Chinese Emotion Recognition Based on Three-Way Decisions

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Abstract. In recent years, affective computing has become a research hotspot in the area of natural language processing and Chinese emotion recognition is an important constituent. This paper proposes a method of Chinese emotion recognition based on three-way decisions. Given the emotion dictionary constructed firstly, the grammatical information of sentences, topic features of texts and three-way decisions are integrated and applied into Chinese emotion recognition, thus realizing the multi-label emotion recognition of sentences in Chinese texts. The results of experiments show that the method of Chinese emotion recognition, based on three-way decisions, has achieved excellent results in the emotion recognition of Chinese sentences.

Keywords: Three-way decisions · Probability topic · Emotion dictionary · Affective computing

1 Introduction

With the rapid development of the Internet, more and more common users enjoy expressing their own emotions on the Internet, making comments on product performance and discussing current affairs. It brings large quantities of online text information with subjective emotional such as personal blog, product comment, news comment and so on [1–3]. All these information reflect person's emotional tendency such as happiness, anger, sorrow and enjoy [4]. Through analyzing the emotion of the online information, we can understand the individual emotional state and the level of popular products which people likes or dislikes and get to understand the fondness degree of the users. However, all of this would not be achieved by solely relying on manual handling, which promotes the development of affective computing [5] and making it a research hotspot in the area of natural language processing.

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Affective computing aims to promote the quality of the human-computer communication and obtain more valuable information by revealing the delicate human emotions [4]. After Picard put forward the concept of "Affective Computing", emotion intelligence analysis has drawn more attention from scientists and researchers in the fields of artificial intelligence and computational linguistics.

The text such as weblog, product reviews and news discussion plays a basic role among all the communication mediums in the Internet, so the analysis of text emotion is an important constituent of affective computing. According to the differences of the analysis particle, it can be subdivided into three layers: emotion analysis of words, emotion analysis of sentences and emotion analysis of texts. Emotion analysis of sentences plays the connecting role, which relies on the emotional analysis of words and in the meantime, it can achieve more abundant emotional elements, thus providing support for the emotion analysis of texts.

Emotion analysis of sentences mainly concentrates on the identification of various kinds of emotion object, the extraction of various kinds of emotion owners and judgment of the emotional polarity of sentences and so on. Considering the previous researches, there are two kinds of research: the approach based on emotion knowledge and the approach based on feature classification. The approach based on emotion knowledge [6, 7] mainly relies on the existing emotion dictionary, so it first identifies emotion words in the text, and then emotion polarity weight value is computed for recognizing emotion of the text. Generally, the emphasis of the approach is placed on the extraction and judgment of emotion words. Hu and Liu[1, 2] took advantage of the synonym and antonym relation of WordNet to identify the emotion of words, then recognized the emotion polarity of sentences according the weight of emotion words which have advantages in the sentence. The latter approach mainly adopts machine learning and chooses large numbers of features to achieve the emotion polarity classification of texts by utilizing corpus. Dave etc. [8] used the machine learning approach and studied the emotion analysis of sentences. They collected over 1000 pieces of comments which have been marked emotion polarity and counted the appearance frequency of n-gram combination in the documents; then, according to the proportion of appearance frequency, they graded the emotion polarity of these features and judged the emotion polarity according to these features and the grades.

This paper takes the emotion recognition of sentences in Chinese texts as the research topic, integrates the grammatical information of sentences, the topics of texts and Three-way decisions, and then brings them into the emotion recognition of sentences. A Chinese emotion recognition method based on Three-way decisions is proposed to recognize the emotion of sentences in texts and the experiment result shows that the approach has achieved good results.

The remainder of the paper is as follows: Sect. 2 briefly introduces relative studies including LDA Model, Three-way decisions theory. Section 3 explains in detail the Chinese emotion recognition approach based on Three-way decisions. In Sect. 4, we describe the Chinese emotion corpus (Ren_CECps), the experiment process and the analysis of results. Finally, we summarize the whole paper and some concluding remarks are presented in Sect. 5.

2 Related Work

2.1 Latent Dirichlet Model

LDA model [9] was proposed by Blei in 2003, and it is a three-layer Bayes generation model. The advantage of LDA is that the scale of parameter space is not related to corpus and is suitable to process large-scale corpus.

In LDA model, each document in the corpus can be expressed as a probability distribution composed by some topics, while each topic is a probability distribution composed by several words. As to each document in the corpus, the generative process of the documents in the LDA model is as follows:

1. To each text, choose a topic from topics distribution;
2. Choose a word from the corresponding word distribution of the chosen topic;
3. Repeat the above procedures until every word of the document has been chosen.

The graph model of the generative process is shown as Fig. 1:

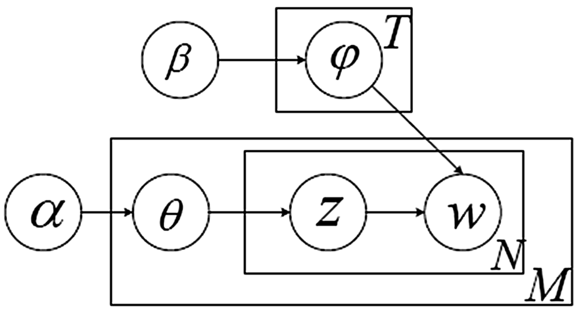

Fig. 1. Graph model representation of LDA

2.2 Three-Way Decisions Theory

Three-way decisions rough set model [10] is adopted to identify the multi-label emotion of sentences in Chinese texts. Compared with other various kinds of existing models, Three-way decisions rough set model takes a pair of threshold value on the basis of classic rough set theory and divide one set into three areas which do not intersect, thus bringing the third choice to delay decision-making so as to avoid the risks brought by direct decisions.

In Three-way decisions rough set, we divide the objects into corresponding positive area, negative area and boundaries by comparing the value of probability and the threshold and these areas correspond to the acceptance decision, rejection decision and delay decision respectively. The delay decision objects are in the boundaries and we need to collect further information to analyze and make corresponding decisions, which is acceptance or rejection. Three-way decisions theory can analyze data effectively and reduce wrong decisions so as to improve the accuracy of decisions.

3 Chinese Emotion Recognition

3.1 Emotion Dictionary

At present, some emotion dictionaries are developed for affective computing such as WordNet-Affect, SentiWordNet and the VSA Chinese-English Emotion Analysis Vocabulary. In this paper, emotion recognition research is completely based on Chinese emotion corpus (Ren_CECps) [11, 12]. In order to better achieve emotion recognition research, we extract all emotion words with emotion polarity and emotion intensity from Ren_CECps and conduct a new Chinese emotion dictionary to apply it into the experiments.

In Ren_CECps, each emotion word in the sentence is labeled for 8 fundamental emotion categories such as surprise, sorrow, love, joy, hate, expect, anxiety and anger. It has been labeled corresponding emotion intensity and expressed as an emotion vector $\vec{e}$. For example, emotion word “无私” (‘selfless’) is labeled as (0.0,0.0,0.7,0.0,0.0, 0.5,0.0,0.0), so it expresses love and expect and its emotion intensities are 0.7 and 0.5 respectively. The emotion word “战争”(‘war’) is labeled as (0.0,0.5,0.0,0.0,0.5,0.0, 0.0,0.0), so it expresses sorrow and hate and its emotion intensities are 0.5 and 0.5 respectively.

In Ren_CECps, all emotion words are extracted and stored in the emotion dictionary.

3.2 Emotion Vector Space Model

According to the traditional “bag of words” hypothesis, sentences of the texts are treated as combinations of emotion words and emotion words are counted for helping recognize the emotion of sentences. Vector space model of sentences can be expressed as $\vec{S} = \{w_1, w_2, \cdots, w_n\}$, here n is the number of emotion words, w_i is the *ith* emotion word. For w_i, it can be expressed as an emotion vector $\overrightarrow{e_i} = (e_i^1, e_i^2, e_i^3, e_i^4, e_i^5, e_i^6, e_i^7, e_i^8)$. The emotion vector space model of the sentence can be further expressed as the following form:

$$\overrightarrow{S} = \{w_1, w_2, \ldots, w_n, \overrightarrow{e_1}, \overrightarrow{e_2}, \ldots, \overrightarrow{e_n}\} \tag{1}$$

3.3 Emotion Vector Space Model Based on Topics

For all sentences of a text, it will separate the correlation of sentences and neglect the dependency of contexts only by using the emotion vector space model in Formula (1) to recognize the emotion of sentences. Suppose the sentence of a text describes the same topic information with the text, so the emotion of the sentence and the text also agree with and the emotion of sentences should be determined by emotion word which can better reflect the topic feature of sentence and the text.

Latent topic features are integrated into emotion vector space model of sentences. For document D, it applies LDA model and obtains T latent topic $\overrightarrow{T} = \{t_1, t_2, \ldots, t_T\}$ and the probability distribution $\vec{\varphi}$ of topic-word, and then utilizes the probability distribution of "text-topic-word" to solve the dependency of the context. The author proposes an emotion vector space model based on topic, finds out the t_m with largest probability weight from T latent topic and further extends the emotion vector space model of sentences. The formula is as follows:

$$\overrightarrow{S} = \{w_1, w_2, \ldots, w_n, \overrightarrow{e_1}, \overrightarrow{e_2}, \ldots, \overrightarrow{e_n}, \varphi_{m1}, \varphi_{m2}, \ldots, \varphi_{mn}\} \tag{2}$$

w_i refers to the *ith* emotion word, $\vec{e}_i$ refers to the emotion vector of the *ith* emotion word, φ_{mi} means the probability distribution of the topic-word of the *ith* emotion word based on topic t_m.

In order to describe the emotion features of sentences more clearly, transform the formula further and we get emotion vector space model based on topics and the form is as follows:

$$\overrightarrow{S} = \left(\frac{1}{n}\sum_{i=1}^{n}(1+\varphi_{mi})e_i^1, \frac{1}{n}\sum_{i=1}^{n}(1+\varphi_{mi})e_i^2, \ldots, \frac{1}{n}\sum_{i=1}^{n}(1+\varphi_{mi})e_i^7, \frac{1}{n}\sum_{i=1}^{n}(1+\varphi_{mi})e_i^8\right) \tag{3}$$

$\frac{1}{n}\sum_{i=1}^{n}(1+\varphi_{mi})e_i^j$ refers to the emotion intensity average of the *jth* emotion of all emotion words of the sentence. The emotion and emotion intensity of the sentence can be got by Formula (3).

There are parts of emotion words that could be defined by negative adverbs, it could weaken or change the emotion of the sentence. In the paper, the negative adverb just before or after the emotion words is considered and the emotion of the emotion words modified by negative adverbs is defined as 0. For example,

"一天十多小时的复习也需要健健康康的身体来支撑，否则万一晕倒在自习室里可就不妙了" (焦虑: 0.5).

"To review for over 10 h a day needs a healthy body. Otherwise, it would be no good if you faint in the self-study room" (anxiety: 0.5)

The emotion word "miao" (good) has the meaning of "love", but there is the negative adverb "no" before the emotion word which negates the emotion information. Therefore, the sentence does not have the "love" emotion and recognizes the sentence has the "anxiety" emotion according to other emotion words.

3.4 Chinese Emotion Recognition Based on Three-Way Decisions

After the initial multi-label recognition of the emotion of all sentences, each sentence in the text is labeled with certain emotions and intensity, and the emotions of each sentence is represented as an 8-dimension emotion vector which is treated as the input data of three-way decisions classifier.

According to the rules of three-way decisions, the threshold values α_t and β_t are set in advance to recognize whether the give testing sentence x has emotion k. The decision process is as follows:

(1) If $P(k|[x]) \geq \alpha_t$, then the sentence x has emotion k.
(2) If $P(k|[x]) \leq \beta_t$, then the sentence x does not have emotion k.
(3) If $\beta_t < P(k|[x]) < \alpha_t$, it means the sentence x may have emotion k, or may not have emotion k, and it needs further processing;

If sentences cannot be determined whether it has emotion k, a threshold value θ_t is set and the process is followed:

(1) If the number of the *kth* emotion words in the sentence x is equal or greater than θ_t, then sentence x is judged to have emotion k.
(2) If the number of the *kth* emotion words in the sentence x is smaller than θ_t, then sentence x is judged not to have emotion k.

3.5 Multi-label Emotion Recognition Framework

In the paper, the multi-label emotion recognition framework of sentence is shown as Fig. 2. The left is the training process, and the right is the test process, and we also apply emotion dictionary, LDA model and three-way decisions into it. The multi-label emotion recognition process of sentences is divided into 6 steps, and the specific description is as follows:

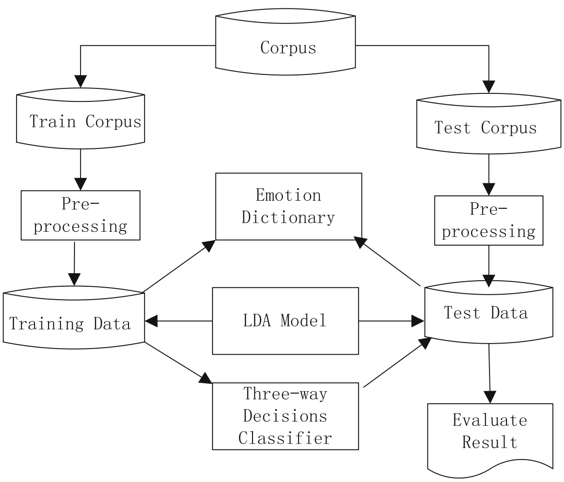

Fig. 2. Multi-label emotion recognition framework

Step 1: Draw the experimental data randomly from Ren_CECps corpus for training corpus and testing corpus;

Step 2: Pre-processing respectively the training corpus and the testing corpus. Remove small quantities of sentences without emotion polarity and the non-emotion words in sentences; only retain the emotion words in sentences.

Step 3: Utilize experiment corpus, make up emotion dictionary;

Step 4: Apply emotion dictionary and LDA model respectively on training data and testing data, make up the emotion vector space model based on topics features;

Step 5: Take advantage of training data to achieve all the threshold values needed by Three-way decisions classifiers;

Step 6: Apply Three-way Decision Classifier to the testing data and evaluate experiment result;

4 Experiment and Analysis

4.1 Experiment Data

The Ren_CECps Chinese emotion corpus is adopted for the experiments. The corpus contains 1487 Chinese blog which have altogether 11255 paragraphs, 35096 sentences and 878164 words, selected from Chinese websites as the initial text corpus.

In Ren_CECps Chinese emotion corpus, all the language information related to emotion expression is labeled manually and all emotions are divided into 8 basic emotion categories which are: surprise, sorrow, love, joy, hate, expect, anxiety and anger. The emotion category and intensity of texts, paragraphs and sentences are labeled as an 8-dimensional emotion vector, and is represented as follows:

$$\overrightarrow{e} = (e^1, e^2, e^3, e^4, e^5, e^6, e^7, e^8) \tag{4}$$

In the formula, e^i is labeled as the emotion intensity of a basic emotion category of 8 emotion category and the scope of the intensity is from 0.1 to 1.0.

In the experiment, 1000 blogs are selected randomly from Ren_CECps Chinese emotion corpus, which are altogether 21225 sentences. 10-fold cross-validation is performed on the whole data for each experiment.

4.2 Experiment Setting

The goal of the experiment is to recognize the multi-label emotion of sentences. BR (Binary Relevance) is a classic representative of multi-label classification algorithm and suitable to situations with small label quantity q. While there are only 8 types of emotion in Ren_CECps corpus, so BR algorithm is adopted as multi-label classification algorithm and Naïve Bayes is adopted as the basic classifier.

The paper adopts evaluation approach based on labels [13, 14] and the formula for the macro average accuracy of multi-label classification is as follows:

$$Macro - accuracy = \frac{1}{|K|}\sum_{k=1}^{|K|}\frac{tp_k + tn_k}{tp_k + tn_k + fp_k + fn_k} \tag{5}$$

tp_k denotes the correct positives label number, tn_k denotes the correct negatives label number, fp_k denotes the wrong label number, and fn_k denotes the wrong negatives label number.

In order to evaluate the accuracy degree of Chinese emotion recognition, the author also proposes three evaluation standards, which are single type of emotion identification, two types of emotion identification and all types of emotion identification, and the formulas are as follows:

$$One - match - accuracy = \frac{the\ number\ of\ sentences\ at\ least\ one\ emotion\ matched}{the\ total\ number\ of\ sentences} \tag{6}$$

$$Two - match - accuracy = \frac{the\ number\ of\ sentences\ at\ least\ two\ emotions\ matched}{the\ total\ number\ of\ sentences} \tag{7}$$

$$All - match - accuracy = \frac{the\ number\ of\ sentences\ all\ emotions\ matched}{the\ total\ number\ of\ sentences} \tag{8}$$

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4.3 Analysis of Experiments Result

The emotion categories of this experiment are 8 types (surprise, sorrow, love, joy, hate, expect, anxiety and anger) and it does not consider sentences with neutral emotion. In the experiments, the parameter setting is as follows: $\alpha = 0.5$, $\beta = 0.1$, the type of emotions $L = 8$, the number of topics $T = 3$, $\alpha_t = 0.6$, $\beta_t = 0.3$, $\theta_t = 0.6$. All of the parameters are all empirical value and can be got from training set.

The NB algorithm is adopted as the benchmark and Table 1 gives the comparison of the result of the two methods.

Table 1. Comparison of the experiment

	NB approach	Approach based on three-way decisions
One-match-accuracy	0.040	0.601
Two-match-accuracy	0.029	0.306
All-match-accuracy	0.022	0.113
Macro-accuracy	0.807	0.752

Table 1 indicates that the approach based on three-way decisions is better than NB and can identify the emotions of the sentences accurately in single emotion identification, two emotion identification and all emotion identification. However, in macro accuracy, NB is a little better than the approach based on three-way decisions, which is because each sentence in the corpus only has several emotions and the value of tn_k is large, so the macro-accuracy of NB is higher, but it also indicates that the approach based on three-way decisions is better than NB approach.

Compare NB, the accuracy of 8 types of basic emotion is shown as Fig. 3. In Fig. 3, the method based on three-way decisions is better than NB for recognizing the emotion of joy, love, expect, while it is lower for other 5 type. Through studying the Ren_CECps corpus, we find that lots of sentences have positive emotion in the corpus such as joy, love and expect and the number of sentences containing negative emotion such as hate, sorrow, anger and surprise is few. So the value of tn_k in formula 5 is great when recognizing the negative emotions and the result also indicates that the method based on three-way decisions has more advantages for recognizing the positive emotion of the sentences. It is the future work that how to further complete and enrich the Ren_CECps Chinese emotion corpus.

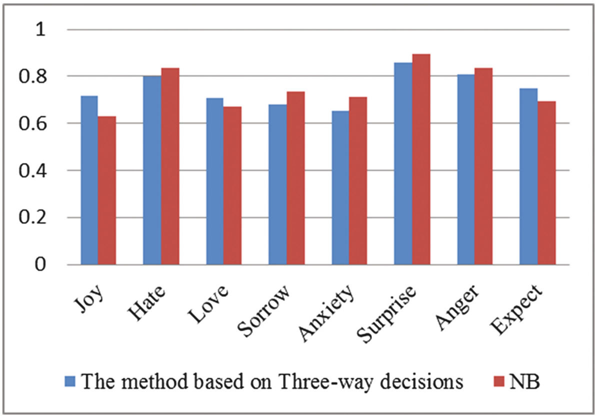

Fig. 3. Accuracy of 8 types of basic emotion recognition

5 Conclusion

The paper focuses on the multi-label emotion recognition of sentences and proposes the Chinese emotion recognition approach based on three-way decisions. The Ren_CECps Chinese emotion corpus is taken as the data of experiments, the context dependency between sentences is solved by using topic features and the emotion recognition of negative sentences is addressed by taking advantage of the negative adverbs. Lastly three-way decisions classifier is applied to recognize multi-label emotion of sentences, such as surprise, sorrow, love, joy, hate, expect, anxiety and anger.

The paper utilizes the negative adverbs, topic features and three-way decisions theory to study the multi-label emotion recognition of Chinese sentences and still has a lot to improve. It is a hot topic in the future how to improve the multi-label emotion recognition accuracy of sentences and how to recognize the emotion of texts by utilizing the emotion information of words and sentences.

References

1. Hu, M., Liu, B: Mining and summarizing customer reviews. In: Proceedings of the 10th International Conference on Knowledge Discovery and Data Mining, pp. 168–177 (2004)
2. Liu, B., Zhang, L.: A Survey on Opinion Mining and Sentiment Analysis. Mining Text Data. Springer, New York (2012)
3. Jo, Y., Oh, A.H.: Aspect and sentiment unification model for online review analysis. In: Proceedings of the 4th ACM International Conference on Web Search and Data Mining, pp. 815–824 (2011)
4. Ren, F.: Affective information processing and recognizing human emotion. J. Electron. Notes Theor. Comput. Sci. **225**, 39–50 (2009)
5. Picard, R.W.: Affective Computing. MIT Press, Cambridge (1997)
6. Taboada, M., Brooke, J., Tofiloski, M.: Lexicon-based methods for sentiment analysis. J. Comput. Linguist. **37**(2), 267–307 (2011)
7. Rao, D., Ravichandran, D.: Semi-supervised polity lexicon induction. In: Proceedings of the EACL, pp. 675–682 (2009)
8. Dave, K., Lawrence, S., Pennock, D.M.: Mining the peanut gallery: opinion extraction and semantic classification of product reviews. In: Proceedings of WWW-03, 12th International Conference on the World Wide Web, pp. 519–528. ACM, Budapest (2003)
9. Blei, D.M., Ng, A.Y., Jordan, M.I.: Latent Dirichlet allocation. J. Mach. Learn. Res. **3**, 993–1022 (2003)
10. Yao, Y.: An outline of a theory of three-way decisions. In: Yao, J., Yang, Y., Słowiński, R., Greco, S., Li, H., Mitra, S., Polkowski, L. (eds.) RSCTC 2012. LNCS, vol. 7413, pp. 1–17. Springer, Heidelberg (2012)
11. Ren, F.: Document for Ren-CECps 1.0 (2009). http://a1-www.is.tokushima-u.ac.jp/member/ren/Ren-CECps1.0/Ren-CECps1.0.html
12. Quan, C., Ren, F.: A blog emotion corpus for emotional expression analysis in Chinese. J. Comput. Speech Lang. **24**(4), 726–749 (2010)
13. Tsoumakas, G., Katakis, I.: Multi-label classification: an overview. Int. J. Data Warehouse. Min. **3**(3), 1–13 (2007)
14. Tsoumakas, G., Katakis, I., Vlahavas, I.: Mining multi-label Data, Data Mining and Knowledge Discovery Handbook, 2nd edn. Springer, Heidelberg (2010). Part 6