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Fine-Grained Emotion Analysis Based on Mixed Model for Product Review

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Abstract

Nowadays, with the rapid development of B2C e-commerce and the popularity of online shopping, the Web storages huge number of product reviews comment by customers. A large number of reviews made it difficult for manufacturers or potential customers to track the comments and suggestions that customers made. This paper presents a method for extracting emotional elements containing emotional objects and emotional words and their tendencies from product reviews based on mixed model. First we constructed conditional random fields to extract emotional elements, lead-in semantic and word meaning as features to improve the robustness of feature template and used rules for hierarchical filtering errors. Then we constructed support vector machine to classify the emotional tendency of the fine-grained elements to achieve key information from product reviews. Deep semantic information imported based on neural network to improve the traditional bag of word model. Experimental results show that the proposed model with deep features efficiently improved the F-Measure.

Keywords: emotional element detection; emotional tendency judgment; deep features; semantic clustering

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1. Introduction

Fueled by numerous Internet users, Internet shopping has stepped on a stage of rapid growth. Online shopping is not only more convenient, but also can provide consumers more overall shopping reference information. In addition, with the popularity of the micro-blog, network users often comment on the popular products to publish their love or disgust for various characteristics of the products. The reviews originally only in e-commerce sites or professional online comment sites began appearing on the micro-blog platform quietly.[1] Thus, product review data become more and more huge.

Different from the business promotion, the product reviews tend to be more objective in reflecting the real situation of the product, such as appearance, quality and user experience. Access and analyze these comments accurately and quickly not only can provide support for user's purchase decisions, but also can help the business know the opinions and suggestions of the customers in order to improve their product's quality and service.[2] Therefore, it is more necessary to know people's shopping emotion and the factors that affect online shopping. However, people can't optimize their purchase decisions easily in face of large amount and complex content of product reviews.[3]As we all know, it is difficult to get the valuable information from a flood of online review data.

In order to solve this problem, a number of e-commerce sites used star rating to quantify the user's comment of the product. This method simplifies a product review to a certain extent. It is convenient for users to get the evaluation, but also lost a lot of important details. Then, some websites refined the evaluation classification and listed some major attributions to overcome the shortcomings of the general five-star system. This method lets users evaluate on each product attribute which is listed and provides the evaluation to customs as a shopping reference. But it also brings some disadvantages. First, the properties of people concerned may change at any time. So the fixed set of attributes may gradually become unreasonable with the passage of time. Secondly, people usually prefer to use natural language to express their feelings and emotions, so a fixed set of attributes is not conducive to enhance the user experience. How to analyze the review data quickly and find the information we need is a challenging task. Using natural language to express idea and cognition is the most natural way of human. Thus, using natural language processing (NLP) technology to deal with user's product review data is the most ideal way currently. Researchers have developed some effective review emotion classification system based on NLP.[4, 5, 6]Among them, T. Wilson et al.[7] developed a system called OpinionFinder which can recognize the subjective sentences from product reviews and mark various aspects of the subjectivity in these sentences, including emotional tendency.

2. Related Work

Product review mining is mainly divided into four tasks: review element extraction, subjective sentence tendency judgment, user review extraction, [8] user review tendency judgment.[9] Although good progress has been made in these tasks,[10, 11] there are still some problems that need to be solved. This paper focused on product element extracting and tendency judgment automatically from the massive product review data using NLP. It contains two subtasks. One is emotional element detection which contains emotional object and emotional word detection, the other is emotional tendency judgment based on the emotional element.

B. Ge et al.[12] proposed a method based on HowNet to calculate lexical semantic similarity. D. Garcia and F. Schweitzer[13] introduced particularities of emotional communication in reviews, customer preferences in valence dynamics to model collective emotions in product reviews. The proposed model can reappear positive and negative emotions expressed in product reviews. F. V. Ordenes et al.[14] proposed a linguistics based approach framework by surrounding three value creation elements: activity, resource and context to analyze customer textual feedback. N. Hu et al.[15] used emotional seed word expansion to construct emotional lexicon, then obtained the sentiment score of the reviews by calculating the number of the matched terms to analyze the sentiment. L. Liu et al.[16] combined conditional random fields with syntax tree pruning for the fine-grained emotion analysis of product reviews. The tri-training method based on MapReduce was used to get the emotional words. Liu and Ma[17] adopted frequent item set mining algorithm Apriori[18] to realize the feature detection of product reviews. Then they used the co-occurrence relation between the product characteristic words and emotional words to achieve the detection of emotional words.

Emotion classification can be divided into three levels according to different granularity: word level,[19, 20] sentence level,[21, 22] and chapter level.[23, 24] Up to now, there are many researches on sentence level and chapter level, but the word level is relatively less. W. Shi et al.[25] analyzed public microblog sentiment by constructing fuzzy ontology of emotion and calculating the influence of text. He discovered that there is a close relationship between the public's emotional expression and the government's response to the incident. S. M. Kim and E. Hovy[26] used the N-gram model with the position feature and word evaluation feature for sentence level sentiment classification. H. X. Shi and X. J. Li[27] used a semantic annotation for shallow semantic analysis and calculated the emotional tendency of the sentence by a statistical method. L. J. Zheng et al.[28] compared the difference between sentence level sentiment classification and chapter level sentiment classification, then found that particle level has a great influence on the classification accuracy. B. Y. Li et al.[29] proposed a method to analyze the chapter sentiment based on a single annotation cascade model which combined sentence patterns with sentence position as the characteristic.

In this paper, a fine-grained emotional element detection and emotional tendency judgment method based on conditional random fields (CRFs) and support vector machine (SVM) was proposed. First, syntactic feature, semantic role feature, part-of-speech feature and other features are introduced into this method and CRFs is constructed for emotional word and emotional object detection. Then emotional element collocation, syntactic feature, deep semantic of emotional element and emotional word polarity feature are used to construct SVM for emotional tendency judgment. Finally, get the three-tuple <emotional object, emotional word, emotional tendency>. The emotional tendency in the three-tuple represents the emotional object tendency in the sentence environment.

3. Emotional Element Detection

Emotional element detection is the main task in the field of opinion mining. We used sequence labeling to solve this problem. The most representative and commonly used model is conditional random field.

3.1. Basic principles of conditional random fields

Conditional random fields (CRFs) are undirected graph learning model proposed by Lafferty in 2001 based on the maximum entropy model (MEM) and hidden markov model (HMM).[30] CRFs combined many excellent properties of HMM and MEM, these excellent properties make CRFs are very suitable to solve the sequence labeling problem. CRFs normalization in the global scope, they don't have the assumed constraints like HMM. Thus, CRFs can really connect the context. At the same time the probability statistical considered path of CRFs is on all the states, so no path on part of states could be optimal, this overcomes the label bias problem of MEMM.

Three key steps to CRFs are the selection of the feature function, the parameter estimation and the model inference. The selection of the feature function directly determines the performance of the model, the training speed of CRFs is slow, the selection of a good feature function can greatly improve the performance of CRFs, the parameter estimation is to learn the parameters of CRFs model by the labeled training set, equivalent to the process of training; model inference is to infer the most likely state sequence based on the model parameters.

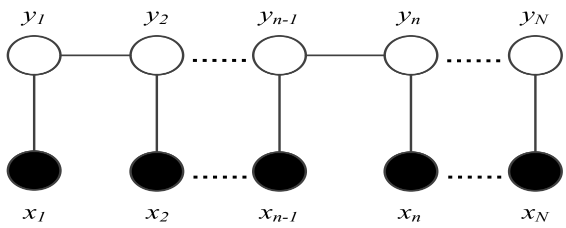

Fig. 1. Structure of linear chain CRF

CRFs is to calculate joint probability of the tag sequence with the given observation sequence. Fig. 1 shows the linear chain CRF used in this paper, it is an efficient implementation of CRFs. Assume the given input sequence is $x(x_1,x_2,x_3...x_n)$, and the conditional probability for a state sequence is $y(y_1,y_2,y_3...y_n)$. According to the conditional random field theory:

$$p(y \mid x, \Delta) = \frac{\exp(\sum_{n,m} \lambda_m f_m(y_{n-1}, y_n, x, n))}{M(x;\Delta)}. \quad (1)$$

Where $f_m(y_{n-1}, y_n, x, n)$ represents the combined feature function of transitional feature function $t_j(y_{n-1}, y_n, x, n)$ which says the transitional probability between position n-1 and n in the observation sequence and state feature function $s_k(y_n, x, n)$ which represents the state feature of the position n in the observation sequence. *M(x;Δ)* is the normalization for each input:

$$M(x;\Delta) = \sum_y \exp(\sum_{n,m} \lambda_m f_m(y_{n-1}, y_n, x, n)). \quad (2)$$

Emotional word and emotional object detection can be regarded as a sequence labeling process. So emotional words and objects can be extracted synchronously by CRFs.

3.2. Select multi-granularity features

Most traditional methods extracted emotional objects by using CRFs,[31] while emotional words were ignored. Or found the emotional words first and then extracted the emotional objects by association rules.[32] Different from the traditional element detection, emotional objects and emotional words will be extracted synchronously in this article. This article focused on the sentence structure and semantic, so the dependency syntax features and syntax tree features were introduced. The features used in the detection are as follows:

- Word Feature (WF): Words are the smallest grammatical unit that can express the meaning of words. Emotional words and emotional objects are both consisted of word.
- Part of Speech Feature (POS): POS is an implicit feature, one of the characteristics of natural language processing frequently used. Some POS used in this article are as follows:

> Structure word, Preposition, Entity name, Adjective, Personal Pronouns, Onomatopoeia, Place name, Verb, Omit the word, Demonstrative Pronoun, Emoticon, Interjection, Modal Particle, Tense word, passive participial，……

- Semantic Role Dependency Parsing (DP): Semantic role dependency parsing is not only a more advanced and more in-depth implicit feature, but also is a manifestation of sentence semantic. The semantic roles used are as follows:

> Subject, Object, Preposition, Relevance, Complement, Questions linked, Punctuation, Sigh, Tense, Parallel, Linked, de structure, Attribute, Adverbial, Quantity, Voice, structure of modification

- Parent of the word in syntax parse tree (PW): In the syntax parse tree, each word has a parent node and has some kind of relationship with its parent node. The output form of syntax tree parser is like W_i/DP_i /$Index_i$, it represents that the parent node of the word W_i is the word $Index_i$, and there a relationship DP_i between the two words. It can be formalized as follows：

$$\begin{cases} W_i = Word(i) \\ parent(i) = Word(Index_i) \\ relation(i) = DP_i \end{cases}. \quad (3)$$

Where *parent(i)* is the parent node of the i-th word, *Word(i)* is the i-th word, *relation(i)* is the relation between *Word(i)* and *Word(Index$_i$)*.The word itself, part of speech and semantic role of a word's parent node in judging whether a word is an emotional object or emotion word can play an important role.

- The Part of Speech of a word's parent in syntax tree (PPOSE).
- The Semantic Role of a word's parent in syntax parse tree (PDP).

3.3. Sequence labeling with CRFs

Emotional word and emotional object detection can be considered as marking out some specific words from the word sequence. Therefore, this problem can be handled by CRFs. The label list and the meanings are as showed in Table 1. This paper only considered the situation of the emotional objects and the emotional words in pairs. The output format of CRFs is emotional object and emotional word pair.

Table 1. Label list for conditional random fields

Label	Description
BA	Emotional object in front of emotional word
BB	Emotional word in front of emotional object
EA	Emotional object behind emotional word
EB	Emotional word behind emotional object
SA	Emotional object without emotional word
SB	Emotional word without emotional object
P	Punctuation
O	Others

In the label list, BA and EA both represent emotional object, BB and EB both represent emotional word. The difference between them is the location relationship. Different location relationship should be treated differently. Examples:

(i) Keyboard/BA is/O very/O good/EB
(ii) very/O good/BB Keyboard/EA

In sentence i, Keyboard is an emotional object in front of the emotional word good. In sentence ii, Keyboard is an emotional object behind an emotional word good. These two types cannot be regarded as the same situation and need to be distinguished according to the order.

Strictly speaking, SA is not emotional object, it is just object. Although SB is an emotional word, but cannot find the emotional object corresponding to it. But SA and emotional objects have many similar characteristics, and also SB and emotional word have many similar features. Therefore, in order to prevent the CRFs tagging errors, separate them into two new categories. The number of labeled O is much more than others. To balance the data, punctuations are separated from O, and marked as P.

3.4. Emotional object and word detection

The complexity of labels increased the difficulty of detection, so some rules as follows were used for hierarchical filtering errors.

Algorithm: hierarchical filtering errors with rules

```
Begin:
   if WordLabel= SA OR WordLabel = SB OR WordLabel = O:
     no processing
   else if  WordLabel =P OR CurrWord reach the end of a sentence:
        if  SS != NULL:
        put SS into SSSet;
        if  SSSet not empty AND SW != NULL:
        put SSSet and SW into WPSet;
        Reinitialization
        else if  WordLabel = BA OR WordLabel =EA:
           if  CurrWord and SS are parallel relationship:
           put SS into SSSet, set SS=CurrWord
           else: SS and CurrWord are spliced into SS
         else if  WordLabel =BB:
         set SW=WordLabel, SS=NULL;
         else if  WordLabel =EB:
       set SW=CurrWord and do same processing as WordLabel =P
End
```

In the pseudocode above, CurrWord is current word. WordLabel is the label of the current word. SS is current emotional object. SW is current emotional word. SSSet is a collection of emotional objects. WPSet is the emotional object and emotional word pair collection. BA and EB, BB and EA are in pairs in most cases, but some special structure of sentence and CRFs mislabeled could cause BA, BB, EA, EB appear alone or in the wrong order. It would reduce the detection accuracy if these errors cannot be deal with. Some examples as follows:

(i) yesterday/O received/O computer/SA
This is a non-opinion sentence, just have an object computer, no emotional word, so just simply ignore it.
(ii) Processor/BA and/O graphics-card/BA are/O both/O very/O Strong/EB
Processor and graphics-card are both marked as BA and they are parallel relationship. So they are both extracted as emotional object.
(iii) The/O type/O of/O phone/BA is/O cheap/EB and/O good/EB
There are two emotional words in this sentence. In order to prevent cross-contained between words, just one emotional word would be extracted.

By using the rules above, most interfering data can be filtered, and the accuracy of emotional object and emotional word detection can be improved.

4. Emotional Tendency Judgment

This part aimed at analysis the tendency of emotional object and emotional word pairs, so it belongs to phrase level. Phrase level emotion classification is lack of context features, thus we introduced syntactic structure information to improve the accuracy of sentiment classification.

4.1. Basic principles of support vector machine

SVM was proposed by the Cones and Vapnik in 1995.[33] It is a statistical machine learning method and is mainly used to solve classification problem. In the case of binary linear separable categories, there are numerous splitting planes which can divide samples into two types correctly. SVM can maximize classification interval, as shown in Fig. 2.

H_1 and H_2 are parallel to H and they are close to the two kinds of samples. Such distance between H_1 and H_2 is called the interval. The optimal classification line is to find the classification line which makes the interval maximum. The samples on H_1 and H_2 called support vector. Use the following formula to express the classification line:

$$w \cdot x + b = 0 \quad w \in R,\ b \in R. \tag{4}$$

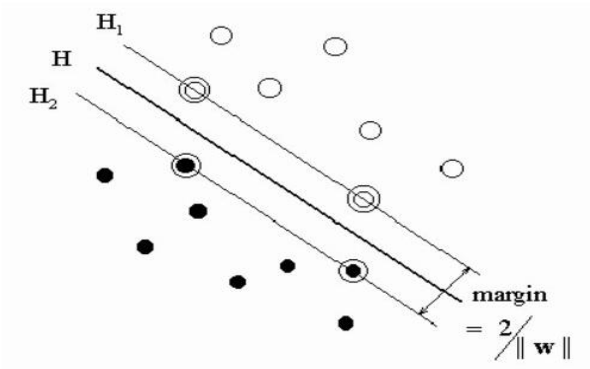

Fig. 2. Separating hyperplane

Only by minimizing the $\|w\|^2/2$ then we can get the optimal classification line. $\|w\|$ is the two norm of w. Because the fine-grained analysis of the emotional tendency in this article can be regarded as a classification problem, so SVM can be used to solve this problem.[34]

4.2. Select deep features for support vector machine

The same emotional word would possibly exhibit different emotions when it modified different emotional objects. Therefore, to analyze the emotional tendency more accurately, only consider the emotional word is not enough. The sentence structure and the dependent relationship of emotional words and emotional objects must be combined. Since this article just analyzes the emotional tendency of emotional word and emotional object pair, so the syntactic structure of the whole sentence does not to be considered. We only consider whether there are some words can reverse the emotion and the combination of emotional words and emotional objects. Following are some features and descriptions adopted in emotional tendency judgment:

- Emotional object (SS): As mentioned above, the same word when modified the different emotional objects, tendency may be different. So the impact on the final analysis result by emotional object need be taken into consideration.
- Emotional word (SW): Emotional words indicate emotional tendency, each word has a basic emotional feeling.
- Emotional object semantic code (SSC): Assuming the emotional tendency of "processor frequency is very high" is known, but "CPU" specific meaning is unknown. And also the relationship between "CPU" and "processor" is unknown. It is difficult to know the emotional tendency of "CPU frequency is very high". If the fact that "processor" and "CPU" have the same meaning is known, then the latter's emotional tendency can be judged correctly and easily.

  Human can easily understand "processor" and "CPU" are similar, but for computer, it is very hard. In order to make the computer also know two words whether have similar meaning, the code of emotional object semantic (SSC) was introduced. If w_1 and w_2 have the same semantic code, it can be expressed as follows:

$$\mathrm{SSC}_{w_1} = \mathrm{SSC}_{w_2}. \tag{5}$$

  In chapter 4.3, a method would be introduced in detail to get the semantic code.
- Emotional word semantic code (SWC): Like SSC, SWC is used to show two emotional words whether have the same or similar meaning.
- Emotional tendency inversion (ETI): Whether there is a word to reverse emotional tendencies. For example, "the product quality is not very satisfied." If not consider the negative word, the emotional tendency of the sentence will be misjudgment as positive. In the syntax parsing tree, "not" as an adverbial modifier "satisfied". So to know whether there is a word to reverse the emotional tendency, just go through from the syntax parsing tree to find the sentence whether contains a negative word as adverbial to modify emotional word.

$$feature = \begin{cases} 1 & \text{modified by negative word} \\ 0 & \text{not modified by negative word} \end{cases}. \tag{6}$$

- Basic emotional tendency of emotional word (BPW): The basic emotional polarity of emotional word is the fundamental basis for emotional tendency classification. In most cases, the tendency of emotional object and emotional word pair is same as the basic emotional polarity of emotional word. The basic emotional polarity can get from HowNet. If the word is not in HowNet, the basic emotional polarity can get by SO-PMI algorithm. Pointwise Mutual Information (PMI) is calculated by the following formula:

$$PMI(w_1, w_2) = \log \frac{P(w_1, w_2)}{P(w_1)P(w_2)} . \tag{7}$$

$P(w_1,w_2)$ is the co-occurrence frequency of w_1 and w_2.SO-PMI is calculated by the following formula:

$$SO\_PMI(\mathrm{w}) = \sum_{pw \in p_{set}} PMI(w, pw) - \sum_{nw \in N_{set}} PMI(w, nw) . \tag{8}$$

Here, P_{set} is positive emotion word collection and N_{set} is negative emotion word collection.

4.3. Deep learning based semantic code acquisition

Semantic code refers to a code number of a word collection in which the words have the same or similar meaning. That is to say if two words have a similar meaning, they belong to a same collection, also have a same semantic code. A word could belong to multiple collections with multiple meanings code because of multiple meanings. Semantic code can be constructed by a synonym dictionary, but the existing synonymous dictionaries are not complete. Lots of words did not appear in them, especially the oral vocabulary. And synonym dictionary was usually fixed, once developed will no longer modify. Therefore the approach of getting semantic code through synonym dictionary is poor. So we proposed an algorithm to convert the word into SSC as follows.

To cluster words, the first step is to map the word to the N-dimensional vector space according to its context. Semantic code for each word can calculate by automatic coding neural network like Feedforward Neural Network Language Model (NNLM), [35] it divided neural network into the input layer, hidden layer and output layer. The computational complexity per each training example is:

$$Q = N * D + N * D * H + H * V \cdot \tag{9}$$

Where N is the n of the n-gram, D is the dimension of each word, H is the number of nodes in the hidden layer, and V is the number of nodes in the output layer. Most of the complexities are caused by the term. Therefore, removal of hidden layer can be accelerated, and the computational complexity per each training example is (for the output layer uses the Huffman codes):

$$Q = N * D + D * \log_2(V) . \tag{10}$$

Through multilayer neural network, each word can be mapped to a N-dimensional space, and can easily calculate the Euclidean distance between any two words w_i and w_j.

$$S(i,j) = \sqrt{\sum_{k=1}^{n} \left(x_{ik} - x_{jk} \right)^2} . \tag{11}$$

Then using the K-means algorithm to cluster all the words according to their meaning vector, center coordinates of each category is calculated by the following formula.

$$x_i = \sum_{j=1}^{m} x_{ji} \Big/ m . \tag{12}$$

According to the formula $\arg \min_{1 \le i \le k} S(i,j)$, the words belong to which category can be determined. By the above method to learn from a large number of data, thus the words can convert into vectors, then using the K-means algorithm to cluster all the words according to their meaning vector, give each category a fixed unique number, this number is the semantic code of this category words.

5. Experiment and Result Analysis

5.1. Emotional element detection

In order to verify the effectiveness of the proposed method, we have carried out a series of comparison experiments. First we used the product reviews from www.tmall.com to construct review corpus. It contains 20 types of electronic product review, 4146 review data (artificial tagging). We used 2500 as the training set, and the rest as a test set, marked as Corpus 1. We used the method based on CRFs model and the method based on association rules to detect the emotional objects and emotional words. The result is shown in Fig. 3.

5-fold cross-validation was used to optimize parameters on the training set. We can see that the precision is high and the recall rate is relatively low.

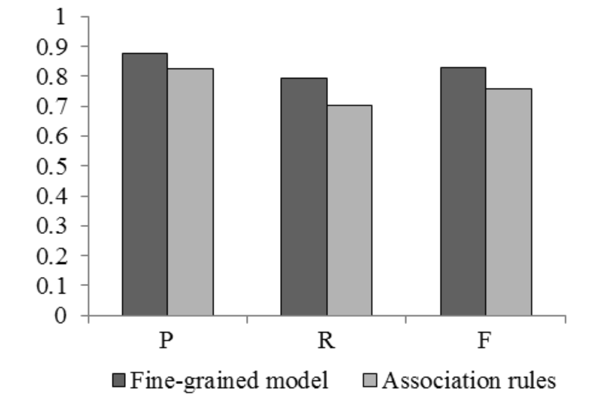

Fig. 3. Emotional element detection result comparison on product reviews

The high accuracy is because the features selected make the detection rules stricter. As long as the condition gets satisfied, almost can guarantee it corrects. Recall rate is relatively low not only because of the great arbitrariness of colloquial language in comments expressed. Another important reason is that there are lots of typos and punctuation missing in the reviews. It reduced the accuracy of word segmentation and POS tagging.

We can also see that the method based on CRFs get a better result than the method based on association rules because the limitation of the method based on association rules is relatively bigger. It can get good effect on regular sentences, but it performed badly for the complex sentences of greater freedom degree.

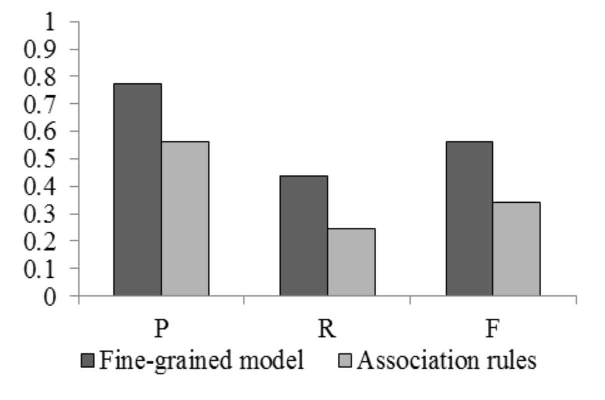

Fig. 4. Emotional element detection result comparison on micro-blog

In order to improve the robustness of the method, we collected 2000 micro-blog review data and made artificial marks on them. Then 1000 of them were used as the training data and the other as the test data to construct micro-blog corpus which marked as corpus 2. The result is shown in Fig. 4. We can see that though the result is not good as the previous result on review data, but it is still a good result. The decline of precision is not obvious which verified the effectiveness of the proposed detection method. The recall rate fell more, mainly because the content of micro-blog is more diverse than the reviews. It means more complex sentences and more new words. So emotional object and emotional word detection is more difficult. This is also the reason why the research on micro-blog corpus generally got low recall rate.

5.2. Emotional tendency judgment

Emotional tendency labeling was performed by artificial for the emotional object and emotional word pair which extracted in the previous section. In order to verify the validity of the fine-grained sentiment classification method, we used three methods to judge the emotional tendency on the same corpus for comparing.

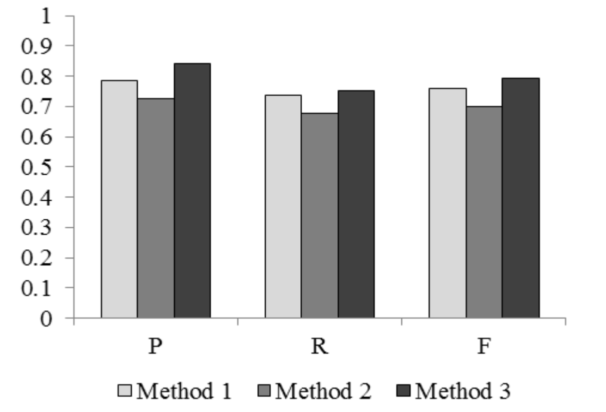

Fig. 5. Emotional tendency judgment result comparison on product reviews

Method 1: the method based on sentence; Method 2: the proposed fine-grained classification method; Method 3: the proposed fine-grained classification method with semantic code. The unlabeled review and micro-blog mixed data containing 500 thousand product reviews and 500 MB micro-blog were used to get the semantic code. The comprehensive result is shown in Fig. 5. It should be noted that the fine-grained model is based on the emotional element detection which is only recognized the objects and words that extracted in section 5.1. So the results of the previous task have a direct impact on the recall rate of current experiments. We did the same comparison experiment on the corpus 2. The result is as shown in Fig 6.

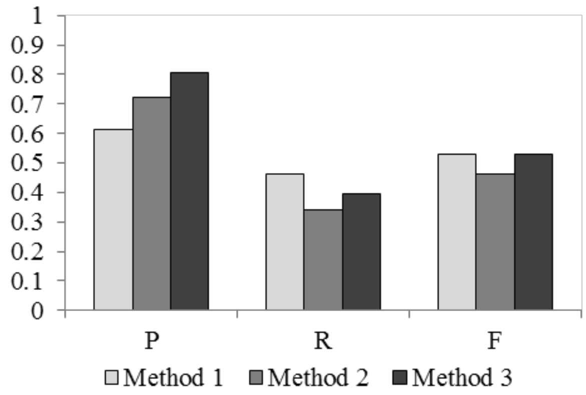

Fig. 6. Emotional tendency judgment result on micro-blog

It can be observed from Fig. 5 and Fig. 6 that the fine-grained classification model with semantic code is significantly better than the sentence level emotional judgment. The introduction of semantic code greatly improved the accuracy of emotion classification. The reason why semantic code can get a better result is that fine grained itself is targeted to emotional objects and emotional words. The introduction of semantic code further made up the loss of the sentence and semantic. And the method based on sentence classification is so general that erroneous judgement was happened easily for the sentence of more than one emotional object.

To have an intensive study on the deep learning based semantic code, we used the two different sources to obtain the SC. One is the mixed unlabeled corpus used in section 5.2; the other is a text source of 1GB micro-blog data.

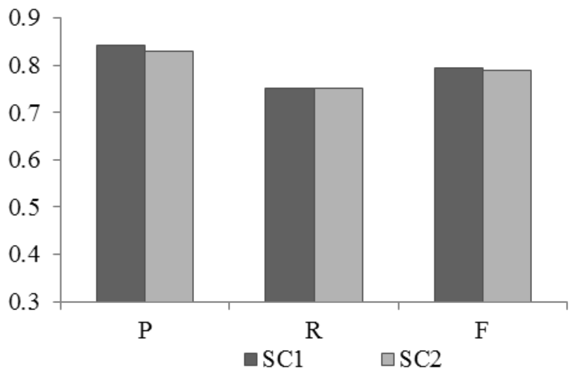

Fig. 7. Semantic code research on product reviews

The only difference between them is we changed the product reviews in the first data into micro-blog data. Then we did the emotional tendency judgment on both corpus 1 and corpus 2.The result of corpus 1 is shown in Fig. 7 and the result of corpus 2 is shown in Fig. 8.

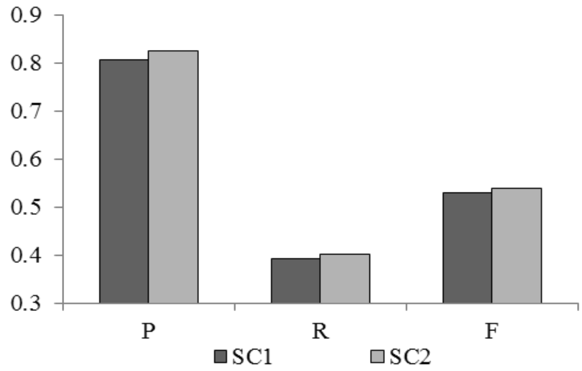

Fig. 8. Semantic code research on micro-blog

The experimental results tell us an important index of corpus which can train a better semantic code from Fig. 7 and Fig. 8. That is type. When we changed the product review data into micro-blog data, we can see the result of corpus 1 get worse and the result of corpus 2 get better. In other words, SC1 gets by product reviews have a bigger influence on product review corpus than micro-blog corpus and the SC2 gets by micro-blog as well has a bigger influence on micro-blog corpus. This means the consistent performance of the corpus can effectively improve the final emotion judgment. This phenomenon is due to the expression and word usage habit of the different types of corpus will result in large differences, for example, great difference between journalism and micro-blog. So the characterization ability of semantic codes iterated from different corpus will have differences in different areas. The experimental results above further demonstrated the effectiveness of the proposed method in this paper.

6. Conclusion and Future Work

By analyzing the experimental results, it can be concluded that the proposed method can ensure the correct rate and the recall rate of product review corpus is high. Although the recall rate of micro-blog corpus is low, but compared with other similar methods, also achieve a higher performance because of the introduction of semantic information with deep features.

Although this article has achieved good experimental results, but for cross-cutting and complex sentences, accuracy and recall rate can still be further improved. Further work will be carried out from the following aspects. A large number of wrong spelled words, new words, emoticons and special symbols exist in microblogging which seriously affects the accuracy of word segmentation and POS tagging, especially the construction of the parse tree. Such phenomenon should be further processed. And the features and the template currently used were so strict that flexibility and generalization are not enough. Though this can ensure the correct rate, but also reduced the recall. Appropriate adjustments can make a best balance between precision and recall rate.

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