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Sentiment Analysis of Text Using Deep Learning-based Natural Language Processing Models

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Abstract: This paper conducts research on text sentiment analysis based on the current advanced deep-learning natural language technology. It includes data preprocessing for text sentiment analysis, the establishment of text sentiment analysis models based on deep learning natural language technology, and the training of text sentiment analysis models based on deep learning natural language technology. It is hoped that this analysis can provide a reference for the rational application of the model to achieve intelligent analysis of text sentiment.

Keywords: Deep learning; Natural language; Sentiment analysis model; Model building; Model training

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1. Introduction

Text data information is most common in sentiment analysis processing. In general, the text contains the most abundant emotional intensity, so it is necessary for researchers to take the text as the analysis object and analyze its emotion with a deep learning natural language processing model.

2. Text sentiment analysis data preprocessing

In text sentences, when the dependency analysis of text sentence components, researchers can take the dependency mechanism between each word as the basis to improve the model's semantic understanding ability. Based on this, in this study, the researchers mainly used the Stanford grammar dependency analysis tool as the dependency analysis tool for text sentences and visualized the analysis results through Graphviz (open-source visualization software) [1]. For example, in the preprocessing of the text statement "I just thought it was kind of stupid," the researcher can first obtain a visual analysis result through Graphviz. The subject is represented by nsubj. According to its dependency, the subject of the word "kind" is "it"; the cop is the relative verb, and the relative verb of the word "kind" is "was." By analyzing the dependency of the syntax of the text, the study can get a reasonable grasp of its structure information, and the structure also has an emotional correlation with the whole sentence.

Based on this, by extracting the information of the sentence itself and its grammatical structure features, researchers can complete the construction of the corresponding emotion classification model [2]. Then, with the help of a graph neural network, the feature vector integration of the current node itself and its neighboring nodes is implemented. To achieve this goal, in this study, the researchers specially introduce the node self-loop, that is, introduce an identity matrix into the graph adjacency matrix, to ensure the effect of data preprocessing.

3. The establishment of a text sentiment analysis model based on deep learning natural language technology

3.1. Overall structure of the model

In this text sentiment analysis based on deep learning natural language technology, the researchers proposed a grid structure model named GA-BERT. For graph neural networks, the researchers mainly build them by extracting syntactic dependency information in sentences and pre-trained models [3–5]. At the same time, as the data is constructed according to the dependencies of the syntax of the sentence itself, the structure will be able to simulate the human to understand the sentence in most cases. Through the reasonable setting of the residual module and normalization module, the model can maintain stability in the training process and reduce the probability of gradient disappearing or gradient explosion. Finally, the model can be used to predict the emotion of the text, and reasonable emotion analysis results can be obtained.

3.2. Graph convolutional network

The graph convolutional network is the main component of this model. The coding layer in the BRRT model adds a special tag[*cls*] at its starting position to implement task classification. Add a self-loop to the adjacency matrix, which will then be defined as $\tilde{A} = A + I_N$, I_N add value representing a self-loop. The syntactic dependency graph constructed through sentence dependency structure is represented as $G = (V, E)$, V is the set of all nodes (words) in the graph, E is a set of relations between edges (interdependence between words and words) [6]. Researchers can define graph data in text sentiment analysis as follows: $G = (X_t, A)$. Two layers of convolution processing by graph convolutional neural network should be defined before processing, which belongs to the graph matrix $G\tilde{A} = \check{D}^{-1/2}\tilde{A}D^{-1/2}$, $\check{D}$ belongs to the $\tilde{A}$ graph matrix. Finally, the feature acquisition after the completion of the convolution can be realized. The feature is Z_i, the following is its output definition:

$$Z_i = \tilde{A}\mathrm{Re}Lu(\tilde{A}XW^{(0)})W^{(1)} \tag{1}$$

Where $\tilde{A}$ is the activation function; Re*Lu* $W^{(0)}$ is the weight matrix possessed by the hidden layer; $W^{(1)}$ is the output values for the hidden layer weight matrix.

3.3. Time domain convolutional network

After the convolutional processing is implemented by the graph neural convolutional network, the obtained results are different from the feature dimensions extracted in the text training model, so researchers need to control the dimensions by using the one-dimensional time domain convolutional network to keep them consistent [7–9]. The following is the process formula:

$$\{X_t, Z_i\} = convId(\{X_i, Z_i\}, k_{\{t,i\}}) \tag{2}$$

Wherein, the features extracted from the text pretraining model and the graph convolutional network features after one-dimensional convolution processing. Since the $k_{\{t,i\}}$ value is much larger than that formed in the graph convolutional neural network, in order to avoid the production of large dot product or gradient region after softmax function processing, researchers can implement scaling processing to transform it into $X_tZ_t\bar{X}_t\bar{X}_t'$, Z_tZ_t' The following is its scaling process formula:

$$X_t' = \frac{X_t}{\sqrt{\|X_t\|_2}} \quad (3)$$

$$Z_t' = \frac{Z_t}{\sqrt{\|Z_t\|_2}} \quad (4)$$

3.4. Integration of attention modules

The model will continue to connect it with the residual module, X_t. Through the reasonable construction and application of this module, the original data can always maintain the existing structure. As the core component module of GA-BERT model, the main application function of fused attention module is to implement intelligent adjustment of word weights in sentences in the form of dynamic attention by the organic combination of graph convolutional network and BERT model pretraining features [10].

For the feature attention extracted from the model and the attention in the graph neural network, the fusion processing needs to be further implemented, so that the words can be dynamically adjusted [11]. In this process, the basic method is to sum the attention in the two units, so as to obtain an attention matrix in the weight fusion mode, the formula is as follows:

$$w_f = w_t + w_i + \beta_i + b \quad (5)$$

Where w_f represents the weight value of the model pretraining unit; w_t w_i represent the weight value of the graph neural network unit; b represents the bias value. In order to reduce the adverse effects of different lengths of two units, researchers can introduce masking matrix, where the position of the word token is represented by 0, and the additional filling position is represented by -∞, which is calculated as follows:

$$W_m = soft\max(w_f + M) \quad (6)$$

Where, W_m represents the attention matrix formed by the fusion of the above two features. This value was multiplied with the output value in the last layer of the model to achieve the scientific acquisition of the final attention, which is calculated by:

$$X_{ATT} = W_m V_m \quad (7)$$

4. Text sentiment analysis model training based on deep learning natural language technology

4.1. Training methods

In this training, the researchers mainly used BERT model pre-training to obtain feature attention, and then fused it into the graph convolutional network attention, to achieve dynamic adjustment of word weights in sentences. In the specific training, the word dimension extracted by the model is 768, and the maximum sentence length limit is 200 sentences [12]. A total of 1,284 texts were put into training to perform sentiment analysis. Stanford syntactic dependency is used as a tool to extract syntactic structure, and the convolutional network is tested and compared many times. Finally, the number of layers of the model is determined to be 2. As the sentence adjacency matrix has different sizes, the batch value is set to 1 during training. The number of epachs (iterations) is set to 15 to ensure the convergence rate of the model during training and to keep its convergence stable. Use Adam as the optimizer and set its learning rate at 2e-5. For the linear learning rate, set its training ratio at 0.1 during the predicted warm-up.

4.2. Verification of excellence

For the excellence verification of the model, in this experiment, the researcher specially introduced Accuracy (accuracy value), F1 score (F1 score value) and MAE (average absolute difference between target and prediction). The so-called accuracy refers to the classification accuracy rate of all emotional data. The main problem of this study is the binary classification of emotion, and the text emotion is classified into seven categories according to the Leek scale in Yuan's dataset label. The so-called F1 score is the implementation of accuracy statistics on the binary model, including its accuracy and recall rate. The MAE is the average absolute value of the difference between the target and the predicted emotional strength [13]. To determine the effectiveness of this model in text sentiment analysis, the researchers also introduced some typical intelligent models for text sentiment analysis. This includes Lstm (long short-term memory network model), BiLstm (bidirectional long short-term memory network model), TextCnn (Convolutional Neural network model), RCnn (joint detection model of region nomination and convolutional neural network), and DCnn (deep convolutional neural network model). Through the comparison of the experimental parameters of each model, the excellence of this research model in text sentiment analysis was analyzed. **Table 1** shows the verification results of the excellence of various intelligent algorithm models selected in this study in text emotion classification.

Table 1. The verification results of the excellence of all kinds of intelligent algorithm models selected in text emotion classification

No.	Model	Test results			
		Dichotomous	F1 score values	Seven categories	MAE
1	Lstm	75.1%	75.6%	31.2%	0.951
2	BiLstm	78.2%	78.1%	33.2%	0.915
3	TextCnn	79.8%	79.2%	36.5%	0.874
4	RCnn	80.5%	80.6%	38.4%	0.862
5	DCnn	80.9%	80.8%	39.9%	0.849
6	GA-BERT	82.9%	82.7%	39.9%	0.796

Compared with the above experimental data, it can be seen that compared with other typical intelligent models of text sentiment analysis, the BERT model studied in this study has higher accuracy in both binary classification and seven-classification, and its F1 score is higher and MAE value is lower. It can be seen that this model has higher excellence than other typical models, and if it is applied to text sentiment analysis, more accurate analysis results will be obtained.

4.3. Visualization of results

For the text sentiment analysis model constructed in this study, to make its internal working situation present, the researcher uses tsne (High dimensional data dimensionality reduction visualization tool) to visualize its test results in real-time. The basic method is to first extract the output of the graph convolutional network, and then reduce the dimensionality of the finally obtained attention fusion results, and output them in the form of visualization [14,15]. **Figure 1** shows the test results of the graph convolutional network output (left) and attention fusion results (right).

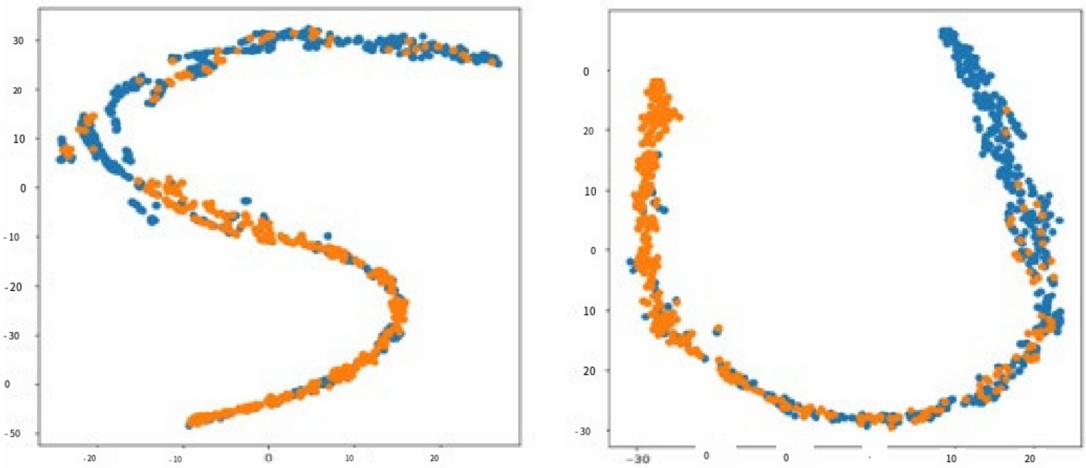

Figure 1. shows the test results of the convolutional network output (left) and attention fusion results (right) of the visualization processing results.

It can be seen from the experiment that the graph convolutional network extracted the valid information in the text and formed a basic emotion classification outline before the attention fusion processing was implemented. After fusion processing, the model obtains a clearer outline of text emotion classification. It can be further determined that there is a certain dependency between the feature information of each node and the text syntax in the convolutional network, and this relationship is helpful to the understanding of text emotion.

5. Conclusion

To sum up, with the continuous development of modern artificial intelligence technology, text analysis based on artificial intelligence algorithm models has become the main content of intelligent emotion analysis. However, because artificial intelligence technology is different from the human brain, many traditional intelligent text analysis models often difficult to obtain idealized analysis results in practical applications. To further improve the accuracy of text emotion analysis in the mode of artificial intelligence technology, researchers can use the current advanced deep learning natural language processing technology as a supporting technology, and implement intelligent analysis of the analyzed text emotion through GA-BERT model construction and attention fusion processing. In this way, the advantages of the artificial intelligence algorithm model can be better utilized, the accuracy of text sentiment analysis can be improved, and the corresponding needs of text sentiment analysis can be better met.

Disclosure statement

The author declares no conflict of interest.

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