Chinese Sentence-Level Sentiment Classification Based on Fuzzy Sets

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Abstract

This paper presents a fuzzy set theory based approach to Chinese sentence-level sentiment classification. Compared with traditional topic-based text classification techniques, the fuzzy set theory provides a straightforward way to model the intrinsic fuzziness between sentiment polarity classes. To approach fuzzy sentiment classification, we first propose a fine-to-coarse strategy to estimate sentence sentiment intensity. Then, we define three fuzzy sets to represent the respective sentiment polarity classes, namely positive, negative and neutral sentiments. Based on sentence sentiment intensities, we further build membership functions to indicate the degrees of an opinionated sentence in different fuzzy sets. Finally, we determine sentence-level polarity under maximum membership principle. We show that our approach can achieve promising performance on the test set for Chinese opinion analysis pilot task at NTCIR-6.

1 Introduction

With the explosive growth of the user-generated content on the web over the past years, opinion mining has been attracting an ever-increasing amount of attention from the natural language processing community. As a key issue in opinions mining, sentiment classification aims to classify opinionated documents or sentences as expressing positive, negative or neutral opinions, and plays a critical role in many opinion mining applications such as opinion summarization and opinion question answering.

Although recent years have seen a great progress in sentiment analysis, it is still challenging to develop a practical sentiment classifier for open applications. This is largely due to the particularities of subjective languages. Unlike factual text, opinion text is usually expressed in a more subtle or arbitrary manner (Pang and Lee, 2008). Moreover, the sentiment orientation of a subjective expression is often context, domain and/or even order-dependent (Pang and Lee, 2008). This makes it hard to explore informative cues for sentiment classification. In particular, the final semantic orientation of an opinionated sentence often depends on the synthetic effects of all sentiment units (e.g. sentiment words or phrases) within it. Therefore, sentiment granularity selection and polarity aggregation are two important factors that affect sentiment classification performance.

In addition, real opinion texts do not contain precisely-defined criteria of membership with respect to polarity classes. Most current work employs supervised machine learning techniques like naive Bayesian models and support vector machines to perform sentiment classification. While they have shown a good performance in traditional topic-based text classification tasks (Wang, 2006), their applications in sentiment classification are far from satisfactory (Pang *et al.*, 2002). The reason might be the intrinsic fuzziness between sentiment polarity classes. Relative to the concept of objective topics like *sports* and *politics* in traditional text classification, the division between *positive sentiments* and *negative sentiments* is rather vague, which does not make clear boundary between their conceptual extensions. Such vague conceptual extension in sentiment polarity inevitably raises another challenge to sentiment classification.

Coling 2010: Poster Volume, pages 312–319,
Beijing, August 2010

To address the above problems, in this paper we exploit fuzzy set theory to perform Chinese sentiment classification at sentence level. To approach this task, we first consider multiple sentiment granularities, including sentiment morphemes, sentiment words and sentiment phrases, and develop a fine-to-coarse strategy for computing sentence sentiment intensity. Then, we reformulate the three classes of sentiment orientations, namely positive, negative and neutral sentiments, as three fuzzy sets, respectively. To describe the membership of an opinion sentence in a special sentiment fuzzy set, we further construct membership functions based on sentence sentiment intensity, and thus determine the final semantic orientation of a given opinionated sentence under the principle of maximum membership. We show that the proposed approach can achieve a promising performance on the test set for Chinese opinion analysis pilot task at NTCIR-6.

The remainder of the paper is organized as follows: Section 2 provides a brief review of the literature on sentiment classification. In Section 3, we describe the fine-to-coarse strategy for estimating sentiment intensity of opinionated sentences. Section 4 details how to apply fuzzy set theory in sentiment classification. Section 5 reports our experimental results on NTCIR-6 Chinese opinion data. Finally, section 6 concludes our work and discusses some possible directions for future research.

2 Related Work

Sentiment classification has been extensively studied at different granularity levels. At lexical level, Andreevskaia and Bergler (2006) exploit an algorithm for extracting sentiment-bearing adjectives from the WordNet based on fuzzy logic. Following (Turney, 2002), Yuen *et al.* (2004) investigate the association between polarity words and some strongly-polarized morphemes in Chinese, and present a method for inferring sentiment orientations of Chinese words. More recently, Ku *et al.* (2009) consider eight morphological types that constitute Chinese opinion words, and develop a machine learning based classifier for Chinese word-level sentiment classification. They show that using word structural features can improve performance in word-level polarity classification. At phase level, Turney (2002) presents a technique for inferring the orientation and intensity of a phrase according to its PMI-IR statistical association with a set of strongly-polarized seed words. More recently, Wilson *et al.* (2009) distinguish prior and contextual polarity, and thus describe a method to phrase-level sentiment analysis. At sentence level, Yu and Hatzivassiloglou (2003) propose to classify opinion sentences as positive or negative in terms of the main perspective being expressed in opinionated sentences. Kim and Hovy (2004) try to determine the final sentiment orientation of a given sentence by combining sentiment words within it. However, their system is prone to produce error sentiment classification because they only consider sentiment words near opinion holders and ignore some important words like adversative conjunctions. To compute sentiment intensity of opinionated sentences, in this study we propose a fine-to-coarse strategy, which take into account multiple granularity sentiments, from sentiment morphemes, sentiment words to sentiment phrases, and can thus handle both unknown lexical sentiments and contextual sentiments in sentiment classification.

Most recent studies apply machine learning techniques to perform sentiment classification. Pang *et al.* (2002) attempt three machine learning methods, namely naive Bayesian models, maximum entropy and support vector machines in sentiment classification. They conclude that the traditional machine learning methods do not perform well enough in sentiment analysis. Wilson *et al.* (2009) further employ several machine learning algorithms to explore important features for contextual polarity identification. Different from most existing works that focus on traditional text classification techniques, in this study we attempt to resolve sentiment classification problems under the framework of fuzzy set theory. We choose fuzzy set theory because it provides a more straightforward way to represent the intrinsic fuzziness in sentiment.

3 Sentence-Level Sentiment Intensity

In this section, we describe a fine-to-coarse strategy to compute sentence-level sentiment intensity. After a brief discussion of the relationship between Chinese sentiment words and their component morphemes in Section 3.1, we extract a dictionary of sentiment morphemes from a sentiment lexicon, and compute their opinion scores using a modified chi-square technique. Then, we develop two rule-based strategies for word-level and phrase-level polarity identification, respectively. Finally, we calculate the final sentiment intensity of an opinionated sentence by summing the opinion score of all phrases within it.

3.1 Sentiment words and morphemes

As shown in Table 1, Chinese sentiment words can be categorized into static polar words and dynamic polar words. The polarity of a static polar word remains unchanged while a dynamic polar word may have different polarity in different contexts or domains.

Type		Example
Static polar word	Positive	美丽 'beautiful', 温柔 'gentle'
	Negative	卑劣 'beggary', 错误'wrong'
	Neutral	还可以 'acceptable'
Dynamic polar words		大'big', 高'high'

Table 1. Types of Chinese sentiment words

For a static polar word, its polarity can be easily determined by referring to a sentiment lexicon. However, a precompiled dictionary cannot cover all sentiment words in real text, which raises an issue of predicting the polarity of out-of-vocabulary (OOV) sentiment words. To address this problem, we introduce sentiment morphemes. As Table 2 shows, here we consider two types of sentiment morphemes, namely positive morphemes and negative morphemes.

Morpheme types	Sentiment morphemes	Sentiment words composed by sentiment morphemes
Positive morphemes	美'beauty'	精美 'exquisite'
		优美 'graceful'
	爱'love'	喜爱 'like'
		爱慕 'adoration'
Negative morphemes	污'dirty'	污染 'pollution'
		贪污 'corruption'
	败'fail'	腐败 'corruption'
		败坏 'undermine'

Table 2. Types of Chinese sentiment morphemes

In most cases, the polarity of a sentiment word is closely related to the semantic orientation of its component morphemes. In other words, word-level polarity can often be determined by some key component sentiment morphemes within sentiment words. Take the following three sentiment words for example, 败坏 'undermine', 腐败 'corruption', and 败类 'degenerate'. They share a same negative sentiment morpheme 败 'fail', and thus have the same negative orientation. Based on this observation, here we use morpheme-level polarity, rather than a sentiment lexicon, to predict the polarity of static sentiment words, particularly the OOV sentiment words in real text.

As for dynamic sentiment words, traditional lexicon-based methods do not work for their real polarity changes with contexts. We will discuss the problem of dynamic polarity identification in Section 3.4.

3.2 Identifying morpheme-level polarity

Sentiment morphemes prove to be helpful in dealing with OOV polarity (Ku et al, 2009). However, there is not a dictionary of sentiment morphemes available for sentiment analysis. To avoid this, we propose to automatically extract sentiment morphemes from some existing sentiment lexicon using chi-square (χ^2) technique. Formula (1) presents the χ^2 of a morpheme *m* within a sentiment word of category *c*.

$$\chi^2(m,c) = \frac{n \times (n_{11} \times n_{22} - n_{12} \times n_{21})^2}{(n_{11}+n_{12})(n_{21}+n_{22})(n_{11}+n_{21})(n_{12}+n_{22})} \quad (1)$$

where *m* denotes a sentiment morpheme. $c \in$ {positive, negative} denotes the polarity of a certain sentiment word *w* that contain *m*. *n* is the total number of sentiment words in the lexicon. To calculate χ^2, we need to construct a 2×2 contingency table from the sentiment lexicon. As shown in Table 3, n_{11}, n_{12}, n_{21} and n_{22} denote the observed frequencies, respectively.

Polar word *w*	belong to *c*	not belong to *c*
contain *m*	n_{11}	n_{12}
not contain *m*	n_{21}	n_{22}

Table 3. The 2×2 contingency table for χ^2

The traditional χ^2 statistics in Formula (1) can demonstrate the degree of contributions that a sentiment morpheme forms a special group of sentiment words. However, it cannot indicate whether the morpheme and the sentiment category are either positively- or anti-correlated.

Such information is very important for inferring word-level polarity from sentiment morphemes. To compensate for this deficiency, we modify the traditional χ^2 by injecting positive correlation and anti-correlation. Following (Wang, 2006), we introduce the following two rules in determining the sign of correlation between the sentiment category of words and their component sentiment morphemes.

- If $n_{11}\times n_{22}-n_{12}\times n_{21}>0$, the morpheme and the sentiment category are positively correlated. In this case, a larger χ^2 implies a higher likelihood that the morpheme belongs to the sentiment category.
- If $n_{11}\times n_{22}-n_{12}\times n_{21}<0$, the morpheme and the sentiment category are anti-correlated. In this case, a larger χ^2 value implies a higher likelihood that the morpheme does not belong to the sentiment category.

Thus, we obtain a modified χ^2 statistics as follows.

$$\chi^{2}{}'=sign(n_{11}\times n_{22}-n_{12}\times n_{21})\frac{n\times(n_{11}\times n_{22}-n_{12}\times n_{21})^2}{(n_{11}+n_{12})(n_{21}+n_{22})(n_{11}+n_{21})(n_{12}+n_{22})} \quad (2)$$

With the $\chi^{2}{}'$ statistic, we can build a dictionary of sentiment morphemes from a source sentiment lexicon, and further determine the polarity of each sentiment morpheme using the two rules as shown in Definitions 1 and 2.

Definition 1 (positive sentiment morphemes). If the $\chi^{2}{}'$ statistic between a morpheme *m* and positive sentiment words is greater than zero, then *m* can be identified as positive.

Definition 2 (negative sentiment morphemes). If the $\chi^{2}{}'$ statistic between a morpheme *m* and positive sentiment words is smaller than zero, then *m* can be identified as is negative.

Table 4 illustrates some extracted sentiment morphemes and their $\chi^{2}{}'$ values.

Types of morphemes	Examples	$\chi^{2}{}'$
Positive morphemes	美‘beautiful’	111.78
	爱‘love’	65.88
	喜‘happy’	40.72
Negative morphemes	死‘die’	-104.97
	败‘failed’	-45.28
	恶‘evil’	-72.37

Table 4. $\chi^{2}{}'$ values of sentiment morphemes

3.3 Identifying word-level polarity

To determine word-level polarity, we employ morpheme-based rules. First of all, we normalize the $\chi^{2}{}'$ value of each sentiment morpheme *m* into [-1, 1] by dividing it with the maximum absolute value. Such normalized chi-square, denoted by *chi*(*m*), is further viewed as the opinion score of the sentiment morpheme *m*. Thus, we can determine whether a word is a sentiment or not using a simple rule: if a word contains sentiment morphemes, it is a sentiment word. Finally, we can calculate the opinion score of a word *w* consisting of morphemes m_i, $(1\le i\le 2)$[1], using the following two rules.

- If m_1 is a negation, e.g. 不 ‘not’ and 非 ‘non-’, then $Score(w)= -1\times chi(m_2)$.
- If m_1 is not a negation morpheme, then $Score(w)=Sign(chi(m_i))\times Max(|chi(m_i)|)$. Where, $Max(|chi(m_i)|)$ is the largest absolute value among the opinion scores of morphemes within a word *w*, $Sign(chi(m_i))$ denotes the positive or negative sign of *m*, namely ‘-’ and ‘+’.

3.4 Identifying phrase-level polarity

To handle contextual polarity, we apply lexical polarity to determine the sentiment orientation of phrases within an opinionated sentence. Based on (Hatzivassiloglou and Wiebe, 2000) and (Turney, 2002), we consider four types of structures (as shown in Table 5) during sentiment phrase extraction. To simplify the process, we reduce some function words like 的 ‘’s’ and 与 ‘and’ from the input sentences before extraction in that they have no influence on sentiment orientation determination, and focus on extracting two consecutive words. Different from (Turney, 2002), we consider phrases with negations as their initial words. In this way, we can handle the local negation that may reverse polarity.

Phrase structures	Examples
Phases containing a adjective	成功率高 ‘high success rate’
Phrases containing a verb	详细讨论‘carefully discuss’
Phrase containing an idiom	企图掩人耳目/‘intent to deceive the public’
Phrases beginning with a negation	没有证据‘no evidence’

Table 5. Structures of opinion phrases

[1] For words that contain three or more characters, particularly the four-character idioms, their polarity can be determined using the second rule.

After opinion phrase extraction, we continue to calculate the opinion score of the extracted phrases using rules that are similar to (Hu and Liu, 2004). Before going to the details of phrase-level opinion score calculation, we need to give some definitions in advance.

Definition 3 (increased dynamic polar words). An increased dynamic polarity word can increase the orientation strength of sentiment words that it modifies without changing their polarity. For example, the word 大 'serious' in the phrase 污染大 'serious pollution' and the word 高 'high' in the phrase 效益高 'high benefit'.

Definition 4 (decreased dynamic polar word). A decreased dynamic polarity word can decrease the orientation strength of sentiment words that it modifies and at the same time, reverse their polarity. For example, the word "小" 'little' in the phrase 污染小 'little pollution' and the word 低 'low' in the phrase 效益低 'low benefit'.

To calculate phrase-level opinion scores, we construct a dictionary of dynamic polar words by extracting adjectives and verbs that contain a single-character seed morpheme like 少 'little' from the training corpus. Table 6 illustrates some increased and decreased dynamic polar words and their signs for changing polarity.

Dynamic polar word	Example	Polarity sign
Increased	高 'high' 增加 'increase' 提升 'upgrade'	*Sign*(increased)=1
Decreased	下降 'down' 减少 'reduce' 缩小 'diminish'	*Sign*(decreased)=−1

Table 6. Dynamic words and their polarity sign

With these dynamic polar words, we can then calculate the opinion score of a given opinion phrase p_i that consists of two words (denoted by w_j, $j\in\{1,2\}$), using three rules as follows.

- If w_1 is a negation, e.g. 不 'no' and 没有 'without', then $Score(p_i) = -1\times Score(w_2)$.
- If p_i involves a dynamic word w_d, then $Score(p_i) = Sign(w_d) \times Score(w_j)$. Where, $Sign(w_d)$ denotes the polarity sign of dynamic words shown in Table 6.
- Otherwise, $Score(p_i) = Sign(w_j) \times Max(|Score(w_j)|)$. Where $Max(|Score(word_j)|)$ is the largest absolute value among the word-level opinion scores.

4 Sentence Sentiment Classification

4.1 Sentiment fuzzy sets and membership functions

As we have mentioned above, sentiment polarity is vague with regard to its conceptual extension. There is not a clear boundary between the concepts of "positive", "neutral" and "negative". To better handle such intrinsic fuzziness in sentiment polarity, we apply the fuzzy set theory by (Zadeh, 1965) to sentiment classification. To do so, we first redefine sentiment classes as three fuzzy sets, and then apply existing fuzzy distributions to construct membership functions for the three sentiment fuzzy sets.

In our formulation, all the opinionated sentences under discussion are represented as a sorted set, denoted by X, in terms of their opinion scores. Thus, we have $X = [Min(Opinion\ Score(S_i)), \ldots, Max(Opinion\ Score(S_i))]$. Where, $i=\{1,\ldots,n\}$, $Min(Opinion\ Score(S_i))$ and $Max(Opinion\ Score(S_i))$ denotes the respective minimum and maximum opinion scores. The details of the fuzzy sets and their membership functions are given in Definitions 5, 6 and 7, respectively.

Definition 5 (positive sentiment fuzzy set). if X is a collection of sentiment opinions (denoted by x), then a positive sentiment fuzzy set $\tilde{P}$ in X can be defined as a set of ordered pairs, namely

$$\tilde{P} = \{(x, \mu_{\tilde{P}}(x)) \mid x \in X\},$$

where $\mu_{\tilde{P}}(x)$ denotes the membership function of x in $\tilde{P}$ that maps X to the membership space M.

We choose the rise semi-trapezoid distribution (Zimmermann, 2001) as the membership function of the positive sentiment fuzzy set, namely

$$\mu_{\tilde{P}}(x) = \begin{cases} 0\,, & x < a \\ \dfrac{x-a}{b-a}\,, & a \le x \le b \\ 1\,, & x > b \end{cases} \tag{3}$$

where x denotes the opinion score of a sentence under discussion. The adjustable parameters a and b can be defined as $a = Min(x_i) + \lambda_1(Max(x_i) - Min(x_i)/k)$ and $b = Min(x_i) + \lambda_2(Max(x_i) - Min(x_i)/k)$, respectively. $Max(x_i)$ and $Min(x_i)$

denote the respective minimum and maximum values within X. λ_1, λ_2 and k are parameters. Here we set $\lambda_1 = 5.2$, $\lambda_2 = 5.4$, and $k = 10$.

Definition 6 (neutral sentiment fuzzy set). if X is a collection of sentiment opinions (denoted by x), then a neutral sentiment fuzzy set $\tilde{E}$ in X can be defined as a set of ordered pairs, namely

$$\tilde{E} = \{(x, \mu_{\tilde{E}}(x)) \mid x \in X\},$$

where $\mu_{\tilde{E}}(x)$ denotes the membership function of x in $\tilde{E}$ that maps X to the membership space M.

As shown in Formula (4), we also select the semi-trapezoid distribution (Zimmermann, 2001) as the membership function of the neutral sentiment fuzzy set.

$$\mu_{\tilde{E}}(x) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \le x < b \\ 1, & b \le x < c \\ \frac{d-x}{d-c}, & c \le x < d \\ 0, & x \ge d \end{cases} \tag{4}$$

where x denotes the opinion score of a sentence under test. a, b, c and d are adjustable parameters that can be defined as a = Min(xi) + λ1(Max(xi)-Min(xi)/k), b=Min(xi) +m1(Max(xi) - Min(xi)/k), c = Min(xi) + m2(Max(xi) - Min(xi)/k) and d= Min(xi) + λ2(Max(xi) - Min(xi)/k), respectively. Max(xi) and Min(xi) denotes the respective minimum and maximum values within X. λ1, λ2, m1, m2 and k are parameters, Here we set λ1 = 5.2, λ2 = 5.5, m1 = 5.26, m2 = 5.33, and k = 10.

Definition 7 (negative sentiment fuzzy set). if X is a collection of sentiment opinions (denoted by x), then a negative sentiment fuzzy set $\tilde{N}$ in X can be defined as a set of ordered pairs, namely

$$\tilde{N} = \{(x, \mu_{\tilde{N}}(x)) \mid x \in X\},$$

where $\mu_{\tilde{N}}(x)$ denotes the membership function of x in $\tilde{N}$ that maps X to membership space M.

To represent the membership function of the negative sentiment fuzzy set, we employ the drop semi-trapezoid distribution (Zimmermann, 2001), namely

$$\mu_{\tilde{N}}(x) = \begin{cases} 1, & x < a \\ \frac{b-x}{b-a}, & a \le x \le b \\ 0, & x > b \end{cases} \tag{5}$$

where x denotes the opinion score of a subjective sentence under discussion. The adjustable parameters a and b can be defined as $a = Min(x_i) + \lambda_1(Max(x_i) - Min(x_i)/k)$ and $b = Min(x_i) + \lambda_2(Max(x_i) - Min(x_i)/k)$, respectively. $Max(x_i)$ and $Min(x_i)$ refer to the corresponding minimum and maximum values in X. λ_1, λ_2, and k are parameters. Here we set λ_1=5.2, λ_2=5.3 and k=10.

4.2 Determining sentence polarity

Based on the above membership functions, we can now calculate the grade of membership of a given opinionated sentence in each sentiment fuzzy set, and thus determine its polarity under the principle of maximum membership. The basic idea is as follows: Let $\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_n$ be the fuzzy sets of X. $\exists x_0 \in X$, if

$$\tilde{A}_k(x_0) = \max_{1 \le i \le n}\{\tilde{A}_i(x_0)\}$$

then x_0 is a membership of the fuzzy set $\tilde{A}_k$.

5 Experiments and Results

To assess the effectiveness of our approach, we implemented a classification system for Chinese sentence-level sentiment analysis. The system involves three main modules, namely a lexical analysis module, a subjectivity detection module and a sentiment classification module. To explore lexical cues for sentiment analysis, the morpheme-based chunking technique by (Fu, Kit and Webster, 2008) is employed in the lexical analysis module to carry out word segmentation and part-of-speech tagging tasks. To conform to the NTCIR-6 evaluation, a sentiment density-based naive Bayesian classifier is also embedded in the second module to perform opinionated sentence detection. The details of this classifier can be seen in (Wang and Fu, 2010). To evaluate our system, we conducted experiments on the NTCIR-6 Chinese opinion data. This section reports the experimental results.

5.1 Experimental setup

In our experiments, we use the same test set for the Chinese opinion analysis tasks at NTCIR-6. The basic statistics is presented in Table 7. For comparison, the performance is reported in terms of the same metrics as used in NTCIR-6. They are F-score (F), recall (R), precision (P) under the LWK evaluation with lenient standard.

Item	Number
Topics	32
Documents	843
Sentences	11907
Opinionated sentences under the lenient standard	62%

Table 7. Basic statistics of the test set for Chinese opinion tasks at NTCIR-6

The basic sentiment lexicon used in our system contains a total of 17138 sentiment words, which is built from the CUHK and NTU sentiment lexica by excluding some derived opinion words like 不美丽 'not beautiful'. In addition, we also construct a list of 95 dynamic polarity words using the method described in Section 3.4.

5.2 Experimental results

The experiments are designed to examine the following two issues:

(1) As we have discussed above, it is a key issue to select a proper granularity for sentiment classification. To determine the sentiment orientation of an opinionated sentence, we use a fine-to-coarse strategy that considers three types of sentiment units, namely sentiment morphemes, sentiment words and sentiment phrases. Therefore, the first intention of our experiments is to investigate how the use of different sentiment granularity affects the performance of Chinese sentence-level sentiment classification. To do this, we take the above three sentiment granularity as the basic units for computing sentence-level sentiment intensity, respectively, and examine the relevant sentiment classification results.

(2) To the best of our knowledge, this study may be the first attempt to apply the fuzzy set theory in Chinese sentiment classification. Therefore, our second motivation is to examine whether it is feasible to apply fuzzy set theory in sentiment classification by comparing our system with other public systems for Chinese opinion analysis pilot task at NTCIR-6.

Table 8 presents the experimental results with different sentiment granularities. It can be observed that the system with word as the basic sentiment units slightly performs better than the system based on sentiment morphemes. But a prominent improvement of performance can be obtained after using sentiment phrases. This reason may be that under the fine-to-coarse framework, sentiment classification based on sentiment phrases can handle both internal and external contextual sentiment information, and can thus result in performance improvement.

Granularity	P	R	F
Morpheme	0.389	0.480	0.430
Word	0.393	0.485	0.434
Phrase	0.415	0.512	0.458

Table 8. Performance on sentiment classification with different sentiment granularity

Table 9 illustrates the comparison of our system with the best system for Chinese opinion analysis pilot task at NTCIR-6, namely the CUHK system (Seki *et al.*, 2007; Xu, Wong and Xia, 2007). As can be seen from Table 9, our system outperforms the CUHK system by 5 percents with regard to F-score, showing the feasibility of using fuzzy set theory in sentiment classification.

System	P	R	F
CUHK	0.522	0.331	0.405
Our system	0.415	0.512	0.458

Table 9. Comparison of our system with the best system at NTCIR-6 under lenient standard

6 Conclusion and Future Work

In this paper, we have described a fuzzy set theory based framework for Chinese sentence-level sentiment classification. To handle unknown polarity and contextual polarity as well, we consider three types of sentiment granularities, namely sentiment morphemes, words and phrases in calculating sentiment intensity of opinionated sentenced. Furthermore, we define three fuzzy sets to represent polarity classes and construct the relevant membership functions, respectively. Compared with most existing work, the proposed approach provides a straightforward way to model the vagueness in conceptual division of sentiment polarity. The experimental results show that our system outperforms the best system for Chinese opinion analysis pilot task at NTCIR-6 under the lenient evaluation standard.

The encouraging results of the fuzzy set-based approach suggest several possibilities for future research. Our experiments demonstrate that the incorporation of multiple granularity polarity has a positive effect on sentiment classification performance. To further enhance our system, in future we intend to exploit more tailored techniques for aggregating multiple-granularity polarity within opinionated sentences. Moreover, we plan to optimize the proposed membership functions for fuzzy sentiment classification.

Acknowledgments

The authors would like to thank Chinese University of Hong Kong, National Taiwan University and NTCIR for their data. This study was supported by National Natural Science Foundation of China under Grant No.60973081, the Returned Scholar Foundation of Educational Department of Heilongjiang Province under Grant No.1154hz26, and Harbin Innovative Foundation for Returnees under Grant No.2009RFLXG007, respectively.

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