RoBERTa-IAN for aspect-level sentiment analysis of product reviews

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Abstract. Accurately mining the emotional information contained in product reviews is of great significance to product sales. Existing research on sentiment analysis of product reviews often ignores the importance of modelling aspect words and context separately. Therefore, this paper proposes a sentiment analysis model for product reviews based on RoBERTa-IAN. Firstly, the context and aspect words of product reviews are transformed into low dimensional vectors through the RoBERTa pre-training model. Then, the low dimensional vector is used as the input of Bi-GRU model to extract semantic features and get the hidden representation. Finally, the attention matrices of context and aspect words are obtained by using the Interactive Attention Networks (IAN), which are used as the input of sentiment classification layer to analyse and classify the sentiment polarity of product reviews. The experimental results on the real commodity Chinese dataset show that the accuracy of RoBERTa-IAN has reached more than 90%.

1. Introduction

Nowadays, e-commerce has greatly promoted the vigorous development of online shopping. In the process of online shopping, consumers usually use other users' shopping reviews as a reference to decide whether to purchase goods. Therefore, sentiment analysis of product reviews has some implications for improving seller service.

Aspect sentiment analysis of product reviews mainly has three methods based on sentiment dictionary, machine learning and deep learning. The method of sentiment dictionary is to classify the text sentiment according to a certain method after word segmentation. Machine learning is the use of support vector machine (SVM), Naive Bayes and other methods for emotion classification after data pre-processing of text information. For example, Pang et al. used machine learning to classify sentiment in movie review sentiment analysis [1]. However, machine learning relies too much on feature design. Dong et al. provided the in-depth study method Ada-RNN to classify Twitter emotions according to context and the syntactic relationship between words [2].

Sentiment analysis of product reviews can be divided into sentiment analysis on sentence and sentiment analysis on aspect in terms of granularity [3]. Ding et al. gives a dictionary-based skill to solve context-related words and some special words, syntax [4]. Kirtchencko et al. proposed a combination of
emotional dictionary and machine learning to judge aspect-level emotional polarity [5]. Liu et al. used LSTM model for modelling which improved the accuracy of classification [6]. Tai et al. advanced a tree-structured Tree-LSTM algorithm combining semantics and dependencies [7]. Tang et al. found that the classification accuracy of the TD-LSTM and TC-LSTM models that added the aspect word information was significantly improved [8]. Ruder et al. Put forward a H-LSTM model, which uses the internal relationship between sentences to model, and proves that the hierarchical network structure is better [9].

At present, researchers combine attention mechanism with deep learning and find that it has achieved better results. Wang et al. Adopt attention machine-processed to seize the significance of sentences, the correctness of emotion analysis [10]. Ma et al. come up with IAN model, to associate aspect words with context for sentiment classification [11]. Chen et al. Linked multi-layer attention with neural networks and achieved good results [12].

However, although the above sentiment analysis models have achieved good results, they have not considered the same importance of the aspect words and the context and the problem of polysemy in input. Therefore, this paper proposes a model of sentiment analysis of product reviews based on RoBERTa-IAN. First, we use RoBERTa to transform the input aspect words and context into word vector coding. Then, input the word vector encoding of the aspect words and the context into the Bi-GRU to extract characteristic. Finally, IAN is used to learn the influence matrix of aspect words on the context and the influence matrix of context on aspect words, and the eigenvectors are reconstructed by the influence matrix and input to the emotion prediction layer for prediction output.

2. Problem definition and model

2.1. Problem definition
When analysing the sentiment of product reviews, \( n \) Chinese character aspect words and \( m \) Chinese character context are given. The task of sentiment analysis is to analyse the sentiment polarity \( a \) of each aspect word \( t \) in the context \( c \). Sentiment polarity \( a = \{ \text{Positive, negative} \} \).

2.2. RoBERTa-IAN sentiment analysis model of product reviews
The RoBERTa-IAN model proposed in this paper consists of input layer, semantic extraction layer, interactive attention networks layer and emotional output layer. The RoBERTa-IAN model is shown in Figure 1.

2.2.1. Input layer. The input layer uses the RoBERTa pre-training model. The RoBERTa model employs a larger learning rate and is able to learn the input sentences better than BERT. RoBERTa pre-training model maps each Chinese character \( w_i \) in the context \( c \) and aspect word \( t \) of the input product review into a low-latitude vector representation \( v_i \in R^{d_v} \). Among them, \( v_i \in R^{d_v} \) is the vector dimension. The output of the input layer is \( \{v_1, v_2, ..., v_n\} \) and \( \{v'_1, v'_2, ..., v'_n\} \).

2.2.2. Semantic extraction layer. Semantic extraction layer is composed of Bi-GRU. Bi-GRU consists of two GRU network models, a forward network \( \overrightarrow{h} \) with sequential learning input and a backward network \( \overleftarrow{h} \) with reverse sequential learning input. The forward network \( \overrightarrow{h} \) is computed by input information at present \( x_t \) and the hidden layer \( \overrightarrow{h}_{t-1} \) at the previous. The same goes for backward networks \( \overleftarrow{h} \). The forward network \( \overrightarrow{h} \) and the backward network \( \overleftarrow{h} \) will be weighted and averaged to get the information at the moment \( h_t \). As shown in formulas (1), (2), (3).

\[
\overrightarrow{h} = GRU(x_t, \overrightarrow{h}_{t-1}) \quad (1)
\]
Among them, $w_t, v_t$ represents the weight matrix, $b_t$ which is the bias.

$$\overline{h_t} = GRU(x_t, \overline{h_{t-1}}) \quad (2)$$

$$h_t = w_t \overline{h_t} + v_t \overline{h_t} + b_t \quad (3)$$

Figure 1. RoBERTa-IAN sentiment analysis model of product reviews

2.2.3. Interactive attention networks layer. In the RoBERTa-IAN product review aspect sentiment analysis model, the influence weight between the aspect word and the context is very important for the output result. Therefore, the model uses an IAN to capture the important components of aspect words and context. First, we take the hidden layer state of the aspect words and context obtained by the semantic extraction layer and the hidden layer state of the context to obtain the initial representation. As shown in formulas (4) and (5).

$$t_{avg} = \frac{\sum_{i=1}^{n} h_i^t}{n} \quad (4)$$

$$c_{avg} = \frac{\sum_{j=1}^{m} h^c_j}{m} \quad (5)$$
Taking the initial representation of context and aspect terms as input, Obtain the attention matrix $\alpha_i$ based on aspect words and the attention matrix $\beta_i$ based on context respectively through the attention mechanism. As shown in formulas (6) and (7).

$$\alpha_i = \frac{\exp(\gamma(h^i_c, t^c_{avg}))}{\sum_{j=1}^{n} \exp(\gamma(h^j_c, t^c_{avg}))} (6)$$

$$\beta_i = \frac{\exp(\gamma(h^i_t, c^t_{avg}))}{\sum_{j=1}^{m} \exp(\gamma(h^j_t, c^t_{avg}))} (7)$$

Among them, $\gamma$ is the important scoring function of aspect words in the context, as shown in formula (8). The calculation is the same in the context of $\gamma$.

$$\gamma(h^i_c, t^c_{avg}) = \tanh(h^i_c \cdot W_{a} \cdot t^c_{avg} + b_{a}) (8)$$

Among them, $W_{a}$ is weight matrix, $b_{a}$ is bias value.

After obtaining the attention matrix of the context and aspect words $\alpha_i$ and $\beta_i$, use the attention matrix to recalculate the representation of the context and aspect words, as shown in formulas (9) and (10).

$$c_r = \sum_{i=1}^{n} \alpha_i h^i_c (9)$$

$$t_r = \sum_{i=1}^{m} \beta_i h^i_t (10)$$

2.2.4. Emotional output layer. The emotional output layer cascades the aspect words and context representations of the interactive attention layer into the SoftMax to classify the emotional polarity of the aspect words in the product review context. As shown in formulas (11) and (12).

$$r = t_r \oplus c_r (11)$$

$$p = \text{softmax}(w \cdot r + b) (12)$$

Among them, $w$ is weight matrix and $b$ is bias value respectively.

3. Experimental results and analysis

3.1. Data set
The dataset uses the mobile Chinese datasets from SemEval2016 Task 5. The Chinese data set includes two emotional polarities, positive and negative, which are represented by positive and negative respectively. This article uses 80% of the data set as the training set and 20% as the test set.

3.2. Evaluation index and parameter setting
The accuracy of the experimental indicators is selected as shown in formula (13):

$$\text{Accuracy} = \frac{TP + FN}{(TP + FN) + (TN + FN)} (13)$$
Among them, four types TP, FP, TN, FN are divided into the combination of the predicted emotion polarity category and the true emotion polarity category in the sample RoBERTa-IAN.

### Table 1. The parameters of RoBERTa-IAN are set as follows.

| Parameter name     | Parameter value |
|--------------------|-----------------|
| Vector dimension   | 768             |
| Maximum sequence length | 250          |
| Batch size         | 16              |
| Learning rate      | 2e-6            |
| epoch              | 4               |

This paper conducts aspect sentiment analysis on mobile review text, and uses accuracy indicators to measure performance verification. Compare and analyse with the following models:

- **ATAE-LSTM**: After the aspect words and context are unified and input into the LSTM for encoding, the attention mechanism is combined to perform sentiment analysis and prediction.
- **RoBERTa**: Use the RoBERTa model to dynamically encode aspect words and context and then perform sentiment classification prediction.
- **RoBERT-BiLSTM**: After dynamically encoding the terms and context through the RoBERT model, the Bi-LSTM model is used for further semantic extraction of features and then prediction.

### Table 2. The accuracy analysis of different models.

| Model              | Accuracy |
|--------------------|----------|
| ATAE-LSTM          | 0.6425   |
| RoBERTa            | 0.8585   |
| RoBERTa-BiLSTM     | 0.8658   |
| RoBERTa-IAN        | 0.9065   |

The table shows the experimental results of the four aspects of sentiment analysis model on the mobile phone Chinese data set of SemEval2016 task 5. Compared with other baseline models, RoBERTa in the RoBERTa-IAN model can dynamically encode word vectors, and the interactive attention network effectively learns the relationship between aspect words and context. Through the experimental results, it can be seen that the RoBERTa-IAN better than other model in prediction accuracy, and the accuracy is increased by about 4%.

Among the other selected models, the ATAE-LSTM model that inputs the aspect words and context uniformly is not good. Because the internal self-attention mechanism transformer in RoBERTa, and the consideration of inputting the aspect words separately, the accuracy of the RoBERTa model compared to the ATAE-LSTM model is increased by about 20%. In view of the fact that RoBERTa uses Bi-LSTM to extract the deeper features of aspect words and context after dynamic encoding, the semantics obtained are more accurate and the effect is better. Therefore, the accuracy of the RoBERTa-BiLSTM model that further extracts semantic features on RoBERTa has increased by about 1.1%.

### 4. Conclusion

At present, most aspect sentiment analysis models unify aspect words and context as the input of the model, ignoring the importance of separate input of aspect words. This paper proposes a sentiment analysis model for product reviews based on RoBERTa-IAN. In the input layer, aspect words and context are modelled separately to get vector representation of aspect words and context. Then use the semantic extraction layer to extract the in-depth semantic information of the context and the aspect word, and then learn the important part of the aspect and context through the interactive attention networks.
layer. Finally, the sentiment polarity classification is judged through the output layer. The experimental results show that the RoBERTa-IAN model has better function in sentiment analysis of product reviews.

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