Automatic Annotation of Word Emotion in Sentences Based on Ren-CECps

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Abstract

Textual information is an important communication medium contained rich expression of emotion, and emotion recognition on text has wide applications. Word emotion analysis is fundamental in the problem of textual emotion recognition. Through an analysis of the characteristics of word emotion expression, we use word emotion vector to describe the combined basic emotions in a word, which can be used to distinguish direct and indirect emotion words, express emotion ambiguity in words, and express multiple emotions in words. Based on Ren-CECps (a Chinese emotion corpus), we do an experiment to explore the role of emotion word for sentence emotion recognition and we find that the emotions of a simple sentence (sentence without negative words, conjunctions, or question mark) can be approximated by an addition of the word emotions. Then MaxEnt modeling is used to find which context features are effective for recognizing word emotion in sentences. The features of word, N-words, POS, Pre-N-words emotion, Pre-is-degree-word, Pre-is-negativeword, Pre-is-conjunction and their combination have been experimented. After that, we use the two metrics: Kappa coefficient of agreement and Voting agreement to measure the word annotation agreement of Ren-CECps. The experiments on above context features showed promising results compared with word emotion agreement on people's judgments.

1. Introduction

In artificial intelligence, emotion technology can be an important component, which including multiple modalities emotion recognition. Textual information is an important communication medium contained rich expression of emotion and can be retrieved from many sources. Textual emotion analysis also can reinforce the accuracy of sensing in other modalities like speech or facial recognition, and to improve human computer interaction systems. However, automatic detection of the emotional meaning of texts presents a great challenge because of the manifoldness of expressed meanings in words. Word emotion analysis is fundamental in the problem of textual emotion recognition. Since new words are constantly emerging on Internet, current available emotion lexicons are not enough for Internet emotion analysis. Computing word emotions automatically is required. In previous researches, some methods have been proposed for this task. Strapparava (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 (emotional salience). Based on structural similarity, Bhowmick et al. (2008) computed the structural similarity of words in WordNet to distinguish the emotional words from the non-emotional words. Kazemzadeh measured similarity between word and emotion category based on Interval Type-2 Fuzzy Logic method.

Different from existing work, we focus on the following three points in word emotion analysis:

(1) The characteristics of word emotion expression.

(2) The role of emotion word for sentence emotion recognition.

(3) Which features are effective for word emotion recognition in a certain context?

The remainder of this paper is organized as follows. Section 2 presents an introduction of Ren-CECps. Section 3 presents an analysis of the characteristics of word emotion expression. Section 4 describes the role of emotion word for sentence emotion recognition. Section 5 describes MaxEnt modeling for exploring features for word emotion recognition. Section 6 concludes this study with closing remarks.

2. Introduction of Ren-CECps

Ren-CECps [1] (a Chinese emotion corpus developed by Ren-lab) is constructed based on a relative fine-grained annotation scheme, annotating emotion in text at three levels: document, paragraph, and sentence. In document and paragraph levels, emotion category, emotion intensity, topic words and topic sentences are annotated. In sentence level, annotation includes emotion categories (expect, joy, love, surprise, anxiety, sorrow, angry and hate), emotion intensity, emotional keyword/phrase, degree word, negative word, conjunction, rhetoric, punctuation, objective/subjective, and emotion polarity.

The main purpose of constructing this emotion corpus is to support the development and evaluation of emotion analysis systems in Chinese. The all dataset consisted of 1,487 blog articles published at sina blog, sciencenet blog, baidu blog, qzone blog, qq blog, and other blog websites. There are 11,255 paragraphs, 35,096 sentences, and 878,164 Chinese words contained in this corpus. The annotated output files are organized in XML documents. An example document is listed in Figure 1.

More detail information about this corpus can be found in (Quan and Ren, 2009).

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

```xml
<?xml version="1.0" encoding="GB2312" standalone="yes" ?>
- <document>
    <Joy>0.8</Joy>
    <Hate>0.0</Hate>
    <Love>0.9</Love>
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    <Anxiety>0.0</Anxiety>
    <Surprise>0.0</Surprise>
    <Anger>0.0</Anger>
    <Expect>0.0</Expect>
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  - <title T="地震背后：解读8 0后的社会责任">
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        的/u 社会/n 责任/n</Segmented_S>
      <S_Length>15</S_Length>
      <Opinion_Fact>opinion</Opinion_Fact>
      <Polarity>中性</Polarity>
      <Joy>0.0</Joy>
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      <Love>0.0</Love>
      <Sorrow>0.0</Sorrow>
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      <Surprise>0.0</Surprise>
      <Anger>0.0</Anger>
      <Expect>0.0</Expect>
    </title>
  - <paragraph>
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      <Hate>0.0</Hate>
      <Love>0.0</Love>
      <Sorrow>0.6</Sorrow>
      <Anxiety>0.0</Anxiety>
      <Surprise>0.0</Surprise>
      <Anger>0.0</Anger>
      <Expect>0.0</Expect>
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      <Summarize_Sentences>1</Summarize_Sentences>
    - <sentence S="静夜，沉思过往！">
        <S_no>第1段第1句标注</S_no>
        <Segmented_S>静夜/n ， /w 沉思/v 过往/v ！
          </Segmented_S>
        <S_Length>8</S_Length>
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          Opinionholder="0" Love="0.0" Joy="0.0" Hate="0.0"
          Expect="0.0" Anxiety="0.0" Anger="0.0">沉思
          </Keywords>
        <Opinion_Fact>opinion</Opinion_Fact>
        <Polarity>消极</Polarity>
        <Joy>0.0</Joy>
        <Hate>0.0</Hate>
        <Love>0.0</Love>
        <Sorrow>0.4</Sorrow>
        <Anxiety>0.0</Anxiety>
        <Surprise>0.0</Surprise>
        <Anger>0.0</Anger>
        <Expect>0.0</Expect>
      </sentence>
    + <sentence S="继汶川地震一篇建议书后再也没有更新博文，为逝
        去的同胞默哀、也为思考人生抑或生命的价值，包括我自己！">
    </paragraph>
  + <paragraph>
  + <paragraph>
  + <paragraph>
  + <paragraph>
  + <paragraph>
  </document>
```


Figure 1: An annotated document in XML format

3. The characteristics of word emotion expression

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 (Francisco and Gervás, 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 characteristic 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 Ren-CECps showed that 84.9% of all emotion words have one emotion, 15.1% have more than one emotions. Multi-emotion words are indispensable for expressing complex feelings in use of language.

With the above analysis, we need an appropriate way to express word emotion in text. In Ren-CECps, emotions of each word are represented by an emotion vector.

$$\overrightarrow{w} = < e_1, e_2, ..., e_i, ..., e_n > \tag{1}$$

Here, $e_i (1 \leqslant i \leqslant n)$ is a basic emotion class contained in word w. The values of e_i range from 0.0 to 1.0 (discrete), indicating the intensities of the eight basic emotion classes (expect, joy, love, surprise, anxiety, sorrow, angry and hate).

In this work, we use the same way (emotion vector) to express word emotion. With the expression of word emotion vector, it is possible to distinguish direct emotion words and indirect emotion words. Those words always demonstrate similar emotion vectors in different contexts can be regarded as direct emotion words, accordingly, those words demonstrate different emotion vectors in different contexts can be regarded as indirect emotion words. With the expression of emotion vector 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 vectors. The words with multiple emotions also can be expressed by emotion vector.

4. The role of emotion word for sentence emotion recognition

According to the cues for emotion expression, there are two main methods for sentence emotion recognition: emotion provoking event based method and emotion words based method. Regarding the emotion words based method, which is seen as the most naive approach and probably also the most popular method. The weaknesses of emotion words based method was summarized in (Liu, et at., 2003): poor recognition of affect when negation is involved, and reliance on surface features.

The emotions of a sentence can be affected by many factors: emotion words, negative words, conjunctions, puntuations, contexts, and so on. To explore the role of emotion words for sentence emotion recognition, we do an experiment with Ren-CECps. In the first place, we divided sentence into two classes: simple sentences (sentences without negative words, conjunctions, or question mark) and complex sentences (sentences with negative words, conjunctions, or question mark). we desired to know how much can we determine the emotions of a sentence when we get the right emotions of emotion words in this sentence.

In all of 35,096 sentences in Ren-CECps, there are 18,427 simple sentences (about 52.5%) and 16,669 complex sentences (about 47.5%). we use F-value (Equation (2)-(4)) to compare the two kinds of sentences on sentence emotion recognition.

$$Precision = \sum_{i=1}^{m}\sum_{j=1}^{8}\frac{ev(i,j)=1, EV(i,j)=1}{ev(i,j)=1} \quad (2)$$

$$Recall = \sum_{i=1}^{m}\sum_{j=1}^{8}\frac{ev(i,j)=1, EV(i,j)=1}{EV(i,j)=1} \quad (3)$$

$$F = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

In which, m is the number of sentences, $ev(i,j)$ is the output of the j^{th} emotion of sentence i^{th}, which is obtained by an addition of all word emotion vectors in this sentence, see equation (5) and (6). $EV(i,j)$ is the standard answer of the j^{th} emotion of sentence i^{th}, which is annotated by annotators.

$$\overrightarrow{S} =< ev_1, ev_2, ..., ev_8 > \quad (5)$$

$$ev_i = \bigcup_{k=1}^{n} w_k e_i \quad (6)$$

In which, S is sentence emotion vector, ev_i represents the basic emotion i, the value is 0 or 1, which indicate whether emotion i is contained in this sentence. n is the number of emotion words in this sentence, $w_k e_i$ represents the basic emotion i in word w_k. Table 1 shows the results.

Table 1: The role of emotion word for sentence emotion recognition

sentence	F-value
simple	0.738
complex	0.610
all	0.667
Kappa annotation agreement on sentences	0.756

As can be seen from Table 1, the F-value of simple sentences is very close to the agreement of manual annotation, but the F-value of complex sentences is relatively low. From the error analysis, we found that many errors occurred when more than one emotion holders contained in a sentence. So we can conclude that, the emotions of a simple sentence can be approximated by an addition of the word emotions whose emotion holder is the writer in this sentence.

We have done another experiment to compare the role of emotion word for emotion recognition of sentence, paragraph and document. For each sentence (paragraph and document) in Ren-CECps, we obtain its emotion classes through emotion addition of the emotion words in this text, and then compute a similarity measure by cosine between this words-addition emotion vector and the text emotion vector, Table 2 shows the similarities.

Table 2: Cosine similarities of words-addition emotion vectors and text emotion vectors

	Cosine similarity
sentence	0.736
paragraph	0.699
document	0.629
Avg.	0.688

As can be seen from Table 2, we can determine the emotion of text from its emotion words on the degree about 69%. That means that the remaining about 31% need to rely on more grammatical or semantic analysis, such as negative words, conjunctions, syntactic structures, and so on.

5. MaxEnt (Maximum entropy) modeling for exploring features for word emotion recognition

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 (7) and (8). In experiments, we have used a Java based open-nlp MaxEnt toolkit [2].

$$p(e|context) = \frac{1}{Z(context)} \prod_i \alpha_i^{f_i(context,e)} \quad (7)$$

$$Z(context) = \sum \prod_i \alpha_i^{f_i(context,e)} \quad (8)$$

5.1. 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: ($w_{i-n}...w_i...w_{i+n}$).

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 Ren-lab, 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.

5.2. The Performance

We use the documents in Ren-CECps that have been annotated by three annotators independently 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 3. The accuracies are measured by F-value.

Table 3: 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 4 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 4, 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) ($pre\_e_0, ..., pre\_e_{i-1}$) increases the F-value, but previous one word emotion can not increases the F-value.

As can be seen from table 4, 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.

5.3. 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 word 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 computational 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 (9).

$$Agreement_{MV} = Avg(\frac{count(t_i = e_j)}{count(t_i)}) \quad (9)$$

[2] http://maxent.sourceforge.net/

Table 4: F-value for different contextual features in the MaxEnt based 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 +POSF	$f1 = w_i$ $f2 = w_{i-1}, w_i, w_{i+1}$ $f3 = pos_i$	96.8	51.5	71.1
	$f1 = w_i$ $f2 = w_{i-1}, w_i, w_{i+1}$ $f3 = pos_{i-1}, pos_i, pos_{i+1}$	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 +POSF +PNEF	$f1 = w_i$ $f2 = w_{i-1}, w_i, w_{i+1}$ $f3 = pos_i$ $f4 = pos_{i-1}, pos_i, pos_{i+1}$ $f5 = pre\_e_{i-1}$	97.1	51.9	72.0
	$f1 = w_i$ $f2 = w_{i-1}, w_i, w_{i+1}$ $f3 = pos_i$ $f4 = pos_{i-1}, pos_i, pos_{i+1}$ $f5 = pre\_e_0, ..., pre\_e_{i-1}$	97.1	52.4	72.2
WF+NF +POSF +PNEF +PDF +PNF +PCF	$f1 = w_i$ $f2 = w_{i-1}, w_i, w_{i+1}$ $f3 = pos_i$ $f4 = pos_{i-1}, pos_i, pos_{i+1}$ $f5 = pre\_e_0, ..., pre\_e_{i-1}$ $f6 = ?(w_{i-1}\ is\ a\ degree\ word)$ $f7 = ?(w_{i-1}\ is\ a\ negative\ word)$ $f8 = ?(w_{i-1}\ is\ a\ conjunction)$	97.1	53.0	72.7

In which, $t_i \in T$, $e_j \in E$, $T = A \bigcup B \bigcup C$, $E = (A \bigcap B) \bigcup (A \bigcap C) \bigcup (B \bigcap C)$.
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) determining if a word is an emotion or unemotion word; (b) determining the eight basic emotions for emotion words (complete emotion matching); (c) determining the eight basic emotions for emotion words (single matching). (b) and (c) are provided that at least two people to believe the word is an emotion word. Table 4 shows the agreements measured by the two metrics.

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

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 which emotions are contained in a word. Compared with the agreement on people's judgments, our experiments gave promising results.

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. Words play important role in emotion expressions of text.
In this paper we explored word emotion analysis based on Ren-CECps. In the first place, the characteristics of word emotion expression are analyzed. To distinguish direct and indirect emotion words, express emotion ambiguity in words, and express multiple emotions in words, the expression way of word emotion vector is introduced. Then, we have made an experiment to explore the role of emotion word for sentence emotion recognition. We found that the emotions of a simple sentence can be approximated by a simple superposition of the word emotions whose emotion holder is the writer in this sentence. Another experiment have showed that we can determine the emotion of text from its emotion words on the degree about 69%. That means that the remaining about 31% need to rely on more grammatical or semantic analysis, such as negative words, conjunctions, syntactic structures, and so on.
After that, MaxEnt modeling was used to explore which context features are effective for recognizing word emotion in sentences. Some context features and their combinations have been experimented, and the experiments showed promising results compared with word emotion agreement on people's judgments.

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