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Fine-grained Sentiment Analysis of Chinese Reviews Using LSTM Network

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Abstract

Customer reviews on online shopping platforms have potential commercial value. Realizing business intelligence by automatically extracting customers' emotional attitude toward product features from a large amount of reviews, through fine-grained sentiment analysis, is of great importance. Long short-term memory (LSTM) network performs well in sentiment analysis of English reviews. A novel method that extended the network to Chinese product reviews was proposed to improve the performance of sentiment analysis on Chinese product reviews. Considering the differences between Chinese and English, a series of revisions were made to the Chinese corpus, such as word segmentation and stop word pruning. The review corpora vectorization was achieved by word2vec, and a LSTM network model was established based on the mathematical theories of the recurrent neural network. Finally, the feasibility of the LSTM model in fine-grained sentiment analysis on Chinese product reviews was verified via experiment. Results demonstrate that the maximum accuracy of the experiment is 90.74%, whereas the maximum of F-score is 65.47%. The LSTM network proves to be feasible and effective when applied to sentiment analysis on product features of Chinese customer reviews. The performance of the LSTM network on fine-grained sentiment analysis is noticeably superior to that of the traditional machine learning method. This study provides references for fine-grained sentiment analysis on Chinese customer reviews.

Keywords: LSTM network, Fine-grained sentiment analysis, Chinese customer review, Product feature

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1. Introduction

Online shopping allows customers to leave reviews after purchasing and express their evaluation of the product's quality; these reviews contain abundant emotional information that is useful to customers and merchants [1]. Merchants study customers' preferences and dislikes about product features through analyzing customers' purchase decisions and reviews. Thus, products are improved in a targeted manner. However, given the large number of reviews, language style is usually non-professional. The arbitrary and irregular texts lead to difficulty in manually extracting and analyzing the reviews [2]. Therefore, the application of sentiment analysis technology has attracted the attention of scholars. Realizing the automatic mining of customers' emotional attitude towards reviews is one of the key technologies that mark the maturity of business intelligence. Through sentiment analysis on customer reviews, achieving "user-centered, sentiment-driven, self-adaptive, and interactive electronic commerce with semantic understanding" is possible [3].

At present, sentiment analysis based on customer reviews has been a research hotspot. Sentiment analysis technology can be divided into three methods, namely sentiment lexicon-based methods [4, 5], machine-learning-based methods [6–11], and deep-learning-based methods [12–16]. The classification method long short-term memory

(LSTM) [17] used in this study belongs to the deep learning method. Sentiment analysis can be classified into coarse- and fine-grained sentiment analyses in accordance with the granularity sentiment analysis of objects. The former can be classified into document- and sentence-level sentiment analyses, and the latter focuses on the evaluation objects and features. Features are also called aspects or attributes [18]. The present study discusses the sentiment analysis on product features of online purchase reviews.

The main challenge of fine-grained sentiment analysis is its low-accuracy classification and its performance requires further improvements. In English field, researchers have made achievements by using the LSTM network. However, given the complexity of Chinese texts and the difference between Chinese and English, the study results in English cannot be directly applied to Chinese reviews. The differences between Chinese and English texts are as follows:

(1) The structures of Chinese and English texts differ. English words are naturally separated by spaces; thus, the errors of word segmentation may not be produced in the experiment process. By contrast, Chinese texts require word segmentation, the accuracy of which influences the final results of the experiment.

(2) Product features are rarely represented by a single Chinese character, whereas a single English word can be used to represent product features.

(3) Wording is different between Chinese and English. Chinese characters are polysemous. The emotional polarity of the same word is different and even opposite in various contexts.

In view of the significant difference between Chinese and English, this study extends the LSTM model, which

achieves good results in the field of English, to the field of Chinese product reviews. Through this model, the problem of improving the performance of fine-grained sentiment analysis on Chinese customer reviews can be solved.

2. State of the art

According to research objects, the existing studies on sentiment analysis can be classified into document-, sentence-, and word-levels.

Document-level determines whether the overall expression of a given text is positive or negative. Pang et al. [6] adopted the Boolean weight method to provide weight to the feature items of a document. The cumulative sum was then added to judge the overall emotional polarity. Mullen et al. [8] simplified texts into bag of words and then classified them through support vector machine (SVM) classifier after expressing them through feature vector according to the statistics principle. Given that document-level sentiment analysis is actually a classification problem; Liu et al. [11] used Bayesian classifier in sentiment analysis to determine the probability of positive or negative polarity of sentiment words. Turney et al. [19] used search engine to return snippet, an unsupervised machine learning method, for document-level sentiment analysis. Sun et al. [20] incorporated an emotional model into the LDA model. The emotional label of each sentence was sampled, and the hashtags of texts then generated by LDA model sampling.

Sentence-level sentiment analysis is a further refinement of document-level sentiment analysis. This type of analysis determines whether a given statement is positive or negative. For a given sentence, sentence-level sentiment analysis initially classifies it into subjective and objective. The sentence is then determined whether it is positive or negative. Liu et al. [11] introduced the Naïve Bayesian classifier method into subjective and objective classifications of sentences. Gamon et al. [21] proposed a semi-supervised learning method to classify whether a given sentence is positive or negative. Zhang et al. [22] conducted sentiment classification by establishing a directed network diagram map. However, this approach could easily interact with each other when handling sentences from a review with positive and negative evaluations. Based on theory of semantic similarity between sentences, Chen et al. [23] constructed a global vector called the GloVe model to calculate the similarity between sentences. Two clauses with higher semantic similarity have the same polarity. He et al. [24] extracted several sentences from product reviews and established sentiment analysis of sentence-level through C4.5 decision tree, which is a machine learning method.

Word-level sentiment analysis analyzes the evaluation object and its feature level. For example, taking mobile phone as the evaluation object, its features are its corresponding standby function, appearance, screen, speed, and memory. For fine-grained sentiment analysis of customer reviews, the first step is to extract the object of review texts or statements, and the sentiment word that modifies it. Then, the sentiment word is determined as positive or negative. According to the relationship between feature and sentiment words in texts, Wang et al. [9] extracted rules and used SVM algorithm to extract collocation. They analyzed the emotional tendency of product features through sentiment lexicon. Tang et al. [15] established a model of review text by using deep memory neural network combined with attention model. Wang et al.

[25] summarized features and emotional words between the dependency extraction features of sentiment words, and realized the fine-grained sentiment analysis of tourist attractions reviews. Based on the ontology method, Lau et al. [26] analyzed sentiment words, where the features in different fields had their specific modified sentiment words. Jo et al. [27] implemented fine-grained sentiment analysis by constructing joint distribution models of features and sentiment. Chen et al. [28] introduced statistical machine translation into the selection of evaluation objects and words, and achieved good results combined with sentiment lexicon. Liu et al. [29] used a word alignment model, which is a bi-directional selection method, to find sentiment words near commodity features and features near sentiment words.

Document- and sentence-level sentiment analyses belong to coarse-grained sentiment analysis. Coarse-grained sentiment analysis can only determine whether a text or sentence expresses positive or negative feelings. This type of analysis does not represent the evaluation of a specific feature, which shows that the document-level sentiment analysis is extremely coarse to meet the requirements of automatic analysis of product features. Sentiment analysis at word level belongs to fine-grained sentiment analysis. In this study, sentiment analysis of product feature belongs to fine-grained sentiment analysis. The main defects of fine-grained sentiment analysis are: the performance of fine-grained sentiment analysis on Chinese product reviews still needs improvement because of the complexity of Chinese text. In this study, LSTM model used by Tang et al. in English is adopted in the field of sentiment analysis on product feature of Chinese reviews. Given the differences in language structure and emotional expression of Chinese reviews, and the technical difficulties, such as the differences between Chinese and English texts, sentiment analysis on Chinese product reviews is implemented by using the LSTM network.

The rest of this study is organized as follows. Section 3 describes the sentiment analysis method on product features of Chinese reviews based on the LSTM network. Section 4 describes and compares the experimental results, then analyzes and discusses the results. Finally, Section 5 summarizes the study and presents the relevant conclusions.

3. Methodology

The general flowchart of sentiment analysis method of Chinese reviews is illustrated in Figure 1. In Section 4, the experiment is designed according to this flowchart to verify the performance of the sentiment analysis method of Chinese reviews by LSTM network.

The specific steps are as follows:

Step 1: The crawler code is written in Java. Reviews are gathered from Chinese Amazon.

Step 2: Java is used to perform data cleaning operation to review texts, remove all punctuation marks in texts, and mark symbols of network texts. Second, word segmentation for text is performed using the open-source word segmentation tool NLPIR-ICTCLAS2016, which was written by Dr. Zhang of the Chinese Academy of Sciences (Institute of Computing Technology, Chinese lexical analysis system, http://ictclas.nlpir.org/).

Step 3: In combination with the stop word list provided by Harbin University of Technology, the stop words are removed through regular expression in Java, including time, place, personal pronouns, and frequent words without actual

meaning of the word in the corpus, such as "yes," auxiliary verbs, prepositions, and other function words.
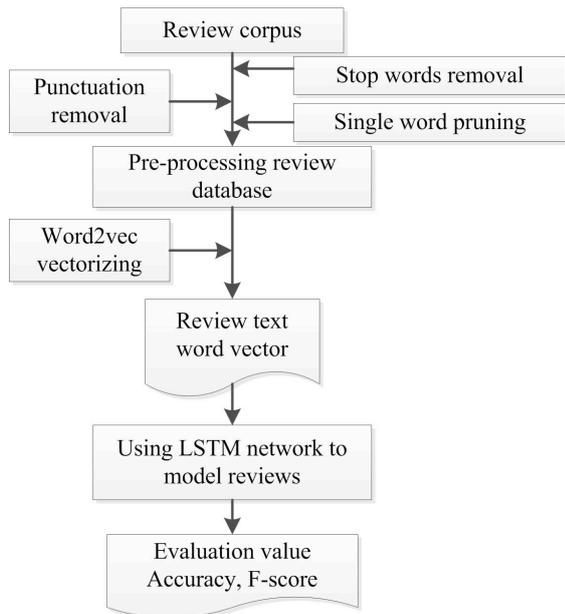

Fig.1. Flowchart of the proposed method

Step 4: In Chinese, single Chinese characters cannot be product features but may be sentiment words that modify features. Therefore, single Chinese character marked as a noun is not vectorized as a product feature. Word pruning is applied.

Step 5: The vectorization of corpus is implemented.

By training word vectors through Google's open source word2vec[30], words can be represented as real-value vectors, and text content processing can be simplified to k-dimensional vector by training. The skip-gram model of word2vec tool is used in this method. The context window size is set at 20, word vector dimension is set at 50, and sample value is set at 1e-5. If a word is not in a pre-trained word vector, then a random initialization is used to represent the word.

Step 6: The LSTM model is constructed.

LSTM model is used to conduct fine-grained sentiment analysis on Chinese product reviews. The LSTM model is essentially a recurrent neural network model. Figure 2 shows the structure of a simple neural network, the mathematical meaning of which is explained in Figure 3 (X represents the eigenvector of the input text, Φ represents the mathematical function in neural network, and Y represents the result treated by the neural network).
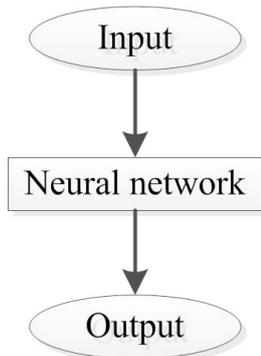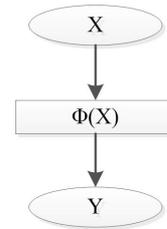

Fig. 2. Simple neural network model

Fig.3. Mathematical model of neural network

In comparison with the simple neural network, the applied LSTM neural network model includes three gates in the data processing unit part of the network layer, namely, input, forget, and output gates, in addition to the multilayer network. These gates save and delete context information by model. The implementation of sentiment analysis for text in the LSTM model depends mainly on the LSTM cell (Figure 4; https://www.zybuluo.com/hanbingtao/note/581764).
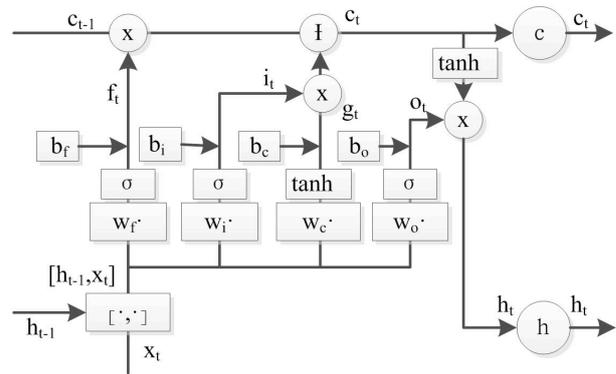

Fig.4. LSTM cell in hidden layer

The mathematical theories of the LSTM cell in hidden layer are as follows (where $\odot$ represents the multiplication of matrix elements σ is the sigmoid function, and tanh is the hyperbolic tangent function):

$$i_t = \sigma(W_i \bullet [h_{t-1}, w_t] + b_i) \tag{1}$$

where W_i is the weight matrix of the input gate, b_i is the offset of the input gate, and it is the feature matrix after the output gate treatment.

$$f_t = \sigma(W_f \bullet [h_{t-1}, w_t] + b_f) \tag{2}$$

where W_f is the weight matrix of the forget gate, b_f is the offset of the forget gate, and f_t is the feature matrix after the forget gate selection.

$$o_t = \sigma(W_o \bullet [h_{t-1}, w_t] + b_o) \tag{3}$$

where W_o is the weight matrix of the output gate, b_o is the offset of the output gate, and o_t is the output feature matrix.

$$g_t = \tanh(W_c \bullet [h_{t-1}, w_t] + b_c) \tag{4}$$

where weight matrix W_c and offset b_c for the currently input cell state are calculated through the previous and current feature matrix inputs.

$$c_t = i_t \odot g_t + f_t \odot c_{t-1} \tag{5}$$

where feature matrix c_t input at the current time is calculated. The feature matrix c_{t-1} output from the previous cell state multiplies f_t according to the characteristic matrix element. The feature matrix element of feature matrix g_t in the input element state multiplies feature matrix g_t to obtain the input information in the LSTM network for text modeling information.

$$h_t = o_t \odot \tanh(c_t) \qquad (6)$$

where h_t is the final output of the LSTM. It is determined by the output feature matrix of the output gate and the feature matrix input of the cell state at the current time.

x_t denotes input characteristics. W_i, b_i, W_f, b_f, W_o, b_o, W_c, and b_c are the parameters of the LSTM model. A softmax layer is added to the output layer in the LSTM model to derive the probability in (0,1), which represents the probability that the product features contained in the input reviews may be positive or negative. The mathematical formula of the softmax function is

$$softmax_k = \frac{\exp(x_k)}{\sum_{k'=1}^{c} \exp(x_{k'})} \qquad (7)$$

where C is the category of emotion, and x_k is the input of the k time steps.

The input of the LSTM model is a series of vectorized texts and the parameters of the LSTM model. The parameters are propagated through the multilayer network of the LSTM model to achieve iterative updating, text feature learning, and satisfactory sentiment classification results.

The sequence in which the context input of the features also affects the determination of the polarity of the product features. Therefore, an improved BiLSTM network is introduced to improve the feature sentiment polarity judgment. In the BiLSTM neural network, two LSTM neural networks are introduced when the corpus is first modeled. One models the review texts at the beginning from left to right, whereas the other models review texts at the end from right to left and fully utilizes feature context information for sentiment analysis. After multi-layer LSTM network processing, the models are classified into the *softmax* layer. Finally, the sentiment label of features is obtained.

Step 7: The processed corpus is annotated manually.

A review may contain multiple features, such as in "The screen is big, and I like it very much, but the signal is not good." Sentiment polarity of the mobile screen is marked as 1, which indicates the positive feeling of the customer toward the mobile screen. Sentiment polarity of the mobile signal feature is marked as −1, which represents the customer's negative feeling for cell phone signal. The labeled corpus is randomly divided into training and test sets. The training set is used for the LSTM model.

The proportion of the quantity of the corpus in the training and test set affects the experimental results during the process. The specific proportion change is shown in Figure.5.

Therefore, the model is trained with the ratio of the training set to the test set of 1:1.

In the experiment, the performance of the model becomes better than before with the increase of corpus. The specific trend is shown in Figure.6.

Step 8: The model is tested using the test set to verify the effectiveness of the model and evaluate its performance.
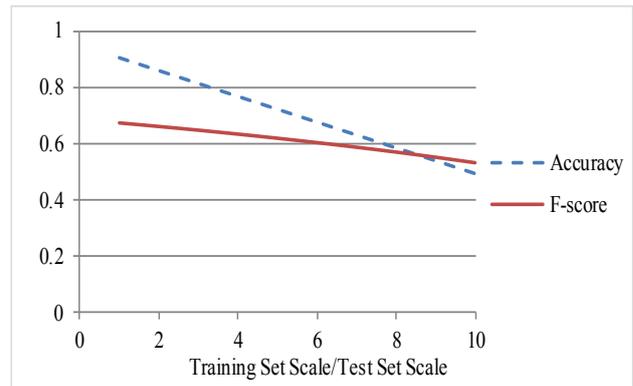

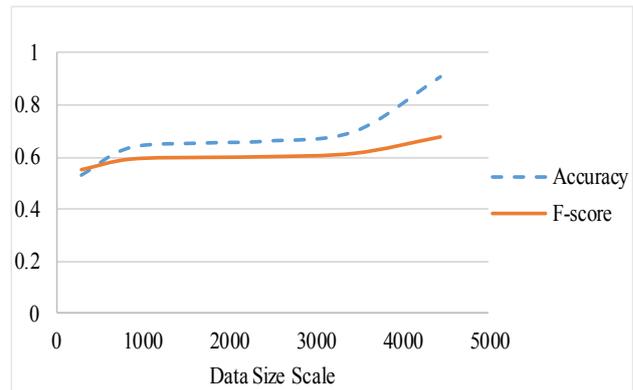**Fig. 5.** Effect of training–test data set ratio on test results

Fig.6. Model performance changes with the scale of the corpus

4. Result analysis and discussion

In this part, the experiment was conducted according to the method proposed in Section 3 to verify the effectiveness of the LSTM network in Chinese fine-grained sentiment analysis.

4.1 Data source
The research objects are mobile phones. This study selected mobile phones as data source because they are widely used in daily life and have multiple product features. The experimental corpus is the reviews of mobile phone on the Chinese Amazon website. Crawler tool is used for 4435 Chinese phone reviews from the Chinese Amazon website.

4.2 Review corpus preprocessing results
The original reviews were conducted with word segmentation and manual annotation through the word segmentation tool. The word segmentation and corpus tagged results in the experiment are shown in Table.1

Table 1. Labeled corpus

Labeled corpus
Cell phones, too, ordinary, batteries usually, standby, 10 days, a day, 3–5 days, T, not strong enough, then, voice, very small signal −1
Communication, quality, good, volume, small, T, long, Amazon, raise price Standby 1
Advantages, light, cheap, standby, long, disadvantages, T, small, difficult, input, phrase, sound, small screen 1

4.3 Experiment results and discussion

The results of sentiment polarity analysis are evaluated by accuracy and F-score.

$$\text{Accuracy} = \frac{\text{the number of correctly classified samples of this type of polarity}}{\text{the number of marked samples of this type of polarity}} \quad (8)$$

$$\text{Recall} = \frac{\text{the number of correctly classified samples of this type of polarity}}{\text{the number of this samples of this polarity}} \quad (9)$$

$$\text{F-score} = \frac{2 * \text{Recall} * \text{Accuracy}}{\text{Recall} + \text{Accuracy}} \quad (10)$$

Table 2. Experiment results

Index value	LSTM model in this experiment	BiLSTM model in this experiment
Accuracy	0.9074	0.9089
F-score	0.6547	0.6770

The experiment results are compared with those of Tang et al., as shown in Table 3.

Table.3. Result comparison

Index value	LSTM model		BiLSTM model	
	Present study	Tang et al. [17]	Present study	Tang et al. [17]
Accuracy	0.9074	0.6650	0.9089	0.7080
F-score	0.6547	0.6470	0.6770	0.6900

The experiment results are compared with the Chinese result obtained by Wang et al. [9] using the SVM model, as shown in Figure.7.
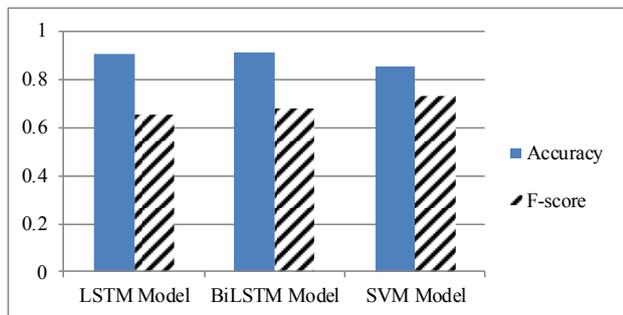

Fig.7. Comparison of results

According to the data comparison in Table 3, the performance of the improved BiLSTM model in Chinese is better than that of the original LSTM. The use of the BiLSTM to model the text in two directions slightly influenced the judgment of the emotional polarity of the features. The reason may be that the LSTM model has a memory function on the context; consequently, the relative position of the text input has no effect on the model, and its absolute position is the key factor that affects the model. From the experimental results, the application of the LSTM model to the Chinese language achieved good results after a series of modifications to Chinese characters was made. In comparison with the results of Tang et al. in English, accuracy and F-scores in Chinese improved, which indicates that the LSTM model is effective in Chinese fine-grained sentiment analysis. The use of the LSTM network in fine-grained sentiment analysis of Chinese customer reviews is

As discussed in Section 4.3, the review corpus is divided into training and test sets according to the proportion. The LSTM network is constructed to conduct the experiment. The experiment results are shown in Table 2.

feasible and effective. As shown in Figure 7, the performance of the sentiment analysis of the LSTM model is greatly enhanced, compared with the traditional learning model, because the use of LSTM networks for sentiment analysis of product features does not require priori knowledge, such as syntactic parsing or sentiment lexicon. Only the LSTM model is used to consider the effect of context on feature emotional polarity. The emotional polarity in product features is judged automatically. Moreover, the LSTM model has long-term memory to the context of reviews text, which makes up for the disadvantage of the traditional sentiment analysis of neglecting product feature text context, which makes the judgment of emotional tendency on product features more accurate.

5. Conclusions

To enhance the performance of fine-grained sentiment analysis on Chinese product aspects and to solve the problem that the differences between Chinese and English make the method in English texts not be directly applied to the Chinese reviews. LSTM and BiLSTM were established to model the Chinese review corpus, and then the fine-grained sentiment analysis of product aspects was realized. Finally, the following conclusions could be drawn:

(1)The accuracy and F-score in this experiment are better than those of the LSTM model based on English corpus. The LSTM model has good modeling capability to Chinese text and good learning capability to Chinese context.

(2)The LSTM model considers the effect of the feature context information on feature emotional polarity. In comparison with the traditional sentiment analysis method based on SVM, Naïve Bayes, sentiment lexicon, and semantics, the accuracy of sentiment analysis has improved. Combined with the feature context, the sentiment polarity of product features can be studied comprehensively. The LSTM model is effective for fine-grained sentiment analysis in Chinese.

The experimental results of the LSTM model in Chinese show that the performance of fine-grained sentiment analysis on Chinese product reviews is noticeably superior to that of traditional machine learning, which has certain reference significance to product feature. However, the LSTM model is a supervised neural network algorithm, which requires pre-trained large-scale corpus. Therefore, the marked corpus entails high costs. In future studies, the LSTM model should be combined with other sentiment analysis models to reduce the annotation of corpus and achieve semi-supervised or unsupervised fine-grained sentiment analysis. Moreover, this study only focused on the sentiment analysis of dominant features of products and did not consider implicit features of

products. The implicit feature sentiment analysis is reserved for future research.

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