" but person 2 labels "-1";
- d represents the quantities that two persons have the same emotion tagging labeled "-1".

In particular, we focus on consistency check of emotion tagging by KAPPA value K:

$$K = \frac{(a+b)/N - [(a+c)(a+b)/N + (b+d)(c+d)/N]/N}{1 - [(a+c)(a+b)/N + (b+d)(c+d)/N]/N}$$

$$= \frac{(459+332)/848 - [480*495/848 + 368*353/848]/848}{1 - [480*495/848 + 368*353/848]/848}$$ (1)

$$\approx 0.863$$

The high KAPPA value means the reliable consistency of emotion tagging. Finally, we keep the words with emotion tagging consistency and finally, obtain 7,478 positive and 11,368 negative opinion-bearing words.

3.3. Multi-features' Description

In the following we will describe the features we employ as input for our CRF model. Opinion target, nouns or noun phrases usually governed by opinion-bearing words/phrases, is what the opinion is about. So we design multiple features to simultaneously identify opinion targets and opinion-bearing words in a sentence.

3.3.1. Token

This feature represents the string of the current token

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[3]National Language Resource Monitoring and Research Center; http://pop.clr.org.cn/networdList.jsp; 2014-4-17

as a feature. Even though this feature is rather obvious, it can have considerable impact on the identification performance for opinion target and opinion-bearing word and should be a good indicator.

3.3.2. Part-Of-Speech

This feature represents the POS tag of the current token as identified by the ICTCLAS2013. Opinion-bearing words are often adjectives or verbs and opinion targets are often nouns or noun phrases. At the same time, the CRF model is provided with additional information to identify opinion targets which are multiword expressions, i.e., noun combinations.

3.3.3. Word Distance

Nouns/noun phrases are good candidates for opinion targets which are often closer to opinion-bearing word in a sentence, and opinion targets usually occur before or after the opinion-bearing word. So we take the Word Distance (WD) as Boolean features [4, 17] have shown that. We will label the current token as 1 when the current token being closest to opinion-bearing word is noun/noun phrase, otherwise the current token is labeled as 0.

3.3.4. The Direct Dependency Relation

In [1, 9, 18] dependency relation in the dependency parse tree to link opinion expressions and the corresponding targets .have been successfully employed All works identify Direct Dependency Relations (DDRs) such as "amod" and "nsubj" as the most frequent and at the same time highly accurate connections between a target and an opinion expression in a sentence. So we label all tokens which have a DDR to opinion-bearing words in a sentence, such as "ATT (attribute)" and "VOB (Verb-Object)", where ATT represents that any adjectival phrase (opinion-bearing adjective) serves to modify the meaning of the nouns/noun phrases and VOB represents that any noun/noun phrase is the (accusative) object of the verb (opinion-bearing verb). The HIT LTP[1] is employed to get the DDR in a sentence, and we label the current token having the "ATT" or "VOB" DDR with opinion-bearing word as 1, otherwise the current token is labeled as 0.

3.3.5. SRL Feature Extraction

In addition to all of the above, we find that SRL has a significant effect on the identification of opinion targets and opinion-bearing words. This is mainly because the semantic role of opinion targets and opinion-bearing words in a sentence is relatively fixed. The semantic role "Arg0/Arg1" often labels opinion

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[1]HIT-SCIR; http://ir.hit.edu.cn/; 2014-4-17

targets but "V" labels opinion-bearing verb. For example, "大家都在愤愤地抱怨" (Everyone angrily complains) where 大家 (Everyone) labels Arg0 (A0) and 抱怨 (complain) labels V. As shown below:
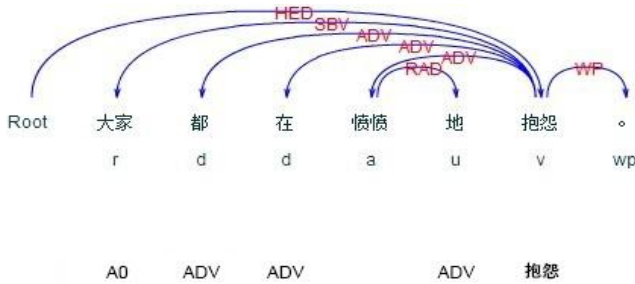

Figure 1. Taking Arg0 (A0) as opinion target.

"我喜欢这部电影" (I like this movie) where 这部电影 (this movie) labels Arg1 (A1) and 喜欢 (like) labels V. As shown below:
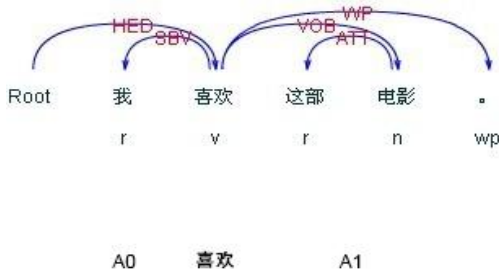

Figure 2. Taking Arg1 (A1) as opinion target.

Figures 1 and 2 reflect that SRL plays a significant role in the process of identifying opinion target. So our task is to extract the right semantic roles from the document, which is annotated by HIT LTP, containing Arg0, Arg1 and V. When Arg0/Arg1 is composed of several words, we only label noun as Arg0/Arg1. Such as "这部电影" (this movie) labels as A1 (Arg1) in Figure 2, but we only choose noun "电影" (movie) as A1 (Arg1). SRL feature extraction is described as follows:

> *For sentences in micro-blog text*
>   *If opinion-bearing word exists in the sentence and is labeled*
>   *as V*
>   *Taking opinion-bearing word and Arg0/Arg1 as*
>   *features*
>   *Else*
>   *Taking Arg0/Arg1 as features*
>   *Other tokens are labeled as **
> *Repeat*
> *End*

4. Simultaneously Identifying Opinion-Bearing Words and Opinion Targets

4.1. Conditional Random Field

With above five features, we simply label all tokens occurring in a sentence, and the features shall enable the CRF algorithm to simultaneously identify opinion

target and opinion-bearing word in a sentence. Our goal is to simultaneously identify opinion targets and opinion-bearing words from sentences which contain opinion targets and opinion-bearing words. This can be modeled as a sequence segmentation and labeling problem. The CRF algorithm receives a sequence of tokens $t_1, t_2, …, t_n$ for which it has to predict a sequence of labels $l_1, l_2, …, ln$.

Generally speaking, the possible labels are represented following the IOB scheme: B-Target, identifying the beginning of a target, I-Target identifying the continuation of a target, and O for other (non-target) tokens. However, in our approach we design a novel scheme to label the token to be predicted in CRF, instead of the IOB scheme. The detailed is describes in section 6.

We model the sentences as a linear chain CRF which is based on an undirected graph. In the graph, each node corresponds to a token in the sentence and edges connect the adjacent tokens as they appear in the sentence. In our experiments, we use the CRF implementation from CRF++0.53[2].

4.2. Preparing Feature Templates in CRF

As CRF++ is designed as a general purpose tool, we have to specify the feature templates in advance. This file describes which features are used in training and testing. During our experiments, we design three kinds of templates to evaluate the simultaneous identification of opinion targets and opinion-bearing words. In order to facilitate the description, we take the template T1 as example, which is used as the default template in CRF++. The template T1 is shown in Table 2.

Table 2. The Template T1.

#Unigram	
#Token	
U01:%x[-1,0]	#The previous token
U02:%x[0,0]	#The current token
U03:%x[1,0]	#The next token
U04:%x[-1,0]/%x[0,0]	#The previous token and the current token
U05:%x[0,0]/%x[1,0]	#The current token and the next token
#POS	
U11:%x[-1,1]	#The POS of previous token
U12:%x[0,1]	#The POS of current token
U13:%x[1,1]	#The POS of next token
U14:%x[-1,1]/%x[0,1]	#The POS of previous token and current token
U15:%x[0,1]/%x[1,1]	#The POS of current token and next token
#WD	
…	…
#DDR	
…	…
#SRL	
…	…
#Bigram	
B	

Where the contents behind # are discarded as Comments and other information can refer to the official web site for CRF++.

In order to contrast the experimental results under the condition of different templates, we additionally design templates T0 and T2. The contextual information appeared in the template T1 is removed, and only the current token information is retained in the template T0 as shown in Table 3. However, template T2 appends some combination information of multiple features on the basis of template T1, as shown in Table 4, namely that the template T2 contains not only the information of T1 but also the combination information of multiple features.

Table 3. The template T0.

#Unigram	
#Token	
U02:%x[0,0]	#The current token
#POS	
U12:%x[0,1]	#The POS of current token
#WD	
U22:%x[0,2]	#The WD information of current token
#DDR	
U32:%x[0,3]	#The DDR information of current token
#SRL	
U42:%x[0,4]	#The SRL information of current token
#Bigram	
B	

Table 4. The combination information of multiple features on the basis of template T1.

#Unigram	
#Token+POS+DDR	
U51:%x[0,0]/%x[0,1]/%x[0,3]	#Combining the information of token, POS and DDR
#Token+POS+SRL	
U61:%x[0,0]/%x[0,1]/%x[0,4]	#Combining the information of token, POS and SRL
#Token+POS+DDR+SRL	
U71:%x[0,0]/%x[0,1]/%x[0,3]/%[0.4]	#Combining the information of token, POS, DDR and SRL
#Bigram	
B	

5. Forwarding-Based Opinion Target Identification Optimization

To some extent, the content of micro-blog is very short, which only contains some opinion-bearing words. There is no explicit opinion target in the short sentence, but it has the related micro-blogs based on forwarding relation. As shown in Figure 3.

Figure 3. Forwarding-based Micro-blog Example.

User calfmom posts the original micro-blog "学院两位优秀学者进入公示：史元春、任天令" (Two outstanding scholars access to the public notice: Yuanchun Shi, Tianling Ren), user 刘奕群 THU

forwards the original micro-blog and express his opinion "威武" (powerful). Based on the forwarding relation, we can get feature-opinion pairs <学者，威武> (<scholar, powerful>) through <学者，优秀> (<scholar, outstanding>) in the original micro-blog.

As for the short micro-blogs without explicit opinion target, we can further boost the performance of the opinion mining by considering the relations between individual micro-blogs. Forwarding relation between individual micro-blogs is common, and we can easily find many related micro-blogs of given micro-blog, such as the micro-blogs replying to or replied by the given micro-blog, and the forwarded micro-blog of the given micro-blog. These related micro-blogs provide rich information about what the given micro-blog expresses and should definitely be taken into consideration for opinion mining of the given micro-blog. Forwarding-based between individual micro-blogs, we can construct a graph using the input micro-blog collection. As illustrated in Figure 4, each circle in the graph indicates a micro-blog. The edges (solid line) indicate forwarding relation. The isolated nodes have not any relations with other micro-blogs.
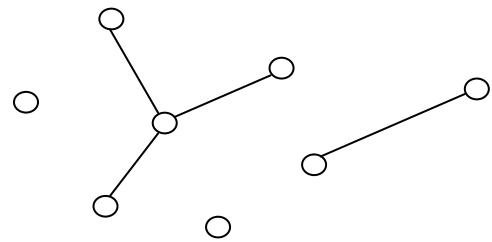

Figure 4. Forwarding-based relation graph.

We assume that the short micro-blog without explicit opinion target has the same opinion target as the closest related micro-blog. When the closest related micro-blog has two (or more) feature-opinion pairs <opinion target, opinion-bearing word>, we take opinion target as the short micro-blog's opinion target, which has the same opinion orientation of opinion-bearing word appeared in both the short micro-blog and the closest related micro-blog. So we achieve forwarding-based opinion target identification optimization algorithm as follows.

Algorithm 1: Forwarding-based opinion target identification optimization algorithm

   Input: The short micro-blog and feature-opinion pairs having forwarding relation with the short micro-blog
   Output: Feature-opinion pairs for the short micro-blog

   For each short micro-blog text
     If opinion-bearing word existing in the short micro-blog text and having forwarding-based feature-opinion pairs
     If numbers of feature-opinion pairs == 1
        Choose opinion target from feature-opinion pairs and opinion-bearing word from the short micro-blog to construct new feature-opinion pairs
     Else

> *Choose opinion-bearing word from the short micro-blog and opinion target having the same opinion orientation of opinion-bearing word from forwarding-based feature-opinion pairs to construct new feature-opinion pairs*
> *Output feature-opinion pairs of the short micro-blog*
> Repeat
> End

6. Experiments

In this study, we consider an opinion-bearing word is a key indicator of an opinion. Therefore, we first identify opinion-bearing word from a given sentence and then label the corresponding opinion target based on multi-features described in section 3.3.

6.1. Data Sets and Experiments Settings

The labeled data sets in NLP and CC 2012[1] and 2013[2], a total of 405 micro-blogs, are provided by Tencent Weibo[3], including four topics: hui_rong_an, ipad, kang_ri_shen_ju_sample and ke_bi_sample. We reserve the sentences labeled with "opinionated=Y" and "forward" in a micro-blog, and then use opinion-bearing words and target_word (opinion target) to generate feature-opinion pairs <opinion target, opinion-bearing word> for our evaluation. There are altogether 600 subjective sentences in data sets, and if there have several subjective sentences in a micro-blog, we firstly extract feature-opinion pairs from the current sentence. When there is no opinion target found in the current sentence, we are looking ahead until the first sentence. If no opinion target is found, we are looking backward from the current sentence until the last sentence.

In the process of training and testing, these data sets are processed into the format required by the CRF++. According to the descriptions in Section 3.3, each token has six columns, followed by the token itself, POS, WD, DDR, SRL and manual annotation category information in that order. Multiple sequences of tokens form a sentence, and these sentences are separated by a blank line. We design the following scheme for manual annotation category information, as shown in Table 5. When two (or more) adjacent tags are the same in a sentence, we combine the tags as one.

Table 5. The Tag Sets and Description in CRF++ Template.

Tag sets	Description
OT	Opinion target
OW	Opinion-bearing word
BG	Other background word

In order to avoid over-fitting or under-fitting, we adopt 10-fold cross-validation in the experiments. Namely data sets would be randomly divided into 10 parts, 9 parts of them are used as training sets and the others are used to test. We repeat the process for 10 times and finally, take the average value. Furthermore, we divide 600 subjective sentences from the labeled data sets into different data size, and respectively use a 10-fold cross-validation so that we can observe the performance under the conditions of different data size. In this experiment, we adopt the default parameters in CRF++0.53 and the window size of token, POS and SRL is set to 3 separately while the window size of WD and DDR is set to 1, namely WD and DDR use the current window.

6.2. Performance Evaluation Method

Performance evaluation is strictly matching in phrase-level, namely only when both opinion target and opinion-bearing word are correctly identified in a sentence, we think that the simultaneous identification of feature-opinion pairs <opinion target, opinion-bearing word> is successful. We adopt Precision (P), Recall (R), and F-measure (F) to evaluate the algorithm performance.

$$\text{Pr}ecision = \frac{Number \ of \ correct \ identified \ feature-opinion \ pairs}{Number \ of \ all \ identified \ feature-opinion \ pairs} \quad (2)$$

$$\text{Re}call = \frac{Number \ of \ correct \ identified \ feature-opinion \ pairs}{Number \ of \ all \ correct \ feature-opinion \ pairs} \quad (3)$$

$$F - measure = \frac{2 * \text{Pr}ecision * \text{Re}call}{\text{Pr}ecision + \text{Re}call} \quad (4)$$

6.3. Performance Comparison

We first establish a baseline system, and reference to the views proposed by [4], they thinks that the POS is an important basis for judging sentiment information. So we only consider the token itself and the POS as basic features in the baseline system. Finally, we take template T1 as the default template and have a 10-fold cross-validation under the conditions of different data size. The results are shown in the following Table 6.

Table 6. The results of baseline system.

Basic features	Data size	Results		
		P(%)	R(%)	F(%)
Token+POS	100	68.7	61.0	64.6
	200	72.7	63.4	67.7
	400	72.6	69.9	71.2
	600	75.5	72.2	73.8

From Table 6 we know the overall performance is constantly increasing when the data size increases, and the precision is higher than the recall, which indicates there are many missing feature-opinion pairs in the process of identification. So we need more features, as illustrated in Table 7, to process 600 subjective sentences using the default template T1.

Table 7. The identification results based on multi-features.

Features	Results		
	P(%)	R(%)	F(%)
Token+POS	75.5	72.2	73.8
Token+POS+WD	75.9	73.1	74.5
Token+POS+WD+DDR	77.3	80.1	78.7
Token+POS+WD+DDR+SRL	81.2	85.5	83.3

On the basis of basic features, we add WD, DDR and SRL into our approach. From Table 7 we know WD, DDR and SRL play an important role in identifying feature-opinion pairs <opinion target, opinion-bearing word>. The experimental results show that adding WD, DDR and SRL can effectively help our approach improve the simultaneous identification for opinion target and opinion-bearing word. Especially using SRL feature makes our approach fully considering the semantic role in the process of training. The generated model would make more accurate prediction to some extent.

However, the above experiments utilize the feature template T1 and ignore the combination information of multiple features in CRF model. So we design three kinds of feature template to verify the effects on feature-opinion pairs, and use five features to do the experiment under the conditions of different data size. The experimental results are shown in Figures 5, 6, and 7.
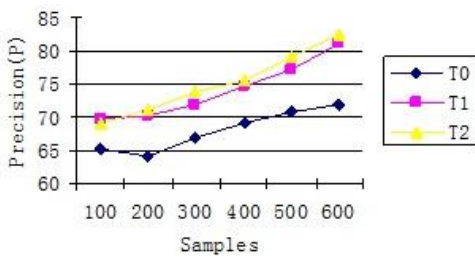

Figure 5. The precision of using different templates and data size.
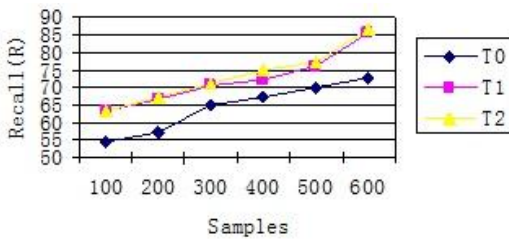

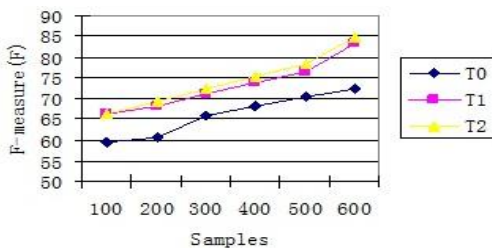Figure 6. The recall of using different templates and data size.

Figure 7. The F-measure of using different templates and data size.

The results from Figures 5 and 6 show that both templates T2 and T1 are essentially the same in recall, but the precision of T2 is slightly ahead of T1.

However, the performance of T0 is the worst because of no considering the context information. In the whole designing process of T1 and T2, we consider the context information of the word. Because the context category label of the word plays a very important role for the judgment of category label of the target word. With the continuous improvement of the templates, the experimental results are relatively better. Especially using the combination information of multiple features of template T2 achieves the best effect on identifying feature-opinion pairs <opinion target, opinion-bearing word>. So from the Figures 7 we know the experiment achieves the best results using above five features and template T2.

Furthermore, there is less "forward" in the labeled data sets, we need more forwarding relation to check forwarding-based opinion target identification optimization, so we manually add 300 "forward" into 405 micro-blogs and construct forwarding-based relation graph using 405 micro-blogs. The comparison of results before and after optimization is shown in Table 8.

Table 8. The comparison before and after optimization.

Identification method	Results		
	P(%)	R(%)	F(%)
Multi-features identification	82.5	86.9	84.6
Forwarding-based optimization	82.9	87.4	85.1

As shown in Table 8, without forwarding-based optimization, the F-measure is 84.6%, which is still higher than those using only template T1 and multi-features. After adding forwarding-based optimization, the F-measure is improved to 85.1%, which suggests that the forwarding between micro-blogs does help identify opinion target. From Table 8 we can see that both the combination of multiple features and forwarding-based optimization all contribute to the overall improvement. In addition, according to opinion-bearing word we can obtain the sentiment polarity of opinion target, and through NLP and CC 2012 and 2013's test data our approach provides better performance than most systems reported at NLP and CC 2012 and 2013.

Take the example in Figure 3 as a case study, we obtain the features (Token, POS, WD, DDR, SRL) through the analysis of "威武//学院两位优秀学者进入公示：史元春、任天令(Powerful//Two outstanding scholars access to the public notice: Yuanchun Shi, Tianling Ren)", and then get feature-opinion pairs <scholar, outstanding> based on the DDR ATT (attribute). Because forwarding relation "//" and opinion-bearing word existing in the short micro-blog text, we can get <scholar, Powerful> according to forwarding-based optimization algorithm. Or the optimization algorithm would compute opinion orientation of opinion-bearing words.

7. Conclusions And Future Works

In this paper, we investigate the problem of

simultaneously identifying opinion targets and opinion-bearing words in opinionated sentences of Chinese micro-blog texts based on multi-features, and then take advantage of forwarding relation between individual micro-blogs to optimize opinion target identification on the basis of the former identification results. Our proposed approach shows good performance through the experiments. In future the work will focus on the following two aspects:

1. There are still more relations between individual micro-blogs, such as commenting, sharing and so on. We need to take more relations into consideration for opinion mining.
2. Handling the negative sentence. Sometimes the sentences contain negative words (or more negative words), and we need further treatment.

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