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A METHOD OF OPINION TARGET EXTRACTION BASED ON SYNTACTIC STRUCTURE

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Abstract. *Sentiment analysis is an important task in the field of natural language processing. This paper has focus on opinion target extraction of sentiment extraction in the primary task of sentiment analysis. First, the features are extracted from preprocessed results. Then, the results of feature extraction with the corresponding template will be input to the CRFs (Conditional Random Fields) module for training and recognition. In the process of feature extraction, three features are applied on the basis of existing features by analyzing syntactic structure. To select template with better performance, many comparison experiments have carried on a variety of templates with different sizes. Experimental results show our method is more effective than the baseline which can exactly extract opinion targets.*
Keywords: Syntactic structure, Sentimental analysis, Opinion target, CRFs

1. **Introduction.** Sentiment analysis is known as opinion mining which is an important and valuable task for analyzing, processing and inducing of opinion texts. Three progressive tasks of sentiment analysis include sentiment extraction, sentiment classification and sentiment retrieval and summarization [1]. Sentiment classification uses the results of sentiment extraction to classify the subjective texts into several categories. Yang et al. [2] adopted supervised method and proposed an improved incremental Naïve Bayesian (Named T-INB) for sentiment classification. The goal of opinion extraction is to extract the theme for serving the sentiment analysis task in the reviews. Existing methods of opinion targets extraction are divided into the approaches based on rules/templates and statistic model.

Hu and Liu [3] first proposed opinion target extraction task and employed association rules algorithm to extract opinion targets. So the nouns with higher frequency will be regarded as opinion targets. Popescu and Etzioni [4] presented the Opinion Information Extraction (OPINE) system for potential opinion targets by defining rules and templates. Zhuang et al. [5] defined movie features, opinion word of related features and feature-opinion pair for mining explicit features and parts of implicit features in the movie reviews. Scaffidi et al. [6] extract feature terms and rank product feature what user needed for opinion target extraction. Zhao et al. [7] made statistics on frequent syntactic paths in sentences and further generalized syntactic paths. Jakob and Gurevych [8] modeled opinion target extraction as a sequence label task and employed Conditional Random Field (CRF) [9] to label opinion targets. Liu et al. [10] proposed a method of Word-based Translation Model (WTM) for opinion target extraction which can capture opinion relations with large span. Liu et al. [11] presented an approach of Partially Supervised

Word Alignment Model (PSWAM) for opinion on the basis of WTM and extracted candidates with higher confidence as opinion targets. Liu et al. [12] verified the performance of approaches based on syntax and alignment for the datasets with different sizes, diverse languages and various domains.

The rules/templates are based on traditional algorithm, and the characteristics of corpora and the words are related to specific domain. The performance may decrease if the rules are used in other domains. Some methods based on statistic model ignore the internal structure information such as the dependency relationship between sentences. Therefore, we take account of syntactic structure information and the dependency among words. A new method is proposed in the paper, and experiments show the effectiveness of our approach.

This paper is organized as follows. Section 2 gives the research status and existing problems of opinion target extraction. Section 3 introduces the method of opinion target extraction based on syntactic structure in detail. The experimental results and analysis will be given in Section 4. Finally, we summarize the paper and indicate our future work in Section 5.

2. **Related Work.** Raw corpora are processed for segmentation, POS tagging and parsing by natural language processing tools of Stanford[1]. First, the features are extracted from preprocessed results. Then, the results of feature extraction with the corresponding template will be input to the CRFs module for training and recognition. In the process of feature extraction, three features are applied on the basis of existing features by analyzing syntactic structure for mining syntactic structural information in subjective texts. Finally, opinion targets are labeled with CRFs[2] model as shown in Figure 1.

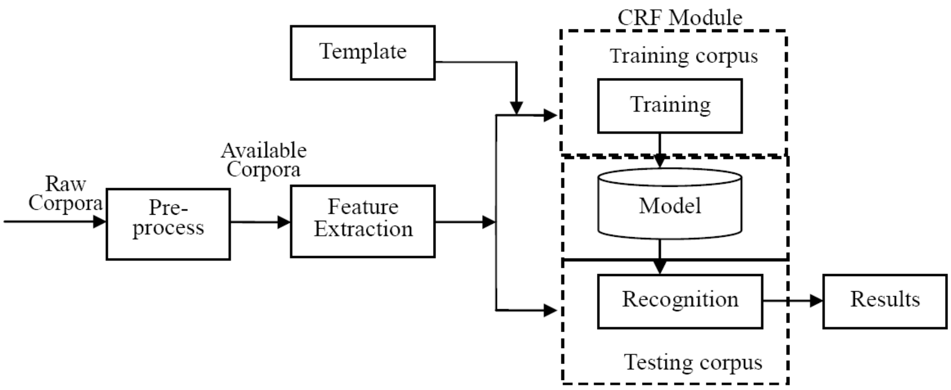

Figure 1. System overview diagram

2.1. **Feature description.** Table 1 shows the existing features and our proposed features. ID 1 to 5 show the existing features, while ID 6 to ID 8 are the features added. To improve experimental performance, the sentiment word is applied, which is an important indicator. Some dependency labels usually contact opinion target and the corresponding word, such as the relations "nsubj", "dobj" and "amod" respectively named subject predicate relation, predicate object relation and adjective modification relation. Dependency relation word clearly shows the word which has dependency relation with current token.

2.2. **Template definition.** Template reflects the context information between words in the reviews. In the definition of templates, to select template with better performance and improve the effect of opinion target extraction, many comparison experiments have carried on a variety of templates with different sizes.

[1]http://nlp.stanford.edu/software/index.shtml
[2]http://chasen.org/~taku/software/CRF++/#features

Table 1. Feature description

ID	Feature	Description
1	Tk	The string of the current token.
2	Pos	The part-of-speech of the current token.
3	dLn	Short Dependency Path. Whether current token has direct dependency relation with sentiment word.
4	wrdDist	Short Word Distance. Whether current token is the nearest to sentiment word.
5	sSn	Opinion Sentence. Whether the sentence which current token is in is a subjective sentiment.
6	stWord	Sentiment Word. Whether current token is a sentiment word.
7	tkRel	Dependency label. Dependency parse tree links current token and corresponding word.
8	rWord	Dependency Relation Word. The word which has direct dependency relation with current token.

Table 2. Definition of Template-tmp1

Definition of template	Meaning
U01:%x$[-1, 0]$	The former. The word before current token.
U02:%x$[0, 0]$	Current token.
U03:%x$[1, 0]$	The latter. The word after current token.
U04:%x$[-1, 0]$/%x$[0, 0]$	The combination of current token and the former.
U05:%x$[0, 0]$/%x$[1, 0]$	The combination of current token and the latter.

Table 3. Definition of Template-tmp2

Definition of template	Meaning
U01:%x$[-2, 0]$	The word before the former.
U02:%x$[-1, 0]$	The former. The word before current token.
U03:%x$[0, 0]$	Current token.
U04:%x$[1, 0]$	The latter. The word after current token.
U05:%x$[2, 0]$	The word after the latter.
U06:%x$[-2, 0]$/%x$[-1, 0]$	The combination of the former and the word before the former.
U07:%x$[-1, 0]$/%x$[0, 0]$	The combination of current token and the former.
U08:%x$[0, 0]$/%x$[1, 0]$	The combination of current token and the latter.
U09:%x$[1, 0]$/%x$[2, 0]$	The combination of the latter and the word after the latter.

To select the template with best performance, we have taken full account of the relations between the words before current word and the words after current word, we discuss the size of the windows as the following: tmp1$-$ = $(-1, 0)$, tmp1 = $(-1, 0, 1)$, tmp1+ = $(0, 1)$, tmp2$-$ = $(-2, -1, 0)$, tmp2 = $(-2, -1, 0, 1, 2)$, tmp2+ = $(0, 1, 2)$ and tmp3 = $(-3, -2, -1, 0, 1, 2, 3)$. They are defined in Table 2 and Table 3, respectively. In particular, "0" in U01 means the 0th column and "1" in U01 means the first row, and so on.

3. Opinion Target Extraction Based on Syntactic Structure Methods.

3.1. **Design of CRF module.** We select existing features [9] as the baseline system for comparison and analysis on different templates. Existing features are shown in Table 1 which contain token, part-of-speech, short dependency path, short word distance and opinion sentence. We employ the evaluation indicators of information retrieval which are precision (P), recall (R) and F-measure (F). Precision is calculated as $Precision = \frac{TP}{TP+FP}$ which means the ratio of identified correct opinion targets and retrieved opinion targets, recall is calculated as $Recall = \frac{TP}{TP+NP}$ which means the ratio of identified correct opinion targets and all the correct opinion targets, and F-measure is the harmonic mean of precision and recall.

To verify the accuracy of system performance, 10-fold cross-validation is used for this paper. Specifically, the results of feature extraction are divided into ten parts: nine parts are regarded as training data and the rest one part is called testing data. Then, the training data and corresponding template are input in the CRF++ for generating model. Opinion targets are labeled by the model. This process is repeated ten times, and the mean values of results will be the final evaluation result.

3.2. **Datasets.** We select the same dataset from three domains as well as baseline system [9] for comparison. The first dataset is Darmstadt Service Review Corpus (DSRC), which contains Services and Universities. The second dataset is the Internet Movie Database (IMDb), which includes the reviews of movies. The dataset statistic is shown as Table 4.

Table 4. Dataset statistic

Dataset	Services	Universities	Movies
Documents	234	256	1829
Sentences	7575	2911	13906
Opinion sentences	1372	1012	5326
Words	119396	57596	243723
Opinion targets	1827	1143	6574

4. Experiment Analysis.

4.1. **Performance analysis of different templates.** To get the template with best performance, we have done research on diverse features, domains and templates in three datasets. The results are respectively shown in Figure 2, Figure 3 and Figure 4.

By analyzing experimental results, we have observed the performance of all the features which consist of existing features and our applied features are better than existing features. Performance of tmp1 is superior to tmp1− and tmp1+, and tmp2 excels tmp2− and tmp2+. It verifies symmetrical templates achieve better performance than asymmetrical templates. And tmp1 which contains the word before current token and the word after current token achieves the best performance. Therefore, employing the appropriate window size will improve experimental performance.

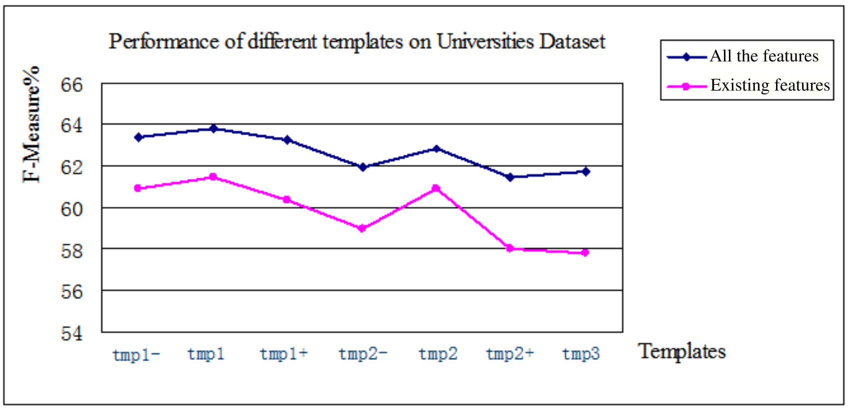

Figure 2. Performance of different templates on Universities Dataset

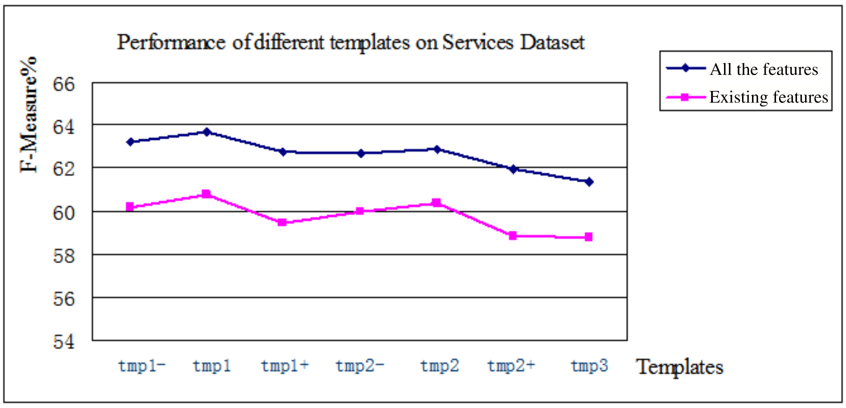

Figure 3. Performance of different templates on Services Dataset

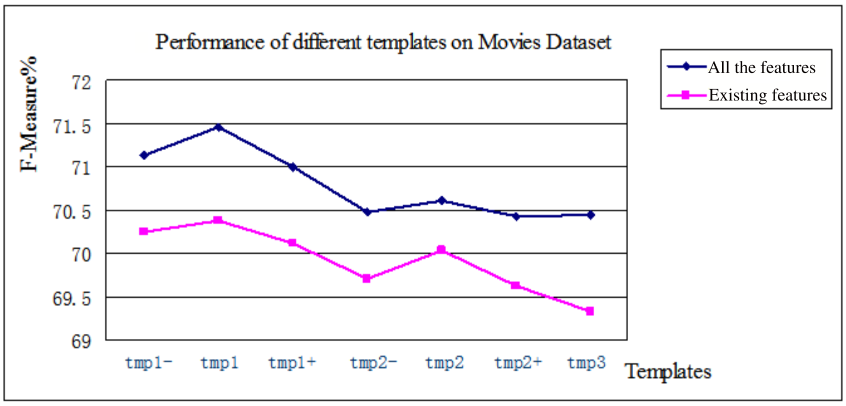

Figure 4. Performance of different templates on Movies Dataset

4.2. **Performance analysis of different features.** Three groups of feature combinations are Base-feature, combination of Base-feature and Single-feature and combination of all the features. To test the effectiveness of feature combinations, we have done experiments on three datasets. F-measure which is the harmonic mean of precision and recall is used for verifying the performance of experiments. Base-feature including token, part-of-speech and their combination is shown in Table 5. The features of ID 1, ID 2 and ID 3 respectively represent token, part-of-speech and their combinations. It proves their combinations are more effective.

ID 4 to ID 9 respectively represent short dependency path feature, short word distance feature, opinion sentence feature, sentiment word feature, dependency label feature and dependency relation word feature. Table 6 shows that the performance of features from ID 4 to ID 9 is superior to the performance of ID 3. The effect of short dependency path feature is more obvious.

Table 5. Base-feature results

Template	ID	Evaluation / Feature	Services			Universities			Movies		
			P (%)	R (%)	F (%)	P (%)	R (%)	F (%)	P (%)	R (%)	F (%)
Tmp1	1	Tk	70.18	43.96	54.05	72.65	44.60	54.98	73.68	62.87	67.85
	2	Pos	61.05	32.22	42.18	50.00	30.30	37.74	60.71	29.32	39.54
	3	Tk+pos	68.90	47.44	**56.18**	70.29	47.51	**56.70**	73.15	65.63	**69.19**
Tmp2	1	Tk	68.38	43.96	53.51	71.19	43.30	53.85	73.51	62.76	67.70
	2	Pos	63.95	30.90	41.67	57.50	26.78	36.49	60.47	28.86	39.04
	3	Tk+pos	67.20	47.73	**55.81**	71.15	46.26	**56.02**	72.96	65.19	**68.85**

TABLE 6. Combination of Base-feature and Single-feature results

Template	ID	Evaluation / Feature	Services			Universities			Movies		
			P (%)	R (%)	F (%)	P (%)	R (%)	F (%)	P (%)	R (%)	F (%)
Tmp1	4	3+dLn	68.57	52.75	59.63	71.63	53.61	61.01	75.23	65.56	70.06
	5	3+wDs	66.90	52.20	58.64	73.91	48.57	58.62	74.97	65.62	69.98
	6	3+sSn	69.58	48.28	56.95	73.62	46.64	57.00	73.28	65.21	69.00
	7	3+stWord	70.15	49.20	57.84	71.33	47.11	56.32	73.58	65.53	69.32
	8	3+tkRel	66.18	49.45	56.60	75.00	44.44	55.81	74.13	65.40	69.45
	9	3+rWord	72.58	47.37	57.32	73.36	47.74	57.84	73.61	65.34	69.23
Tmp2	4	3+dLn	67.91	51.70	58.71	73.17	50.42	59.70	74.89	65.23	69.70
	5	3+wDs	69.42	48.84	57.34	71.08	49.58	58.42	74.64	65.23	69.60
	6	3+sSn	69.04	47.66	56.43	69.45	47.39	56.25	73.06	64.95	68.75
	7	3+stWord	70.16	47.68	56.75	71.43	46.43	56.28	73.16	65.27	68.97
	8	3+tkRel	67.48	48.26	56.27	69.57	44.44	54.24	73.76	65.27	69.25
	9	3+rWord	67.44	47.80	55.95	72.94	46.62	56.88	73.10	64.93	68.76

TABLE 7. Combination of features results

Template	ID	Evaluation / Feature	Services			Universities			Movies		
			P (%)	R (%)	F (%)	P (%)	R (%)	F (%)	P (%)	R (%)	F (%)
Tmp1	10	Existing	72.97	53.16	**61.51**	73.26	52.94	**61.46**	75.53	65.89	**70.38**
	11	10+stWord	70.33	55.34	61.94	77.03	52.78	62.64	76.01	65.89	70.59
	12	11+tkRel	71.62	56.68	63.28	76.43	54.54	63.65	76.12	66.58	71.03
	13	11+rWord	69.86	56.04	62.20	74.02	54.50	62.69	76.00	66.45	70.90
	14	ALL	71.81	57.22	**63.69**	76.60	54.64	**63.78**	77.44	66.72	**71.46**
Tmp2	10	Existing	70.45	52.84	**60.39**	71.95	52.82	**60.91**	75.40	65.42	**70.04**
	11	10+stWord	68.09	55.81	61.34	73.21	52.90	61.37	75.43	66.01	70.38
	12	11+tkRel	68.87	57.14	62.46	72.15	55.43	62.69	75.68	65.91	70.44
	13	11+rWord	72.10	54.61	62.12	71.00	55.67	62.40	75.41	65.62	70.15
	14	ALL	71.43	56.15	**62.87**	74.27	54.62	**62.84**	75.81	65.94	**70.51**

The features of ID 10 present the combinations of existing features, which is better than the performance of features from ID 1 to ID 9 in Table 7. The features of ID 11 obtain better performance than ID 10 which apply sentiment word feature on the basis of ID 10. Sentiment word is a key indicator for opinion target extraction, while, short dependency path feature and short word distance feature indirectly depend on sentiment word feature. The features of ID 12 and ID 13 achieve more optimal performance than ID 11 which respectively add dependency label feature and dependency relation word feature on ID 11 basis. That is to say, some special dependency relations usually link opinion targets with corresponding opinion word. ID 14 means the combinations of all features which get the best performance. We have observed the accuracy in Movies Dataset is higher than others, and the reason is the corpora of Movies Dataset are larger and more standard than Services Dataset and Universities Dataset.

5. **Conclusions.** The paper focuses on the research of opinion target extraction based on syntactic structure. In order to explore more effective features for opinion target extraction, an extraction method is proposed. By comparison with existing features which are the baseline, the performance of opinion target extraction performs better than those methods mentioned in the paper. In the future, we will explore more effective features to improve the accuracy of opinion target extraction. In some cases, many opinion targets are pronouns in the reviews. It may be an appropriate strategy to improve the performance of opinion target extraction with the anaphora resolution.

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