Quantification of emotional values for attributes from sentiment analysis based on mobile phone reviews

Wan Tao, Qiang Zhang, Mengyao Zhang, Yan Jiang
School of Computer and Information Science, Anhui Polytechnic University, Wuhu 241000, China
taowan@ahpu.edu.cn, 15009673@qq.com,

Abstract. E-commerce online reviews are commonly short in length, lack of contextual semantics, and are mixed with explicit emotions and implicit emotions. The subjects of implicit emotions are not easy to be extracted and be defined. Now product-oriented attributes are used to define implicit and fine-grained emotions with the help of the domain emotion dictionary that is constructed by extracted explicit attribute-emotion pairs through using a variety of part-of-speech rules. And implicit emotion and attribute pairs for product “mobile phone” are mined with the help of explicit attribute-emotion pairs and probability calculation method. At last, explicit and implicit emotion values are calculated by considering degree and negative modifiers. The experimental results show that proposed method is effective and has certain commercial value. And the process method is easy to extend to other product fields.

1. Introduction
In recent years, Chinese online trading platforms such as Taobao and Jingdong have developed rapidly. Users have gradually changed roles from recipients of information to providers of information. The platform has accumulated a large number of online reviews from buyers over time. This massive textual information contains all kinds of emotional information of users about commodities, which will affect the views of potential users on commodities and even influence the decision-making of users. Sentiment analysis can be used to analyze the user’s emotional tendencies towards the related attributes of purchased goods from online reviews, which can provide precise feedback information for manufacturers and distributors, thus helping manufacturers and distributors to better carry out future production and marketing activities[1]. In addition, the emotional analysis results of online reviews can provide potential consumers with decision-making information in consumption.

When analyzing specific attributes of objects, attributes can be divided into explicit attributes and implicit attributes when they are expressed. The attributes directly appearing in the comment sentences are explicit attributes, such as: “The price is a little expensive, the appearance is very beautiful.” In this commentary, the attributes are “price” and “appearance”, and the emotions are “expensive” and “beautiful”. The attributes that do not appear literally are implicit attributes. Because users use flexible language in reviews, implicit attributes are very common, such as “P10 is too expensive to afford.” In this sentence, the emotion is “expensive”, but the attribute words do not appear, but it clearly describes “price”. Because online reviews present short text and mixed explicit and implicit states of attributes, how to accurately extract attributes and emotions for different attributes, especially for implicit attributes is a hot and difficult topic in recent years.

Most of mainstream methods such as based on syntax and grammar rules, based on topic model and based on machine learning and other attribute features extraction methods focus on the extraction of
attribute words in commentary sentences[2-5], or through the extraction of emotional words to help the extraction of attribute words. However, single attribute judgment of review sentences is not of great value to the results of emotional analysis. Taking mobile phone reviews as an example, such as “Mobile phones are good at everything, but they are too expensive”, it is obvious that the price of mobile phone is expensive, but the attribute of “price” has been lost. So the attribute and the emotional value of the attribute are separated, cutting down the effect on judging the merits and demerits of each feature of the mobile phone.

Now, this paper transform attention from attribute words extraction to emotional words extraction in online Chinese commentary corpus. Firstly, emotional words (especially some individual emotional words) are extracted by the pre-defined rules from commentary sentences containing explicit attributes and emotions. Secondly, corresponding attributes along with emotional words are extracted out with the help of domain dictionary as well as some new pairs are appended into domain dictionary. Finally, from commentary sentences containing implicit emotion, the implicit attributes of opinion are obtained by combining feature-emotion pairs. The most important thing is to calculate the emotion value of explicit and implicit attribute to make a fine-grained analysis. The experiment shows the effectiveness of the process. It can improve the extraction efficiency of attribute-emotion pairs, and it is also very helpful for the emotional analysis of product attributes.

2. Emotion quantification process from sentiment analysis

Using emotional dictionary is a common method of sentiment analysis. [7] first constructs some feature-opinion pairs in the commentary sentences containing explicit attributes and emotions by means of self-built emotional dictionary and then obtains the implicit attributes of the opinion in the commentary sentences containing implicit emotions by combining attribute-emotion pairs. This paper draws on its implicit attribute acquisition method, but has the following improvements:

1) Constructing a domain emotional dictionary. General Chinese Emotional Dictionary includes HowNet and NTUSD. Compared with general Emotional Dictionary, domain dictionary has stronger domains, which makes the analysis accuracy in corresponding domains higher.

2) Using multi-word rules to mine more explicit feature-emotion pairs. The method in [6] is to extract nouns or noun phrases from commentary sentences as attribute words and adjectives as emotional words. This method has been used by many researchers since Liu [6] first proposed it. However, the effect of using this method in some commentary sentences is not satisfactory. Such as an sentence--“It is very good for P10 to take pictures.” In this sentence “take pictures” can be consider as a verb. But “take pictures” should be treated as an attribute word from semantic perspective. However, according to the method in document [6], the attribute word of “taking pictures” cannot be extracted.

3) The explicit feature-emotion pairs obtained in step 2 are added to the domain emotion dictionary constructed in step 1. On this basis, specific part-of-speech rules and some statistical algorithm are used to extract implicit emotions.

4) Quantitative analysis of emotional value is carried out for explicit and implicit commentary sentences to achieve better results.

The framework of the whole process is shown in the Fig. 1.

Fig.1 Emotion quantification process based on domain dictionary
2.1 Constructing the domain emotional dictionary
In order to reduce the differences caused by different shopping platforms, according to the proportion of platforms crawling, several comments were extracted by random extraction method. Firstly, Jieba word segmentation toolkit is used to analyze the captured Chinese comments and pre-process them to build an emotion dictionary. Then, modifier words such as negative words are extracted to enrich emotional dictionary.

At present, the influence of modifiers on emotional words is rarely considered, especially in Chinese. However, considering the role of modifiers in emotional quantification will make the analysis results more fine-grained, thereby improving the analysis effect. For example, “excellent” or “very good” have stronger emotion than “good”. So, the modifiers are important in words emotion expression.

Now, the segmentation mode of Jieba is defined based on its native dictionary and domain dictionary of mobile phone to consider the influence of modifiers on emotional words. For example, a sentence “Power consumption is very fast” is divided into “power consumption”, “very”, “fast” but not into “power consumption”, “very fast” to consider the effect of modifiers on emotional words. Some modifiers and weights are shown in Tab. 1.

| Degree modifiers | Weights | Frequency modifiers | Weights |
|------------------|---------|---------------------|---------|
| yet              | 0.4     | very few            | 0.4     |
| slightly         | 0.6     | never               | 0.6     |
| still            | 0.8     | occasionally        | 0.8     |
| very             | 1.4     | from time to time   | 1.4     |
| most, really     | 1.6     | often               | 1.6     |
| extremely, excellent | 1.8 | always              | 1.8     |

Weight labelling is carried out by using the existing Hownet modifier dictionary and synonym forest[8]. Weight labelling refers to the weights of modifiers in Hownet dictionary, but the weights in Hownet represent integers ranging from 0 to 10, which affect the subsequent quantitative calculation. Therefore, the data range is standardized from 0 to 2.

In addition, online reviews also contain negative words such as “no” and “don’t”. Although their forms are simple and single, the number of negative words is large, and they can completely change the meaning of comments, which is of great significance.

Emotional dictionaries for specific domain are organized in a five-tuple format as follows:

\[
\{ A, M, N, E, V \}
\]

Where A represents “attribute words”, M represents “modifiers”, N represents “negatives”, E represents “emotional words”, V represents “values of concern”. Among them, the values of “modifiers” and “negatives” can be empty. “values of concern” presents the count of the coexistence of attributes which are the combinations of negative words, modifiers and emotional words. The larger the numerical values of concern, the stronger the emotion of the related attribute.

For example: \{battery, , no, durable, 29\}

In the example, the modifier is empty, the number “29” refers to that exists 29 emotional composition words which contain the meaning of “battery is not durable” in the commentary sentences related to specific attribute to be analyzed.

2.2 Extraction of implicit emotion-attribute pairs
When users comment on product attributes, there are many kinds of statements. For instance, “nice”, and “fashionable” are suitable for describing the appearance of mobile phones, otherwise “nice” can also be used to describe the screen of mobile phones, etc. But “nice” in Chinese context is not suitable for describing “running speed” and “battery” of the mobile phone's attributes.

So a matching rule of emotions and attributes is defined. That is, for the emotional word \(i\), if the number of matches between \(i\) and \(s\) is greater than that between \(i\) and \(t\), then the contribution of the word \(i\) to the feature \(s\) is greater than the contribution of its to the feature \(t\). As a result, emotional word \(i\) and feature word \(s\) can form an emotion-attribute pair \(i, s\).
For example, the number of matches between “beautiful” and “appearance” is “231”, and that between “beautiful” and “taking pictures” is “196”. Obviously, the contribution of the word “beautiful” to “appearance” is higher than that to “taking pictures”. Since a definite feature-affective pair has been formed in the emotional dictionary, it can be used to determine the contribution of the existing emotional words to the specified attributes.

For a non-existent emotional word, the probabilities of its occurrence with different attributes are calculated. The emotional word will be assigned to the attribute which has the largest probability. Then they form a new emotion-attribute pair to append to emotional dictionary.

2.3 Quantification of emotional value

The formula for quantifying the emotional value $S$ of attribute $A$ is shown in formula 1.

$$S(A) = \alpha \times (-1)^n \times M \times E \times V \quad (1)$$

Among them, each comment sentence is used as the smallest separator of emotional semantic unit, and $\alpha$ is the threshold of negative word weight. When the negative word is odd, $\alpha$ is 0.4 (obtained through experimental analysis) and when the negative word is odd, $\alpha$ is 0; $n$ is the number of negative words; $M$ is the weight of modifier given in Tab.1; $E$ is the mark value of emotional words. For an attribute of emotional words, it takes “+ 1” when it is positive, as well it takes “- 1” when it is negative; and $V$ is the concern value given in section 2.1.

When emotions are positive, their emotional value is positive. And when emotions are negative, their emotional value is negative. The absolute value of emotional value reflects emotional intensity.

For Examples: “The phone has an excellent appearance and runs smoothly. It's really bad to take pictures and the screen is not really good, but the standby time can't be better.”

(1) Emotional words: To analyze and describe a certain attribute is good or bad, the most basic method is to judge the emotional words it describes. Positive emotional words such as “good”, “fluent”, “perfect” and negative emotional words such as “bad”, “rotten” and so on. In this example, the emotional marker value of “appearance” is “+ 1”.

(2) There is degree modifiers “excellent” before the word “appearance”. So it is necessary to find out whether there are modifiers to modify the emotional words before they were found, and calculate the modifier score given in section 2.1 according to the degree of modification. For example, the emotional score of “appearance” in “good appearance” is “1”, and the emotional score of the attribute of “appearance” in “excellent appearance” is “1.8*1=1.8” because the weight of the modifier of “excellent” is “1.8.”

(3) Negative words: It is easy to judge that “good” in the sentence—“the screen is not really good”—does not mean “good”, because there is a word “not” before “good” to reverse its meaning. So when emotional words are found, it is needed to look for negative words, such as “not, no, cannot, do not” etc. Because there exists double negative that means affirmative in Chinese grammar, the number of negative words in sentences should be counted. According to formula 1, if the number of negative words is odd, the emotional score is multiplied by “- 1”, and if it is even, the emotional score is multiplied by “+1”. So in the sentence-- “the screen is not really good” the attribute of “screen”.is scored as “1.6*(-1) = - 1.6”

3. Experiment and Discussions

3.1 Data pre-processing

The data used in this experiment are real user reviews on Huawei P10 captured from Taobao, Jingdong and Suning e-commerce platforms from January 2018 to May 2018. The number of relevant reviews collected is 10735, 3721, 1044 and 15342, respectively. Because user reviews contain a large number of low-value texts, and the sentence patterns are not uniform, which will have an impact on emotional analysis, text pre-processing such as text de-duplication, word compression, word segmentation, and part-of-speech tagging is carried out in turn.
Finally, the remaining 15342 comment texts after the above steps are segmented and part-of-speech tagged using the stuttering Jieba segmentation.

3.2 Attribute Emotion Mining and Analysis

(1) Generating domain emotional dictionary

Firstly, 5342 reviews are extracted from 15342 reviews according to the proportion of data sources, and a preliminary emotional dictionary is constructed by manual annotation. Then, a five-tuple domain emotional dictionary is created according to the steps shown in Section 3.1. The specific process is to classify and store the attribute features in Excel file according to "modifier, negation, emotion, value of concern", and name the documents with the attribute words; then expand the synonyms of the attribute words by using the synonym forest of Harbin University of Technology. The expanding process is to mark the appeared modifiers and emotional words as dictionary terms along with taking emotional words and modifiers that do not appear to be as candidates.

(2) Quantification and Visualization of Attribute Emotion

The remaining 10,000 comments are extracted from explicit feature view and compared with the domain emotion dictionary generated before. Next, the first five attributes of explicit attributes concern value and three attributes matched by implicit emotional words are compared and analysed, as shown in Tab. 2. The Radar chart of explicit and implicit emotion values is shown in Fig. 3.

| Features              | Taking pictures | Running | Display | Touch Feeling | Battery Endurance | Sound Effects | Phone Body | Weight |
|-----------------------|-----------------|---------|---------|---------------|-------------------|---------------|------------|--------|
| Explicit value of concern | 1993            | 1392    | 1266    | 1231          | 1150              | 203           | 91         | 17     |
| Implicit value of concern | 350             | 1151    | 44      | 132           | 27                | 16            | 200        | 27     |
| Percentage of Explicit Positive Emotion (%) | 96.43            | 89.72   | 99.05   | 99.35         | 77.83             | 89.16         | 94.51      | 88.24  |
| Percentage of Implicit Positive Emotion (%) | 93.14            | 80.54   | 95.45   | 97.73         | 22.22             | 87.50         | 94.00      | 77.78  |
| Percentage of total Positive emotion (%) | 96.43            | 85.57   | 99.16   | 99.19         | 78.33             | 89.04         | 94.16      | 81.82  |
| Explicit emotion scores | 1.18            | 1.05    | 1.03    | 1             | 0.62              | 0.92          | 0.92       | 0.52   |
| Implicit emotion scores | 1.04            | 0.75    | 1.05    | 1.26          | 0.53              | 0.75          | 1          | 0.54   |
| Total scores | 1.18            | 0.91    | 1.03    | 1.03          | 0.59              | 0.91          | 0.96       | 0.53   |
| Explicit emotion indexes | 0.31            | 0.35    | 0.36    | 0.37          | 0.54              | 0.40          | 0.40       | 0.59   |
| Implicit emotion indexes | 0.35            | 0.47    | 0.35    | 0.28          | 1.70              | 0.47          | 0.37       | 0.58   |

4. Conclusion

This paper takes data from mobile phone user reviews as the research object. In order to improve the efficiency of emotion analysis, firstly the domain-level emotional dictionary is constructed, and the extended grammar extraction rules are combined to extract emotion-attribute pairs in a wider range. Meanwhile, implicit emotions are mined by using part-of-speech rules and probability calculation with the help of explicit emotion and attribute pairs. The proposed method not only is used to determine attribute attribution in implicit comment sentences but also focuses on quantitative analysis of attributes and emotions. The experimental results show that the consumers for Huawei P10 mobile phone focus on the attribute of “battery endurance”. This conclusion is in line with the general recognition of most people and shows the effectiveness of the framework and method put forward.
In the future, follow-up studies will be carried out from the following aspects:

1. Expanding the scale of experimental data sets. Although the data set used in this paper has reached 20,000 items, there is still far from perfect of analysis and mining.

2. Improving the used extracted algorithms in order to further improve the implicit emotion mining technology.

3. Migrating the proposed method to other fields for experiments, to test the availability of the proposed method, and to improve the applicability of the proposed method.

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