Sentence Level Fine-grained Emotion Computation Based on Dependency Syntax Improvement Dictionary

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Abstract

With the rapid development of Internet technology, emotion analysis has been widely used in various fields. However, the different types of emotion corresponding to multiple attribute words in text and the complex syntactic structure bring great challenges to the existing text emotion analysis methods. This paper proposes a sentence level fine-grained emotion computing approach based on dependency syntax improvement dictionary. Firstly, an attribute quad extraction algorithm is constructed based on the dependency relationship. Then we analyze the syntactic structure of the text, and study the influence of the combination mode of sentence pattern, inter-sentence relation, degree adverb and negative adverb on the sentence emotion. Lastly, a fine-grained emotion computing algorithm is designed to calculate the emotion value of sentences. Experiments on collected micro-blog data set show that our method compared with the original dictionaries, the F1 value of emotion classification reaches 81.37%.

Keywords

dependency syntax, emotion dictionary, fine-grained, emotion analysis

1 Introduction

Text emotion analysis, also known as opinion mining, refers to the analysis of the subjective text with emotion color, mining the emotion tendencies contained in it, and dividing the of emotion attitudes [1], which involves artificial intelligence, data mining and other fields [2]. Emotion analysis initially begins as an analysis of words with emotion [3], for instance, "beautiful" is a word with a positive meaning color, while "ugly" is a word with a negative meaning color. In 2010, Brendan O'Connor et al. [4] applied emotion analysis to public opinion texts on Twitter, a foreign social network platform, confirming that there was a strong correlation between voters' emotion tendencies expressed on the Internet and poll results. Emotion analysis gradually attracted people's attention and was applied in many fields. For example, in the field of e-commerce, merchants can master users' satisfaction with related products and predict future sales through the analysis of product reviews [5]. In the media field, the video platform can understand the audience's preferences and reasonably arrange the broadcast time through the comment analysis of TV and films [6]. In addition, text emotion analysis is also widely used in government public opinion monitoring [7], brand monitoring [8], stock market prediction [9] and other aspects, which is of great significance and value.

At present, a series of studies on emotion analysis have been conducted abroad, but due to the differences in grammar, sentence pattern and language habit between Chinese and English, there are still many limitations when these studies are applied to the Chinese field [10]. Therefore, domestic scholars are also actively exploring Chinese emotion analysis. Binary emotion analysis, that is, the user's emotion attitude is only composed of good and bad two extremes. Multivariate emotion analysis introduces neutral emotion category. However, human emotion expression is complex. Emotions are not limited to good, bad and neutral emotions, but also include more emotion states [11], such as anger, panic, disgust, fear, happiness and other finer levels of division. Emotion classification based on emo-

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tion dictionary refers to the use of emotion dictionary to obtain the emotion value of emotion words in the document, and then determine the overall emotion tendency of the document through weighted computation [12-13]. However, due to the limited capacity of the emotion dictionary, scholars will expand the emotion dictionary. At present, there have been researches on multi-category emotion analysis in China, most of which use the method of expanding the emotion dictionary with large-scale corpus. Hu et al. [14] proposed to use seed words in WordNet to generate an emotion dictionary containing both positive and negative adverbs. Cruz et al. [15] proposed to use random forest algorithm to expand the emotion dictionary. Ding et al. [16] summarized the steps of emotion computation in emotion dictionary as marking emotion words, processing emotion reversal words, processing transition words and summarizing emotion score. Although these researches can reduce the influence of the lag of the emotion dictionary to a certain extent, their accuracy is low. At the same time, this method is not suitable for emotion analysis of text with complex sentence structure and multiple attribute words. Popescu et al. [17] identified candidate attribute words by calculating the Pointwise Mutual Information (PMI) between candidate words and commonly used attribute words, but the selection of benchmark words in this algorithm had a great influence on experimental results. Ku et al. [18] use Term Frequency-Inverse Document Frequency (TF-IDF) to identify attribute words, but this model ignores the extraction of infrequent words. Lu et al. [19] combined dependency syntax with domain emotion dictionary for emotion computing, but the granularity of subjects selected in the experiment was relatively coarse, so it was impossible to judge the performance of the algorithm in fine-grained view content mining. Therefore, it is of great significance to extract attribute words and analyse sentence structure in text emotion analysis.

In order to solve the problem of different emotion of multiple attribute words and complex sentence structure, this paper proposes a sentence-level fine-grained emotion computing model based on dependency syntax modified emotion dictionary to conduct text tendency analysis and emotion classification. This paper defines an extraction algorithm of emotion word quad in text based on dependency relation and expands the emotion dictionary. In addition, we define propensity shift rules and fine-grained emotion computing algorithms to achieve fine-grained analysis of text emotion, in order to obtain the polarity of text emotion, emotion classification and emotion value. Then the users' views and attitudes can be more accurately known, laying a foundation for subsequent applications in various fields.

2 Our approach

This paper proposes a method to improve the emotion dictionary by using dependency syntax, and carries out a more detailed emotion analysis of sentences combined with the study of sentence structure. The research in this paper is divided into three parts, namely, the expansion of the emotion dictionary based on dependency syntax, fine-grained emotion computing, and experimental and result analysis. First, attribute words, emotion words, negative adverbs and degree adverbs are extracted from the corpus using dependency syntax, semantic dependency and part of speech. Then, the similarity between the unknown emotion words in the quad and the seed words in the emotion dictionary is calculated, and the unknown words are extended to the emotion dictionary. According to the complex syntactic structure of Chinese text, the sentence tendency transfer rules are defined, and the effects of sentence patterns, sentence relationships, degree adverbs and negative adverbs combination patterns on sentence tendency are studied. Finally, this paper also designed the corresponding emotion data computation algorithm, which is used to classify the text emotion and judge the emotion tendency. The scope of this paper is shown in Figure 1, and we will introduce each module in detail.

2.1 Basic emotion dictionary construction

Emotion dictionary is the basis of emotion analysis. To carry out fine-grained emotion computation, it is necessary to select a dictionary containing both the emotion

polarity of words and the emotion classification of words. Therefore, this paper chooses emotion vocabulary ontology database of Dalian university of technology as the basic dictionary. Ontology database describes a word or phrase from multiple perspectives, including word category, emotion category, emotion intensity and polarity. It mainly includes seven emotion broad categories, namely, joy, like, anger, sadness, fear, disgust, surprise and twenty-one emotion small categories.

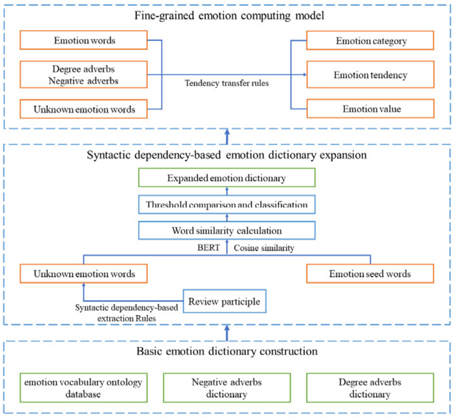

Figure 1 The architecture of this paper.

Negative adverbs are a kind of special adverbs. In most cases, when negative adverbs modify emotion words, the actual emotion expressed will be contrary to the emotion of the word itself, and then change the overall emotion color of the text. However, when negative adverbs modify degree adverbs, the emotion intensity will be reduced. In this paper, fifteen commonly used negative adverbs are selected through manual screening to obtain a negative adverb dictionary, and their emotion weight is -1.

Degree adverbs can deepen or weaken the emotion expressed. When degree adverbs modify the emotion words, the emotion intensity will be expanded by a certain multiple. This degree adverb dictionary comes from the CNKI.com dictionary base, which divides degree adverbs into 6 grades, namely, super, most, very, relatively, slightly and lack, and assigns certain weights to these 6 grades. Examples of partial degree adverbs are shown in Table 1.

Table 1 Examples of DEGREE ADVERB DICTIONARY

Grades	*Degree adverbs*	*Weight*	*Number*
super	excessively, too	3	30
most	extremely, unduly	2.5	69
very	much too, how	2	42
relatively	not big, more	1.5	37
Slightly	a bit, a little	1	29
lack	not that, poorly	0.5	12

2.2 Syntactic dependency-based emotion dictionary expansion

When emotion dictionary is used for emotion analysis, it is usually limited by the dictionary capacity. The words that are not in the dictionary cannot participate in emotion computation, thus affecting the accuracy of analysis. In addition, this method cannot take into account the emotion inconsistency of multiple attribute words in the text.

Therefore, word extraction rules based on dependency relationship are designed to extract the quads of attribute words, emotion words, degree adverbs and negative adverbs in the text to solve the problem of multiple attribute words in the text. At the same time, the representative words are selected from the emotion dictionary as the seed words, and the similarity computation between the unknown emotion words and the emotion seed words in the quad is carried out to obtain the emotion attributes of the unknown words, so as to realize the real-time extraction and emotion computation of the unknown emotion words. Through threshold comparison and classification, unknown emotion words are added to the existing emotion dictionary to obtain the expanded emotion dictionary, and the subsequent text fine-grained emotion computing is carried out.

2.2.1 Syntactic dependency-based emotion dictionary expansion

Chinese text usually consists of multiple clauses to form complex sentences, and there may be description objects in each clause, which are called attribute words. For example, in the sentence “I really like my new mobile phone, take pictures very clearly, and play games do not stuck, but the battery is a little small” have multiple attribute words, namely, “mobile phone”, “take pictures”, “play games”, “battery”, and “like”, “clear”, “not stuck”, “small” are the modifiers corresponding to the four attribute words, namely emotion words.

In addition, the emotion of text is not only determined by emotion words, but also affected by negative adverbs and degree adverbs. Therefore, this paper proposes the construction of attribute as the core of the quad, for each attribute word in the sentence to construct its “attribute word, emotion word, negative adverb, degree adverb” quad.

Dependency syntactic analysis is a common technique in the field of natural language processing, which can determine the dependency relationship between the syntactic structure of a sentence and the words in the sentence. The result of dependency syntactic analysis can be expressed as a tree structure, where stands for node and each word in the sentence is associated with a node. And stands for directed edge, indicating that there is a dependency relation between two words.

In this paper, we define the extraction rules of quad for the common five types of dependency relations. Among the relations, the subject-verb (SBV) relation refers to the relationship between the actor and the action. Verb-object (VOB) relation refers to a pairing relationship between a verb and an object. ATT (attribute) relation refers to the relationship between a modifier and a centre word, modifier is attribute. ADV (Adverbial) relation also refers to the relation between the modifier and the central word, the difference is that the modifier is adverbial. COO (coordinate) relation refers to the relationship between two or more concepts under the same concept [20].

2.2.2 Candidate word emotion judgment and emotion dictionary expansion

After word extraction of the text, the corresponding quad of each attribute can be obtained. The words that contain or may contain emotion colors in the quad are called candidate emotional words. When using the emotion dictionary to calculate emotion, it is usually necessary to use large-scale corpus to expand the emotion dictionary in advance. If unknown words are encountered in the computation, it is impossible to know whether the words contain emotion, which will affect the emotion computing. Therefore, this paper constructs an algorithm to determine the emotional attributes of unknown words, which can directly calculate the emotional attributes of unknown words in the quad, and obtain the emotion intensity, emotion category and emotion polarity

2.2.2.1 Emotion seed words selection

In the emotion judgment of unknown words, the method of calculating the association between words is generally adopted to judge the similarity between unknown words and known words, so as to determine their emotion characteristics. The candidate words with high similarity to the selected seed words are more likely to be emotion words, or are more likely to be emotionless words. Seed words are not only the basis for generating candidate emotion words, but also the benchmark words for judging algorithms.

2.2.2.2 Word embedding

Word embedding refers to mapping a single word into a vector. It is a common technique in the field of natural language processing and has been widely used in text emotion analysis and similarity computation. Word vector is the product of language model training. Commonly used word embedding techniques include Word2vec, Glove, BERT and so on. BERT is an efficient tool to represent words as vectors of real numbers and has made great achievements in the field of natural language processing. BERT used MLM to pre-train the bi-directional Transformers to generate deep bi-directional language representation. Therefore, Bert is used to obtain the word vector in this paper.

2.2.2.3 Cosine similarity

Before the text emotion analysis, the selected seed words are trained as word vectors. During the sentence analysis, the unknown emotion words in the obtained quads are trained as word vectors to calculate the similarity between seed words and unknown words. Cosine similarity is usually selected, which measures the similarity between two vectors by calculating the cosine of the angle between them, and can be used to calculate the cosine distance between two vectors. The higher the value is, the more similar the two words are.

2.2.2.4 Candidate word emotion judgment and emotion dictionary expansion

In the judgment of candidate words, words, while are more likely to be neutral words. Therefore, after the emotion computation of candidate words and seed words, the candidate words are firstly classified, and then their emotion intensity and polarity are calculated. Candidate word emotion judgment and emotion dictionary expansion can be divided into the following five steps:

- Step 1: Train word vectors for candidate and seed words. Firstly, the candidate emotion words in the text are obtained by using the quad matching rules, and then the seed words and candidate words are trained as word embedding vector to form the seed word vector set $SeedList$.
- Step 2: Calculate similarity. The similarity of the selected seed word vector set $SeedList = \{SeedWord_1, SeedWord_2, ..., SeedWord_7\}$ and the emotion word vector to be added is calculated.
- Step 3: Judge the emotion category of word. In the computation results of similarity of emotion values between candidate words and various seed words, the three largest similarity values of this kind of seed words are selected to calculate the average value, and the result is the similarity between the word and this kind of emotion. If the similarity value is greater than 0.85, the emotion category of the word is the emotion category corresponding to the maximum similarity value, or it is classified as no emotion words and does not participate in the emotion computation.
- Step 4: Capture the emotion intensity and polarity of words. After the candidate words are classified, the seed words closest to the unknown words are extracted. The emotion intensity is the intensity of the unknown words, and the polarity is the polarity of the unknown words.
- Step 5: Expand the emotion dictionary. The emotion category, emotion vocabulary and emotion intensity of the above algorithms are successively written into the table to obtain the expanded emotion dictionary, which is used as the emotion dictionary of subsequent emotion computation.

Finally, the expanded emotion dictionary used for fine-grained emotion analysis in this paper mainly consists of four parts: emotion word, emotion category, emotion intensity and emotion polarity. For a comment text, this paper can carry out syntactic analysis and extract the quads according to the defined extraction rules. Then the similarity between the unknown words and the known emotion words is calculated to obtain the emotion attributes of the unknown words, and the subsequent fine-grained emotion calculation is carried out.

2.2.3 Fine-grained emotion computing model

The fine-grained emotion computing model proposed in this paper mainly includes tendency transfer rules and emotion synthesis calculation. The architecture of fine-grained emotion computing model as shown in Figure 2.

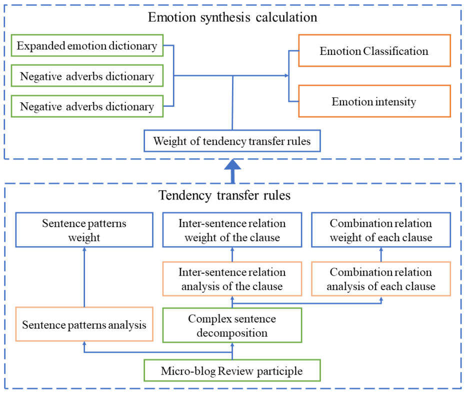

Figure 2 The architecture of fine-grained emotion computing model.

2.2.3.1 Tendency transfer rules

In addition to obtaining the emotion of words, we also need to obtain the value of text tendency transfer rules. First determines the sentence patterns of the text for exclamatory sentences, rhetorical sentences to compute the weight of sentence pattern. Then, the sentences containing multiple clauses are decomposed to obtain each clause, which is matched according to the relationship between clauses in the tendency transfer rules to obtain the weight of the relationship between clauses. Finally, the combination pattern matching of degree adverbs and negative adverbs is carried out to obtain the weight of the combination relation of each clause. Due to space limitation, specific weight calculation rules are not given in this paper.

2.2.3.2 Emotion synthesis calculation

In this paper, we use the extended emotion dictionary combined with the sentence tendency transfer rules to conduct a fine-grained emotion analysis of chinese sentences, including the calculation of emotion values and the judgment of emotion categories. The bottom-up comprehensive emotion calculation is carried out for the Chinese text from word to sentence, and the emotion classification is carried out after the emotion calculation value is obtained.

Based on the characteristics of corpus, this paper combines “joy” into “like” emotion, and the emotion category is subdivided into six granularities: like, anger, sadness, fear, disgust and surpriser. Each emotion granularity forms a unique emotion dictionary. When calculating the emotion value, the existing emotion words in the text are compared with the constructed emotion dictionary. The comprehensive emotion value of sentence is calculated according to the emotion intensity of the corresponding emotion words in the emotion dictionary, the weight of sentence patterns, the relationship between sentences, the combination mode of degree adverbs and negative adverbs. The specific calculation steps are as follows:

- Step 1: Get the emotion intensity value. The emotion words were matched with the ontology database, if the emotion words were in the ontology database, the emotion value sen_i is directly obtained; if not, the similarity calculation of seed words was used to obtain the emotion intensity value.
- Step 2: Get the emotion attribute value. For the degree adverbs and negative adverbs in the word quad, the combination pattern of degree adverbs and negative adverbs is used to obtain the weight. The calculation formula is as follows:

$$E(W) = NA \times sen_i \tag{1}$$

Where $E(W)$ is the emotion attribute value, and NA is the combination weight of negative adverbs and degree adverbs that modify the emotion word.

- Step 3: Calculate the emotion value of clause. The emotion value of each clause in the complex sentence is calculated to judge whether there is an inter-sentence relation in the clause and get the inter-sentence relation weight of the clause. The calculation formula is as follows:

$$E(S_j) = \sum_{i=1}^{n} E(W_i) \times T_j \quad (2)$$

where $E(S_j)$ is the emotion value of the clause, T_j is the inter-sentence relation weight, and $E(W_i)$ is the emotion value of the quad in the clause.

- Step 4: Calculate the emotion value of complex sentence. When calculating the emotion value of the whole text, the emotion value of each clause should be added and the influence of sentence patterns should be considered. As shown in the following formula:

$$E(S) = \sum_{i=1}^{n} E(S_i) \times R_i \quad (3)$$

where R_i is sentence pattern weight.

For any micro-blog text, various emotion values of the text can be obtained by the above emotion calculation formula.

3 Experiments

In this paper, python is used to write crawler code, and 3272 texts are extracted from micro-blog. After word segmentation and removal of stop words, the text content is transferred from traditional to simplified and from uppercase letters to lowercase letters, and then manual emotion annotation is carried out on the text, and emotion category and emotion tendency are marked. In order to reduce errors caused by manual annotation, this paper recruited five college students with experience in annotation to annotate corpus emotion. For a certain micro-blog text, if all annotated emotions are the same, take them as text emotions, or the text is not included in the emotion calculation. In order to verify the effectiveness of the method proposed in this paper, the following three methods are designed for analysis:

- Method 1: Emotion classification by using the basic emotion dictionary, namely, the Emotion Ontology Database of Dalian University of Technology, degree adverb dictionary and negative adverb dictionary.
- Method 2: Tendency transfer rules and basic emotion dictionary, negative adverb dictionary and degree adverb dictionary are used to emotion classification.
- Method 3: Dependency syntactic improved dictionary and Tendency transfer rules are used to emotion classification.

In this paper, joy and like emotion categories are combined as like, and commonly used F1 value as evaluation metric of the model. Meanwhile, evaluation metrics with obvious improvement are shown in bold in Table 2.

Comparation the results between method 1 and method 2, it can be concluded that the emotion dictionary computing model with the tendency transfer rule has better performance in the overall calculation accuracy and various emotion accuracy than the emotion vocabulary ontology database model alone. The effect of sentence patterns, sentence relationships, degree adverbs and negative adverbs on emotion was taken into account. By comparing the results of all kinds of emotion classification, the accuracy of “like”, “sadness”, “fear”, and “surprise” is significantly higher than that of “disgust” and “anger”.

For method 3, it can be concluded by observing the experimental results, the overall accuracy of the emotion classification method based on the dependency syntactic modified emotion dictionary constructed in this paper combined with the tendency transfer rules is much higher than the other two methods. And for all kinds of emotions, the accuracy of emotion judgment has been improved to varying degrees. Since the word embedding method does not consider the meaning of the words themselves, words with similar context have similar word vector embedding, and there are errors in the calculation of word similarity. Although this paper adopts the method of in-class average to judge the emotion category and reduce the accidental error, it is not absolutely accurate to judge the emotion of unknown words. In addition, the choice of seed words also affects the experimental results.

Therefore, the addition of the emotion calculation part of unknown words does not improve the evaluation of all kinds of emotions in the model. The accuracy of “like” and “disgust” is higher than that of “shock” and “anger”.

To sum up, the inclusion of sentence structure into the emotion analysis of microblog text improves the emotion evaluation metrics of multiple categories to a certain improvement compared with simply use the emotion vocabulary ontology database. After adding emotion words based on dependency syntax extraction and calculating similarity to expand the emotion dictionary. Compared with only join the tendency transfer rules in the evaluation metrics has the obvious improvement, presents the better emotion classification effect, this model is verified in micro-blog this fine-grained analysis of the feasibility of emotion.

Table 2 EMOTION CLASSIFICATION RESULTS OF THE THREE METHODS

Category	**F1**		
	Method 1	***Method 2***	***Method 3***
like	0.7177	0.7057	**0.8590**
anger	0.4696	0.4926	0.6188
sadness	0.7980	0.7644	**0.9280**
fear	0.8163	0.8208	**0.9596**
disgust	0.5573	**0.6148**	0.7524
surprise	0.5284	**0.6899**	0.7646
Average F1	0.6479	0.6814	**0.8137**

4 Conclusion

In view of the different types of emotion corresponding to multiple attribute words in the text and the influence of complex syntactic structure on emotion analysis research problems. In this paper, we propose a fine-grained emotion computation based on dependency syntax improvement dictionary which can help mine user views and text values in texts and the validity of the model is verified.

In the next step, we can consider adding the part of network hot words to increase the coverage of the emotion dictionary. The more complete the emotion dictionary, the better the effect of emotion analysis. In addition, the text with unclear emotional expression also needs further research.

5 Acknowledge

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