

An Exploration of Features for Recognizing Word Emotion

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Abstract

Emotion words have been well used as the most obvious choice as feature in the task of textual emotion recognition and automatic emotion lexicon construction. In this work, we explore features for recognizing word emotion. Based on Ren-CECps (an annotated emotion corpus) and MaxEnt (Maximum entropy) model, several contextual features and their combination have been experimented. Then PLSA (probabilistic latent semantic analysis) is used to get semantic feature by clustering words and sentences. The experimental results demonstrate the effectiveness of using semantic feature for word emotion recognition. After that, “word emotion components” is proposed to describe the combined basic emotions in a word. A significant performance improvement over contextual and semantic features was observed after adding word emotion components as feature.

1 Introduction

Textual emotion analysis is becoming increasingly important due to augmented communication via computer mediated communication (CMC). A possible application of textual emotion recognition is online chat system. An emotion feedback system can recognize users’ emotion and give appropriate responses. Another application example is weblog emotion recognition and prediction. Blogspace consists of millions of users who maintain their online diaries, containing frequently-updated views and personal remarks about a range of issues. An emotion recognition and prediction system can understand the public’s reaction to some social issues and predict emotion changes. It

would be helpful for solving some psychological problems or giving early warnings, such as suicide or terrorism.

Textual emotion analysis also can improve the accuracy of other nonverbal modalities like speech or facial emotion recognition, and to improve human computer interaction systems. However, automatic recognition of emotion meaning from texts presents a great challenge. One of the reasons is the manifoldness of expressed emotions in words.

Emotion words have been well used as the most obvious choice as feature in the task of textual emotion recognition and automatic emotion lexicon construction (Virginia and Pablo, 2006; Tokuhisa et al., 2008, etc.). And there are many lexical resources developed for these tasks, such as GI (Stone et al., 1966), WordNet-Affect (Strapparava and Valitutti, 2004), NTU Sentiment Dictionary (Ku et al., 2006), Hownet (Dong and Dong, 2003), SentiWordnet (Esuli and Sebastiani, 2006). In these sentimental or affective lexicons, the words usually bear direct emotions or opinions, such as happy or sad, good or bad. Although they play a role in some applications, several problems of emotion expression in words have been ignored.

Firstly, there are a lot of sentences can evoke emotions without direct emotion words. For example,

(1) 春天在孩子们的眼里、在孩子们的心里。(Spring is in children’s eyes, and in their hearts.)

In sentence (1), we may feel joy, love or expect delivered by the writer. But there are no direct emotion words can be found from lexicons. As Ortony (1987) indicates, besides words directly referring to emotion states (e.g., “fear”, “cheerful”) and for which an appropriate lexicon would help, there are words that act only as an indirect

reference to emotions depending on the context. Strapparava et al. (2006) also address this issue. The authors believed that all words can potentially convey affective meaning, and they distinguished between words directly referring to emotion states (direct affective words) and those having only an indirect reference that depends on the context (indirect affective words).

The second problem is emotion ambiguity of words. The same word in different contexts may reflect different emotions. For example,

(2) 这是目前我**唯一**能做的。(This is currently the only thing I can do.)

(3) 他是我的**唯一**。(He is my only one.)

In sentence (2), the word “**唯一** (only)” may express the emotion of anxiety or expect; but in sentence (3), the word “**唯一** (only)” may express the emotion of love or expect. The emotion categories can not be determined without their certain contexts especially for the words with emotion ambiguity.

In addition, some words can express multiple emotions, such as “**悲喜交加** (mingled feelings of joy and sorrow)”. Statistics on an annotated emotion corpus (Ren-CECps¹, Chinese emotion corpus developed by Ren-lab) showed that 84.9% of all emotion words have one emotion, 15.1% have more than one emotions (Quan and Ren, 2010). Multi-emotion words are indispensable for expressing complex feelings in use of language.

In this work, we explore features for recognizing word emotion in sentences. Based on Ren-CECps and MaxEnt model, several contextual features and their combination have been experimented. Then PLSA (probabilistic latent semantic analysis) is used to get semantic feature by clustering word and sentence. The experimental results demonstrate the effectiveness of using semantic feature for word emotion recognition. After that, the notion of “word emotion components” is proposed to describe the combined basic emotions in a word. A significant performance improvement over only using contextual and semantic features was observed after adding word emotion components as feature and output in MaxEnt based model.

¹<http://a1-www.is.tokushima-u.ac.jp/member/ren/Ren-CECps1.0/Ren-CECps1.0.html>

This paper is organized as follows. In section 2, based on Ren-CECps and MaxEnt, an exploration of using contextual feature for Chinese word emotion recognition is described. In section 3, using PLSA technique, the performance of adding semantic feature is presented. In section 4, the notion of “word emotion components” is proposed and the performance of using encoding feature is presented. In section 5, the discussions are described. Section 6 is conclusions.

2 Chinese Word Emotion Recognition

2.1 Related Works

There are many researches concerning computing semantics of words, while the researches on computing emotions of words are relatively less. Computing word emotions is a challenge task because the inherent of emotion is ambiguous and natural language is very rich in emotion terminology. Using the textual emotion information, several methods have been explored for computing lexical emotions. Wilson et al. (2009) proposed a two-step approach to classify word polarity out of context firstly, and then to classify word polarity in context with a wide variety of features. Strapparava et al. (2007) implemented a variation of Latent Semantic Analysis (LSA) to measure the similarities between direct affective terms and generic terms. Lee and Narayanan (2005) proposed a method of computing mutual information between a specific word and emotion category to measure how much information a word provides about a given emotion category (emotion salience). Based on structural similarity, Bhowmick (2008) computed the structural similarity of words in WordNet to distinguish the emotion words from the non-emotion words. Kazemzadeh (2008) measured similarity between word and emotion category based on interval type-2 fuzzy logic method. Takamura (2005) used a spin model to extract emotion polarity of words.

Different from the above researches, in this work, we explore which features are effective for word emotion recognition. The features include contextual feature, semantic feature and encoding feature.

2.2 Ren-CECps and MaxEnt based Chinese Word Emotion Recognition

Ren-CECps is constructed based on a relative fine-grained annotation scheme, annotating emotion in text at three levels: document, paragraph, and sentence. The all dataset consisted of 1,487 blog articles published at sina blog, sciencenet blog, etc. There are 11,255 paragraphs, 35,096 sentences, and 878,164 Chinese words contained in this corpus (more details can be found in (Quan and Ren, 2010)).

In the emotion word annotation scheme of Ren-CECps, direct emotion words and indirect emotion words in a sentence are all annotated. For example, in sentence (1) “春天 (spring)” and “孩子们 (the children)” are labeled. An emotion keyword or phrase is represented as a vector to record its intensities of the eight basic emotion classes (expect, joy, love, surprise, anxiety, sorrow, angry and hate). For instance, the emotion vector for the word “春天 (spring)” $\vec{w} = (0.1, 0.3, 0.3, 0.0, 0.0, 0.0, 0.0, 0.0)$ indicates the emotions of weak expect, joy and love. In this work, we focus on if a word contains some emotion(s) in a certain context. The analysis on emotion intensity of emotion words is included in our future work.

As word emotion is subjective entity, a word in a certain context may evoke multiple emotions in different people’s mind. A part of documents in Ren-CECps have been annotated by three annotators independently to measure agreement on the annotation of this corpus, which include 26 documents with a total of 805 sentences, 19,738 words. This part of corpus is used as testing corpus to evaluate the experimental results. (Section 5.1 shows the analysis on the annotation agreement on word emotion.)

MaxEnt modeling provides a framework for integrating information from many heterogeneous information sources for classification (Manning, 1999). MaxEnt principle is a well used technique provides probability of belongingness of a token to a class. In word emotion recognition, the MaxEnt estimation process produces a model in which each feature f_i is assigned a weight α_i . The deterministic model produces conditional probability (Berger, 1996), see equation (1) and (2). In

experiments, we have used a Java based open-nlp MaxEnt toolkit ².

$$p(e|context) = \frac{1}{Z(context)} \prod_i \alpha_i^{f_i(context,e)} \quad (1)$$

$$Z(context) = \sum \prod_i \alpha_i^{f_i(context,e)} \quad (2)$$

2.3 Contextual Features

The contextual features used in MaxEnt for Chinese word emotion recognition are described as follows:

Word Feature (WF): Word itself to be recognized.

N-words Feature (NF): To know the relationship between word emotion and its context, the surrounding words of length n for the word (w_i) to be recognized are used as feature: ($w_{i-n} \dots w_i \dots w_{i+n}$).

POS Feature (POSF): The part of speech of the current word and surrounding words are used as feature. We have used a Chinese segmentation and POS tagger (Ren-CMAS) developed by Renlab, which has an accuracy about 97%. The set of POS includes 35 classes.

Pre-N-words Emotion Feature (PNEF): The emotions of the current word may be influenced by the emotions of its previous words. So the emotions of previous n words are used as feature. The value of this feature for a word (w_i) is obtained only after the computation of the emotions for its previous words.

Pre-is-degree-word Feature (PDF), Pre-is-negative-word Feature (PNF), Pre-is-conjunction Feature (PCF): To determine if the previous word is a degree word, a negative word, or a conjunction may be helpful to identify word emotions. The degree word list (contains 1,039 words), negative word list (contains 645 words), and conjunction list (contains 297 words) extracted from Ren-CECps have been used.

2.4 The Performance of Using Contextual Feature

We use the documents in Ren-CECps that have been annotated by three annotators independently

²<http://maxent.sourceforge.net/>

as testing corpus. An output of word emotion(s) will be regarded as a correct result if it is in agreement with any one item of word emotion(s) provided by the three annotators. The numbers of training and testing corpus are shown in table 1. The accuracies are measured by F-value.

Table 1: Number of training and testing corpus

Number	Training	Testing
Documents	1,450	26
Sentences	33,825	805
Words	813,507	19,738
Emotion words	99,571	2,271*

(*) At least agreed by two annotators.

Table 2 gives the results of F-value for different contextual features in the MaxEnt based Chinese word emotion recognition. The results of F-value include: (a) recognize emotion and unemotion words; (b) recognize the eight basic emotions for emotion words (complete matching); (c) recognize the eight basic emotions for emotion words (single emotion matching).

As shown in table 2, when we only use Word Feature(WF), the F-value of task (a) achieved a high value (96.3). However, the F-values of task (b) and (c) are relative low, that means the problem of recognizing the eight basic emotions for emotion words is a lot more difficult than the problem of recognizing emotion and unemotion words, so we focus on task (b) and (c).

When we experiment with Word Feature(WF) and N-words Feature (NF), we have observed that word feature (w_i) and a window of previous and next word (w_{i-1}, w_i, w_{i+1}) give the best results (a=96.5, b=50.4, c=69.0). Compared with (w_{i-1}, w_i, w_{i+1}), a larger window of previous and next two words ($w_{i-2}, w_{i-1}, w_i, w_{i+1}, w_{i+2}$) reduces the F-value. This demonstrates that w_i and w_{i-1}, w_i, w_{i+1} are effective features for word emotion recognition.

When POS Feature (POSF) is added, the F-value is increased. Especially the F-value is increased to (a=97.1, b=51.9, c=72.0) when pos_i and $pos_{i-1}, pos_i, pos_{i+1}$ are added.

We also find that Pre-N-words Emotion Feature (PNEF) ($pre_e_0, \dots, pre_e_{i-1}$) increases the F-

value, but previous one word emotion can not increase the F-value.

As can be seen from table 2, when only contextual features are used, the highest F-value is (a=97.1, b=53.0, c=72.7) when Pre-is-degree-word Feature (PDF), Pre-is-negative-word Feature (PNF), Pre-is-conjunction Feature (PCF) are added.

3 Semantic Feature

To know if semantic information is useful for emotion recognition, we have used probabilistic latent semantic analysis (PLSA) (Hofmann, 1999) to cluster words and sentences. PLSA clusters documents based on the term-document co-occurrence which results in semantic decomposition of the term-document matrix into a lower dimensional latent space. PLSA can be defined as:

$$P(s, w) = \sum_{z \in Z} P(z)P(s|z)P(w|z) \quad (3)$$

where $p(s, w)$ is the probability of word w and sentence s co-occurrence, $P(s|z)$ is the probability of a sentence given a semantic class z , and $P(w|z)$ is the probability of a word given a semantic class z .

For word clustering, We made the assignment based on the maximum $p(z|w)$, if $p(z'|w) = \max p(z|w)$, then w was assigned to z' . Sentence clustering is similar to word clustering. Word clustering and sentence clustering are run separately. The word class_id and sentence class_id are used as semantic feature (SF), which including sentence class feature (SCF) and word class feature (WCF). PeenAspect implementation of PLSA has been used for our experiments³.

Table 3 gives the results of F-value for combined all contextual features and semantic feature in the MaxEnt based Chinese word emotion recognition.

As can be seen from table 3, when SCF is used, the best result is obtained when the cluster number is 100; when WCF is used, the best result is obtained when the cluster number is 100 or 160. The results demonstrate the effectiveness of using SCF is a little higher than using WCF.

³http://www.cis.upenn.edu/datamining/software_dist/PennAspect/

Table 2: F-value for different contextual features in the MaxEnt based Chinese word emotion recognition

(a) recognize emotion or unemotion words

(b) recognize the eight basic emotions for emotion words (complete matching)

(c) recognize the eight basic emotions for emotion words (single emotion matching)

Feature type	Features	F-value		
		(a)	(b)	(c)
WF	$f1 = w_i$	96.3	45.9	63.0
NF	$f1 = w_{i-1}, w_i, w_{i+1}$	94.8	44.8	60.7
	$f1 = w_{i-2}, w_{i-1}, w_i, w_{i+1}, w_{i+2}$	92.4	28.4	40.3
WF+NF	$f1 = w_i; f2 = w_{i-1}, w_i, w_{i+1}$	96.5	50.4	69.0
WF+NF	$f1 = w_i f2 = w_{i-1}, w_i, w_{i+1} f3 = pos_i$	96.8	51.5	71.1
+POSF	$f1 = w_i f2 = w_{i-1}, w_i, w_{i+1} f3 = pos_{i-1}, pos_i, pos_{i+1}$	97.0	51.7	71.6
	$f1 = w_i f2 = w_{i-1}, w_i, w_{i+1} f3 = pos_i f4 = pos_{i-1}, pos_i, pos_{i+1}$	97.1	51.9	72.0
WF+NF	$f1 = w_i f2 = w_{i-1}, w_i, w_{i+1} f3 = pos_i$	97.1	51.9	72.0
+POSF	$f4 = pos_{i-1}, pos_i, pos_{i+1} f5 = pre_{-e_{i-1}}$			
+PNEF	$f1 = w_i f2 = w_{i-1}, w_i, w_{i+1} f3 = pos_i$	97.1	52.4	72.2
	$f4 = pos_{i-1}, pos_i, pos_{i+1} f5 = pre_{-e_0}, \dots, pre_{-e_{i-1}}$			
WF+NF	$f1 = w_i f2 = w_{i-1}, w_i, w_{i+1} f3 = pos_i$	97.1	53.0	72.7
+POSF	$f4 = pos_{i-1}, pos_i, pos_{i+1} f5 = pre_{-e_0}, \dots, pre_{-e_{i-1}}$			
+PNEF	$f6 = ?(w_{i-1} \text{ is a degree word})$			
+PDF	$f7 = ?(w_{i-1} \text{ is a negative word})$			
+PNF	$f8 = ?(w_{i-1} \text{ is a conjunction})$			
+PCF				

4 Encoding Feature: Emotion Components of Word

Researches on the psychology of concepts show that categories in the human mind are not simply sets with clearcut boundaries (Murphy, 2002; Hampton, 2007). Word emotions are certainly related to mental concepts. As for emotion states, most theorists appear to take a combinatorial view. Plutchik (1962), for example, talks about “mixed states”, “dyads” and “triads” of primary emotions. Similarly, Averill (1975) argues for compound emotions based on more elementary ones. And one model, suggested by Ekman (1982) (emotion blends) and Plutchik (mixed states), is that emotions mix (Ortony, 1988). According to these researches, we use an encoding feature: emotion components of word.

“Emotion components of word” describes the combined basic emotions in a word, which is represented by eight binary digits, and each digit cor-

responding to a basic emotion class respectively. For example, the word “喜欢 (like)”, its possible emotion components in a certain context is “01100000”, which expresses the combined emotions by joy and love.

With the expression of emotion components of word, it is possible to distinguish direct emotion words and indirect emotion words. Those words always demonstrate similar emotion components in different contexts can be regarded as direct emotion words, accordingly, those words demonstrate different emotion components in different contexts can be regarded as indirect emotion words. With the expression of emotion components in word, the problem of expressing emotion ambiguity in words can be solved. The same word in different contexts may reflect different emotions, which can be expressed by different emotion components. The emotions of words with multiple emotions also can be expressed by emotion components.

Table 3: F-value for combined contextual features (CF) and semantic feature (SF) (including sentence class feature (SCF) and word class feature (WCF))

Feature type	Cluster number	F-value		
		(a)	(b)	(c)
CF+SCF	20	97.0	53.1	72.8
	40	97.0	53.4	72.7
	60	97.0	53.5	72.8
	80	97.0	52.9	72.5
	100	97.0	53.6	73.1
	120	97.0	53.1	72.7
	150	97.0	53.2	72.9
	180	97.0	53.4	73.1
CF+WCF	40	97.0	53.1	72.8
	100	97.0	53.4	72.9
	160	97.0	53.4	72.9
	220	97.0	53.3	72.9
	280	97.0	53.2	72.8
	370	97.0	53.1	72.8

The statistics of word emotion components in Ren-CECps show that there are a total of 68 emotion components in all of 22,095 annotated emotion words without repetitions. Figure 1 shows the growth curve of word emotion components number with emotion word number increase.

As can be seen from figure 1, the number increase of word emotion components shows a very slow growth rate with the number increase of emotion words. We can conclude that the space of word emotion components is a relatively small space.

In the model of MaxEnt based Chinese word emotion recognition, the Pre-N-words Emotion Feature (PNEF) and emotion output can be encoded to emotion components.

Pre-N-words Emotion Components Feature (PNECF): The emotion components of its previous words for a word (w_i). The value of this feature is obtained only after the computation of the emotion components for its previous words.

Table 4 gives the results of F-value for the combined contextual features and encoding feature.

As can be seen in table 4, when Pre-N-words Emotion Feature (PNEF) is replaced by Pre-N-

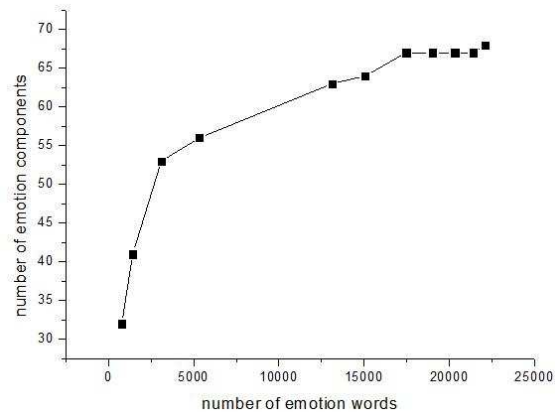


Figure 1: The growth curve of word emotion components

words Emotion Components Feature (PNECF), and emotion components are output as results, F-value is increased up to (a=97.3, b=57.3, c=73.3). Then based on this result, we firstly trained a word emotion based model, then the word emotion outputs of this model are used as Pre-N-words Emotion Feature (PNEF) for the word emotion components based model. A significant F-value improvement of task (b) and (c) (b=62.5, c=73.7) over only using contextual and semantic features was observed after adding the combined word emotion and word emotion components as feature.

5 Discussion

5.1 Word Emotion Agreement on People's Judgments

The final aim of a human-computer interaction recognition system is to get the result close to people's judgments. As word emotion is inherently uncertain and subjective, here we report the annotation agreement on word emotion of Ren-CECps, which can be taken as an evaluation criteria for a algorithm.

To measure the annotation agreement of Ren-CECps, three annotators independently annotated 26 documents with a total of 805 sentences, 19,738 words. We use the following two metrics to measure agreement on word emotion annotation.

(1) Kappa coefficient of agreement (Carletta, 1996). It is a statistic adopted by the computa-

Table 4: F-value for the combined contextual features and encoding feature

Feature type	Features	F-value		
		(a)	(b)	(c)
WF+NF+POSF+PNECF +PDF+PNF+PCF	$f1 = w_i$ $f2 = w_{i-1}, w_i, w_{i+1}$ $f3 = pos_i$ $f4 = pos_{i-1}, pos_i, pos_{i+1}$ $f5 = pre_es_0, \dots, pre_es_{i-1}$ $f6 = ?(w_{i-1} \text{ is a degree word})$ $f7 = ?(w_{i-1} \text{ is a negative word})$ $f8 = ?(w_{i-1} \text{ is a conjunction})$	97.3	57.3	73.3
WF+NF+POSF+PNEF +PNECF+PDF+PNF+PCF	$f1 = w_i$ $f2 = w_{i-1}, w_i, w_{i+1}$ $f3 = pos_i$ $f4 = pos_{i-1}, pos_i, pos_{i+1}$ $f5 = pre_e_0, \dots, pre_e_{i-1}$ $f6 = pre_es_0, \dots, pre_es_{i-1}$ $f7 = ?(w_{i-1} \text{ is a degree word})$ $f8 = ?(w_{i-1} \text{ is a negative word})$ $f9 = ?(w_{i-1} \text{ is a conjunction})$	97.3	62.5	73.7

tional linguistics community as a standard measure.

(2) Voting agreement. It is used to measure how much intersection there is between the sets of word emotions identified by the annotators. It includes majority-voting agreement ($Agreement_{MV}$) and all-voting agreement ($Agreement_{AV}$). $Agreement_{MV}$ is defined as follows. Let A, B and C be the sets of word emotion components annotated by annotators a, b and c respectively. The expert coder is the set of expressions that agreed by at least two annotators, see equation (4).

$$Agreement_{MV} = Avg\left(\frac{count(t_i = e_j)}{count(t_i)}\right) \quad (4)$$

In which, $t_i \in T$, $e_j \in E$, $T = A \cup B \cup C$, $E = (A \cap B) \cup (A \cap C) \cup (B \cap C)$.

Accordingly, the expert coder of $Agreement_{AV}$ is the set of expressions that agreed by all annotators.

The above two metrics are used to measure the agreements on: (a) determine if a word is an emotion or unemotion word; (b) determine the eight basic emotions for emotion words (complete emotion matching); (c) determine the eight basic emotions for emotion words (single matching). (b) and (c) are provided that at least two people to be-

lieve the word is an emotion word. Table 5 shows the agreements measured by the two metrics.

As shown in table 5, it is easier for annotators to agree at if a word contains emotion, but it is more difficult to agree on emotions or emotion components of a word. Compared with the agreement on people’s judgments, our experiments gave promising results.

Table 5: Agreement of word emotion annotation measured by Kappa, Majority-voting (MV), and All-voting (AV)

Measure	Kappa	MV	AV
(a)	84.3	98.5	95.1
(b)	66.7	70.3	26.2
(c)	77.5	100	84.9

5.2 Error Analysis

Conducting an error analysis, we find that a lot of errors occur due to the recognition on multi-emotion words and indirect emotion words, especially in short sentences because the features can be extracted are too few. So more features should be considered from larger contexts, such as the topic emotion of paragraph or document.

There are some errors occur due to more than one emotion holders exist in one sentence, for ex-

ample of sentence (4).

(4) 我发现女儿正看着她感兴趣的玩具。(I found that daughter was looking at the toys of her interest.)

In sentence (4), three annotators all agree that the emotion components of the word “感兴趣 (interest)” is “00000000” since they believe that this word is an unemotion word from the view of the writer. But our system give a result of “00100000” because the emotion holder “女儿 (daughter)” of the emotion word “感兴趣 (interest)” has not been considered in our algorithm. Therefore, the recognition of emotion holder is indispensable for an accurate emotion analysis system.

In addition, Chinese segmentation mistakes and phrasing error also cause errors.

6 Conclusions

Automatically perceive the emotions from text has potentially important applications in CMC (computer-mediated communication) that range from identifying emotions from online blogs to enabling dynamically adaptive interfaces. Therein words play important role in emotion expressions of text.

In this paper we explored features for recognizing word emotions in sentences. Different from previous researches on textual emotion recognition that based on affective lexicons, we believe that besides obvious emotion words referring to emotions, there are words can potentially convey emotions act only as an indirect reference. Also, quite often words that bear emotion ambiguity and multiple emotions are difficult to be recognized depending on emotion lexicons. Emotion of a word should be determined with its context.

Based on Ren-CECps (an annotated emotion corpus) and MaxEnt (Maximum entropy) model, we have experimented several contextual features and their combination, then using PLSA (probabilistic latent semantic analysis), semantic feature are demonstrated the effectiveness for word emotion recognition. A significant performance improvement over only using contextual and semantic features was observed after adding encoding feature (word emotion components). Determining intensity of word emotion and recognizing emotion of sentence or document based on word emo-

tion are included in our future work.

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