Exploring Emotional Words for Chinese Document Chief Emotion Analysis*

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Abstract. In this study, we develop a document emotion analysis model by making use of the function of emotional words annotation. Eight basic emotion categories have been selected, including Expect, Joy, Love, Surprise, Anxiety, Sorrow, Anger and Hate, for both the word and the document level emotion analysis. We introduce two parameters, term relevance and term frequency, to evaluate the relations between the word emotions and the document emotions. Promising experimental results reveal the effectiveness of our document emotion analysis model under different emotion situations.

Keywords: emotional words annotation, document emotion analysis, term relevance, term frequency.

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1 Introduction

Document emotion analysis has become a popular subject in natural language processing studies, which however has been reported to be a challenging problem since people's inner emotions are not easy to be represented exactly only through semantic labels given by machines.

Generally speaking, emotion analysis can be divided into two quite different levels: the coarse emotion analysis and the fine-grained emotion analysis. For the former study, researchers have conducted much work on dividing the documents into three classes according to their polarities: the positive documents, the negative documents, and the neutral documents. While for the latter study, researchers often concentrate on extracting some significant types of emotions, such as Expect, Joy, Love, Surprise, Anxiety, Sorrow, Anger and Hate. And this extracting process covers different textual levels, including words, sentences, paragraphs as well as documents.

In this paper we are focusing on two important parts of the fine-grained emotion analysis: emotional words annotation and document emotion analysis. Totally eight emotion categories are selected, namely, Expect, Joy, Love, Surprise, Anxiety, Sorrow, Anger and Hate.

Under the subject of emotional words annotation, most studies are concentrating on exploring a variety of emotion lexicons. Such studies include (Hu and Liu, 2004; Tokuhisa et al., 2008), in which machine learning techniques are also utilized. However, at most of the time, using emotion lexicons could not be a good idea for analyzing the emotions in the real-world texts, since the emotion lexicons are static while in the real-world the word emotions could always change in different contexts. When a certain number of the matched words are found with different emotion tags according to the emotion lexicon, this method often fails. As reported in (Fragopanagos and Taylor, 2005), emotion analysis could suffer from insufficient or misleading emotion features if context is not taken into account.

Therefore, we explore an automatic document emotion analysis model, which takes the dynamically annotated emotional words as features and explores the statistic parameters extracted from the Ren-CECps[1] (Quan and Ren, 2010) to help correctly predict the document emotions from previously generated word emotions.

We regard Conditional Random Fields (CRFs) (Lafferty et al., 2001) as the appropriate algorithm for capturing the contextual information in a sentence. For the document emotion analysis, we use the function of emotional words annotation and extract the term relevance parameter and the term frequency parameter which help to correctly accumulate the document emotions from the word emotions within this document.

Experimental result reveals that the term relevance parameter makes contribution to the document emotion, and demonstrates the effectiveness of our document emotion analysis model, which can deal with the document under different emotion situations.

The rest of this paper is organized as follows: Section 2 describes the related work. Section 3 demonstrates the emotional words annotation. Section 4 illustrates document emotion analysis. Finally Section 5 concludes this paper.

2 Related Work

Affective information processing is quite a challenging problem for artificial intelligence (Ren, 2009). Especially lots of researches have been focusing on emotion analysis on emotion polarities classification or some specific fine-grained emotions from reviews (Pang et al., 2002; Turney, 2002), feedbacks (Gamon, 2004) and blogs (Yang et al., 2007).

Most emotion classification experiments were carried out by exploring machine learning

[1] Ren-CECps is a Chinese emotion corpus which can be found at http://a1-www.is.tokushima-u.ac.jp/member/ren/Ren-CECps1.0/DocumentforRen-CECps1.0.html

methods such as Support Vector Machine (SVM) (Matsumoto et al., 2005; Chesley et al., 2006) or Conditional Random Fields (CRFs) (Zhao et al., 2008). The emotion classification experiment implemented by (Chen et al., 2007) compared the two methods and proved that the CRFs classifiers performs better.

To tag emotions from words to sentences, (Das and Bandyopadhyay, 2009) made an experiment, by using CRFs on the Bengali corpus. In his study, emotion tags are pre-assigned based on a Bengali SentiWordNet which is translated from English SentiWordNet. However, since the tagging procedure was based on an immovable word list without considering the contextual information, their result is bound to suffer from the curse of emotion lexicon with either high coverage/low precision or low coverage/high precision (Ng et al., 2006).

Recent research on document emotion analysis includes (Pang and Lee, 2002), which proposed a textual categorization based approach to recognize the positive and negative polarities of documents. Also, (Yang et al., 2007) tried to match the word emotions to the document emotions. (Alm et al., 2005) conducted a text based emotion predication experiment by employing machine learning method. These methods are either semi-automatic or automatic but depending on inflexible emotion lexicons.

In this paper, we build an automatic document emotion analysis model, with dynamically extracted emotional keywords as features to predict the document emotions. We use Ren-CECps as our data set, which is a well developed Chinese emotion corpus with emotional words as well as modification components manually tagged out considering the context.

3 Emotional Words Annotation

Emotional words are the keywords that express emotions and affect the emotions of sentences and documents. Research conducted by (Kang et al., 2010) has proved that annotating emotions of words with high precision helps emotion analysis of sentences and documents.

In general, part-of-speeches are considered as the emotional component which can supply additional information. Therefore, POS could be a favorable feature for emotional words annotation. On the other hand, since the word emotions are expressed not only by the word itself but also through the context in a sentence, we also consider three types of modification relationships in the sentence for emotional words annotation.

Our study on emotional words annotation is based on the Ren-CECps, which is a Chinese emotional corpus consisting of 1,487 Chinese blog documents with totally 35,096 sentences. Not only the large text segment such as documents, paragraphs and sentences, but also the most basic lingual units such as the words and phrases are annotated with eight basic emotion tags: Expect, Joy, Love, Surprise, Anxiety, Sorrow, Anger and Hate. Although most emotional words in Ren-CECps are tagged with more than one emotions, we regard the emotions with the highest emotion intensities[2] as the chief emotions, and will assign each emotional word a chief emotion tag.

3.1 Feature Selection

Words

We employ the words string as the feature, since the identities of words themselves are important emotion carriers, which are regarded as the basic element in emotion analysis generally.

POS (part-of-speech) Tags

It has been observed that the POS tag can convey additional information for emotion analysis. (Chesley et al., 2006) has proved the importance of verbs and adjectives through the experiment on polarity determination. In this study, we adopt all the POS tags as features for emotional words annotation.

[2] Emotional intensities (from 0.1 to 1.0) of each emotional words are given in Ren-CECps.

Degree Words
Word emotion could be influenced by the existence of degree word. For example:
"这个问题很幼稚。(This is a very naive question.)"

In the example above, with the emotional word "幼稚(naive)" modified by the degree word "很(very)" in the sentence, the intensity of sentence emotion has been increased apparently. We check each word whether it is modified by the degree word or not, and use these degree modifications as a feature.

Negative Words
With very high frequency, negative words such as "不(no)", "不会(cannot)", are made use of reversing the word meaning and shifting emotion type in the Chinese document. In the following sentence, "我不善长写诗赋词。(I am not good at writing the poems.)". As the emotional word "善长(good at)" is modified by the negative word "不(not)", the sentence emotion express a opposite emotion to the word emotion. Therefore, the appearance of the negative modifications would be considered as a feature.

Conjunctions
Simple sub-sentences can be assembled into a complex sentence with the conjunction. The occurrences of conjunctions are often accompanied with apparent emotion variations in the sentence. For example,
"虽然有些累，但我会坚持下去。(Although I felt a little tired, I will keep it up.)"

The conjunction "虽然...但(although)" is employed in the sentence, so the sentence can express much stronger emotion. As a consequence, we judge whether each word is under a conjunction modification or not, and employ this conjunction modification as a feature.

3.2 CRF Based Emotional Words Annotation

Conditional Random Fields (CRF) has been employed for recognizing the emotional words and their emotion categories. To better understand the function of the context information in emotional words annotation, we experiment on three levels of language modes: 1-gram, 2-gram and 3-gram. As depicted through expression 3.1 to expression 3.5, these N-gram models are built on each emotion features described previously to represent the context of emotional words.

Fw = {1-gram(Word)} ∪ {2-gram(Word)} ∪ {3-gram (Word)}	(3.1)
Fpos = {1-gram(POS)} ∪ {2-gram(POS)} ∪ {3-gram (POS)}	(3.2)
Fdm = {1-gram(D-mod)} ∪ {2-gram(D-mod)} ∪ {3-gram (D-mod)}	(3.3)
Fnm = {1-gram(N-mod)} ∪ {2-gram(N-mod)} ∪ {3-gram (N-mod)}	(3.4)
Fcm = {1-gram(C-mod)} ∪ {2-gram(C-mod)} ∪ {3-gram (C-mod)}	(3.5)

where "D-mod", "N-mod", "C-mod" represent the modification relations between words and degree words, negative words, conjunctions respectively, while Fw, Fpos, Fdm, Fnm and Fcm correspond to the word string features, the POS features, the degree words modification features, the negative words modification features and conjunctions modification features separately. After we filtered out some extremely short sentences, and sentences which only contain punctuations, there are 31,070 sentences left for the emotional words annotation experiments. 24,856 sentences are randomly selected for training, and the rest 6,214 sentences for testing.

3.3 Result and Discussion

Table 3.1 gives the precision, recall and F-score of emotional words annotation. We can find that the three emotions Love, Sorrow and Anxiety, get the best F-scores 60.77%, 44.13%, 44.10%, while Surprise, Hate and Anger emotions get the worst three F-scores 26.11%, 33.02%, 26.01%. For one reason, when a person is in the passive state, he may express multiple negative emotions at the same time, such as Anger and Hate, which makes it difficult even for human to annotate. For the emotion of Surprise, we think that the lack of training data directly lead to the such low recall, since the number of words conveyed Surprise is only 1.96% of whole emotional words.

Table 3.1: Precision, recall and F-score of emotional words annotation

Emotion	Precision	Recall	F-score
No_emo	0.941841	0.987083	0.963931
Joy	0.610493	0.330892	0.429170
Hate	0.553704	0.235248	0.330204
Love	0.673164	0.553813	0.607684
Sorrow	0.586558	0.353374	0.441261
Anxiety	0.531632	0.376790	0.441014
Surprise	0.543210	0.171875	0.261128
Anger	0.551724	0.170213	0.260163
Expect	0.631902	0.314504	0.419980
Av.	0.624914	0.388199	0.461615

4 Document Emotion Analysis

We propose a new method for document emotion analysis by employing the function of automatic emotional words annotation, which has been introduced in Section 3. Two parameters, term relevance tr and term frequency tf, are constructed for evaluating the relation between the word emotion (which is automatically extracted from the document) and the document emotion. Normalization is conducted so that the emotion values could be comparable among documents of different lengths.

We use 211 blog documents collected from the Internet for document emotion analysis. All these articles belong to four blog users in different emotional situations. Each document is previously segmented into words and phrases. Human experts annotated each document with at least one emotion tag from the emotion tag list (Expect, Joy, Love, Surprise, Anxiety, Sorrow, Anger and Hate), while the word emotions are not annotated.

4.1 Document Emotion Assumption

Just as the documents are composed of the words, intuitively, we assume that the document emotions are determined by the word emotions contained in the documents.

There are some reasons for this assumption: First, the document are more likely to convey the same emotion as the emotion of words. Second, although there exists some words that contain different emotions from the overall emotions of the corresponding documents, we find that the most appearance of such words follows some statistical rules. Third, the document emotions constructed by the simple accumulation of word emotions are not exact enough, since the accumulation would cause some difficulties in comparing the emotion values of documents of different lengths, while fortunately the term frequency (TF), which is a widely used parameter for document analysis, could help to normalize our document emotion values.

4.2 Document Emotion Analysis (DEA) Model

The document emotion is constructed from word emotions with two weight parameters. Our DEA model predicts the emotion of a document as an eight dimensional vector, with each element represents the possible value of corresponding emotion. Each part of the calculation processing is illustrated in detail as follows:

1) Emotion Vector of Words

we extract an emotion vector for each word in document , which is a binary-valued eight-dimensional vector with each element $\overset{1}{e_k}$ ($k = 1,2\ldots,8$) representing that the k^{th} emotion (such as Love, Hate, Sorrow, ...) is reflected from the word w_i while $\overset{0}{e_k}$ represents that the k^{th} emotion is not reflected.

We exploit the function of emotional words annotation to recognize the emotional words in the blog documents collected from the Internet. As the documents in the test corpus are just given emotion tags in document level, we have to extract the three modification features for each sentence of test corpus before Emotional words Annotation. Our solution here is that we build three word lists by extracting degree words, negative words and conjunctions respectively from Ren-CECps. The modification words are available by means of word matching in test corpus with the three word lists.

The table 4.1 shows the portion of the eight-dimensional emotional vector of emotional words in the first document in the test corpus.

Table 4.1: Emotion word and emotion type

Emotion Words \ Emotion Types		e1	e2	e3	e4	e5	e6	e7	e8
活力 (vitality)	$e(w_1)$	0	0	1	0	0	0	0	0
幸福 (happiness)	$e(w_2)$	1	0	0	0	0	0	0	0
埋葬 (bury)	$e(w_3)$	0	0	0	1	0	0	0	0
宝贝 (baby)	$e(w_4)$	0	0	1	0	0	0	0	0
幸运 (luck)	$e(w_5)$	1	0	0	0	0	0	0	0
享受 (enjoy)	$e(w_6)$	1	0	0	0	0	0	0	0

2) Term Relevance

we construct a term relevance parameter tr_i , which reveals the relevance between the word emotion and the corresponding document emotion, for each word w_i . This is conducted by thoroughly analyzing the emotional words from the Ren-CECps emotion corpus depicted in

$$tr_i = \frac{\left|\{w_i \mid w_i \in D_j \wedge e(w_i) \sim e(D_j), j = 1,\ldots,M\}\right|}{\sum_{j=1}^{M} n_{i,j}} \tag{4.1}$$

The numerator part of equation (4.1) counts the appearance of word w_i in each document D_j with $j = 1,2,\ldots M$ (Ren-CECps), where $e(w_i) \sim e(D_j)$ signifies the compatibility between the word emotions and the document emotions, say, there is at least one common emotion element shared by the word emotion vector $e(w_i)$ and the document emotion vector $e(D_j)$. Under this condition, we can use a binary variable to represent this relationship:

$$e(w_i) \sim e(D_j) = 1\{\langle e(w_i), e(D_j)\rangle > 0\} \tag{4.2}$$

in which $e(w_i) \sim e(D_j)$ takes the value of 1 if *condition=true*, while the value of 0 if *condition=false*. $\langle a, b\rangle$ represents the inner product between two vectors a and b.

The denominator part of equation (4.1) counts the appearance of words , which is represented by $n_{i,j}$, from each document D_j . Therefore, equation (4.1) gives us an evaluation of the confidence, which we call the term relevance tr , that the emotion of word w_i is compatible with the emotion of the document which it belongs to.

The term relevance values as well as compatibility counts and appearance counts of some words in the first document in the test corpus are listed in table 4.2.

Table 4.2: Term relevance of emotional word

Emotional Word w_i	Compatibility $comp_i$	Appearance Count $count_i$	Term relevance tr_i
有害 (harmful)	5	5	1.000000
宝贝 (baby)	47	52	0.903846
活力 (vitality)	15	19	0.789474
埋葬 (bury)	10	13	0.769231
幸运 (luck)	27	41	0.658537
享受 (enjoy)	143	235	0.608511
幸福 (happiness)	323	670	0.482090
模范 (model)	0	6	0.000000

3) Term Frequency

we construct a term frequency parameter $tf_{i,j}$ for a word w_i from the document D_j as

$$tf_{i,j} = \begin{cases} \dfrac{n_{i,j}}{\sum_{w_k \in W_E} n_{k,j}} & if \quad w_i \in W_E \\ 0 & if \quad w_i \notin W_E \end{cases} \tag{4.3}$$

with $i = 1,2,\ldots,N$ and $j = 1,2,\ldots,M$ (Testing). Again, $n_{i,j}$ counts the appearance of word in document D_j. The term frequency here represents the proportion of the emotion values of word w_i in the emotion values of D_j . Because the document emotion is composed of the word emotions, and the number of emotional words in each document often varies, we need this term frequency to normalize the accumulation effect. Therefore, for each emotional word $w_i \in W_E$, we compute its frequencies among all the emotional words in the document D_j , and for the unemotional words $w_i \notin W_E$, we just ignore their contribution to the document emotion and assign the value of 0.

In this study, term frequency is a significant weighted parameter which measures the importance of a word in our test corpus.

For some words in the first document in the test corpus, the term frequency values as well as appearance counts and total emotional word counts are listed in table 4.3.

Table 4.3: Term frequency of emotional word

Emotional Word w_i	Appearance Count $count_i$	Total Emotional Word Count $total_j$	Term Frequency $tf_{i,j}$
活力 (vitality)	1	185	0.005405
幸福 (happiness)	1	185	0.005405
埋葬 (bury)	2	185	0.010811
宝贝 (baby)	1	185	0.005405
幸运 (luck)	1	185	0.005405
享受 (enjoy)	1	185	0.005405

4) Document Emotion Calculation

Finally, document emotion $e(D_j)$ is accumulated by word emotion $e(w_i)$ within it, weighted by term relevances tr_i and term frequencies $tf_{i,j}$ as equation (4.4) shown below:

$e(D_j) = \sum_{w_i \in D_j} e(w_i) \cdot tf_{ij} \cdot tr_i$	(4.4)
$e(D_j) = \sum_{w_i \in D_j} e(w_i) \cdot tf_{ij}$	(4.5)

4.3 Evaluation Methods

we are considering three levels of precisions for evaluating the model performance, which are depicted in equations 4.6, in which i can take the values of {1, 2, 3}.

$precision\_(i) = \frac{Matched\ \ Document_{(i)}}{All\ \ Documents}$	(4.6)

In the first level of evaluation, we choose the emotion with the highest emotion value from the predicted emotion vector as the predicted document emotion. By comparing this emotion with emotions annotated by human experts, we conclude the predicted emotion is correct, if predicted emotion matches annotated emotion of the corresponding document in test corpus. We count the number of the matched documents, which i takes the value of 1, in the numerator part of equation (4.6), and count the number of documents in test corpus as *All Documents* in the denominator part.

In the second level, we refer to two emotion types with the highest values in the emotion vector as the predicted document emotion. We treat them as a correct matching if there is at least one of the two emotion types could match the annotated emotions of the corresponding document in the test corpus.

In the third level, three emotion types are under consideration as the second level.

4.4 eResults and Discussion

We use 211 documents from four blogs to test the performance of our DEA model. In order to examine the effectiveness of term relevance , we plan to carry out a comparative experiment using equation (4.5), in which term relevance is not employed. We list the three levels of precisions for the documents of each blog, and also counts the precisions of the documents from all the blogs as a whole. The detailed results are shown in the Table 4.4 and Table 4.5.

Table 4.4: Results of comparative experiment in three levels of evaluation methods

Blog ID	Num.Of Documents	Precision_1	Precision_2	Precision_3
ID1	37	0.189189	0.729730	0.837838
ID2	18	0.222222	0.777778	0.888889
ID3	73	0.068493	0.369863	0.616438
ID4	83	0.168675	0.445783	0.662651
Overall	211	0.142180	0.497630	0.696682

Compared with the three precisions of comparative experiment, experiment which utilizes term relevance gets the better performance. Therefore, we believe that term relevance makes a contribution to the document emotion analysis. Nevertheless, the value of precision_2 and precision_3 of ID 1 and ID2 for both experiments are the same, we find that they have the same number of correct predicted document emotions but not the same identities of documents.

Table 4.5: Results of adopted experiment in three evaluation methods

Blog ID	Num.Of Documents	Precision_1	Precision_2	Precision_3
ID1	37	0.270270	0.729730	0.837838
ID2	18	0.277778	0.777778	0.888889
ID3	73	0.082192	0.438356	0.657534
ID4	83	0.192771	0.46988	0.686747
Overall	211	0.175355	0.530806	0.720379

As shown in Table 4.5, the DEA model gets relatively lower precisions in the first level of evaluation for different blog documents, but achieves much better results in the second and the third level. Because most documents are conveying multiple emotions at the same time, the latter two level of precisions also confirm the promising result of our model.

The source of this test corpus also provides some insight into document emotion analysis. The blog documents used for document emotion analysis are collected from four different blog users under different emotional situations: The ID1 blog user lost his son in the earthquake and missed his child in blogs; the ID2 blog user suffered from a serious disease and wrote blogs for encouraging herself; the ID3 blog user lost her boyfriend in an accident, and wrote her beautiful memories in blogs; the ID4 blog user had been betrayed by her husband, so complained in blogs.

These documents from different emotion situations are used to test the robustness of our DEA model: Firstly, the experiment in Table 4.5 shows similar results , which proves that our DEA model can deal with different kinds of emotional situations. Secondly, through a thorough examination, we also find that the documents of the ID3 blog user get the lower emotion precision than the other blog documents. This happens when the blog user uses the positive emotional words to express negative emotions (e.g. the pleased memory of life conveyed the sadness of the current emotion). This turns to be one of the most difficult situations in our document emotion analysis: although the annotators could precisely tag the document with negative emotions, such as sorrow, it is still not easy for machines to judge the real emotions through the large amount of positive emotional words.

5 Conclusions

In this paper, we develop a document emotion analysis model by making use of the function of emotional words annotation. Two parameters, term relevance and term frequency, are introduced to evaluate the relations between the word emotions and the document emotions.

By utilizing the modification relationship in the context, we build an automatic Emotional

Words Annotation system, which could get word emotions with higher context sensitivity compared to traditional emotion lexicons.

We perform document emotion analysis by using the result of our Emotional Words Annotation. Under the relation assumption between document emotions and word emotions, we introduce term relevance and term frequency in the process. Experimental results reveal that our DEA model achieves promising performance under different emotion situations.

We notice that the incorrectly tagged word emotions through Emotional Word Annotation could influence the accuracy of document emotion analysis. One of the most important affects comes from the three word lists from which we extract the modification features for emotional word annotation, as we have mentioned in section 4.2. These word lists are totally empirical, and contain large amount of inaccuracy. The inaccurate modifications employed as the features in CRF model would finally cause the inaccurate annotated emotional words, and indirectly affect the performance of document emotion analysis.

We also find document emotion analysis become more difficult when large amount of positive emotional words are used in a blog document to express negative emotions. Although the annotators could precisely comprehend the negative emotions in the blog documents, which is still not an easy task for machines to judge such real emotions.

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