Research on Sentiment Analysis Algorithm for Comments on Online Ideological and Political Courses

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***Abstract*—The online course teaching platform provides a more accessible and open teaching environment for teachers and students. The sentiment tendency reflected in the online course comments becomes an essential basis for teachers to adjust the course and students to choose the course. This paper combined two deep learning algorithms, i.e., a convolutional neural network (CNN) algorithm and a long short-term memory (LSTM) algorithm, to identify and analyze the emotional tendency of comments on online ideological and political courses. Moreover, the CNN+LSTM-based sentiment analysis algorithm was simulated in MATLAB software. The influence of the text vectorization method on the recognition performance of the CNN+LSTM algorithm was tested; then, it was compared with support vector machine (SVM) and LSTM algorithms, and the comments on online ideological and political courses were analyzed. The results showed that the recognition performance of the CNN+LSTM-based sentiment analysis algorithm adopting the Word2vec text vectorization method was better than that adopting the one-hot text vectorization method; the recognition performance of the CNN+LSTM algorithm was the best, the LSTM algorithm was the second, and the SVM algorithm was the worst in terms of the performance of recognizing the sentiment of comment texts; 86.36% of the selected comments on ideological and political courses contained positive sentiment, and 13.64% contained negative sentiment. Relevant suggestions were given based on the negative comments.**

***Keywords*—Online courses; comment; sentiment tendency; long short-term memory**

I. Introduction

Education is an important cause of social development, and good education can provide more excellent talents for society and further promote the benign development of society [1]. Students are still in the stage of shaping their value system. The information they can receive at that stage is mixed, and the existence of the Internet has exacerbated this process [2]. Once the information has a negative impact on student's value system, it will seriously affect their future growth. Therefore, in addition to learning the necessary knowledge, students need to establish the correct value system through ideological and political education [3]. Traditional classroom ideological and political education aims to popularize education and is student-oriented. Although there are excellent teachers who can take into account the personalized training of different students in classroom teaching, the number of excellent teachers is limited; moreover, as the fixed time and place of traditional classroom education is fixed, students only do homework after school hours [4]. With the development of Internet technology, online teaching platforms have emerged, which are not bound by time and place compared with traditional classroom teaching. In general, the teaching resources provided by the platform are pre-uploaded teaching texts and recorded videos [5], and the platform users can browse and learn anytime and anywhere. Online teaching also has shortcomings. Firstly, the lack of direct interaction between teachers and students makes it difficult for teachers to get feedback. Secondly, students are the main subjects when choosing teaching resources, and the diversity of teaching resources in the platform makes it difficult for students to make effective choices [6]. The comments on teaching resources in the platform can alleviate the shortcomings mentioned above to a certain extent. Teachers can correct the problems of their courses according to the emotional preferences of the comments, and students can make preliminary judgments on teaching resources [7]. However, since there are hundreds of comments for a course and even more comments when comparing different courses, it is difficult to collect and organize the comments by manual means alone. In order to quickly collect and process the sentiment tendencies of online course comments to assist instructors and students, intelligent algorithms are needed to process the comment texts. Intelligent algorithms can analyze the sentiment in the comment area under online ideological and political courses efficiently. Students can select courses based on the tendency of sentiment distribution in the comment area, while teachers can improve courses based on it. This paper studied the sentiment analysis algorithm for analyzing the sentiment tendency of comments on online ideological and political courses, which combines two deep learning algorithms, the convolutional neural network (CNN) algorithm and long short-term memory (LSTM). The CNN algorithm obtained the local and global features of the comment text, and then the sentiment tendency was calculated by the LSTM based on the comment text features extracted by the CNN. Finally, the CNN+LSTM algorithm was compared with support vector machine (SVM) and LSTM algorithms.

II. Literature Review

Related studies are as follows. Yasmina et al. [8] used an unsupervised machine learning algorithm to classify sentiment based on a corpus of data constructed using YouTube comments. They used a point-by-point mutual information

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metric to calculate the similarity of the sentiment to every target sentiment and found that the algorithm had a global accuracy of 92.75%. Atmaja et al. [9] recognized sentiment in natural language by fusing acoustic and text networks using a support vector machine (SVM). The experimental results showed that this two-stage late-fusion approach achieved higher performance than any one-stage processing. Bernhard et al. [10] proposed sent2affect, a tailored form of transfer learning for affective computing. The results showed that recurrent neural network (RNN) and transfer learning consistently outperformed traditional machine learning. Zhi et al. [11] proposed an application framework and design of an intelligent system for emotion recognition and topic mining, aiming at intelligent and personalized learning analysis for Massive Open Online Courses (MOOC). The system could predict the popularity of every course and obtain emotional topic feedback about the course content so that teachers could analyze and improve their teaching strategies. It could also obtain the emotional topic feedback platform support of the relevant course topic so that administrators could improve user experience in the platform. Jin et al. [12] proposed a hybrid deep neural network model for Chinese text sentiment recognition to identify the sentiment tendency of Chinese medical reviews. The results showed that the model was able to obtain better text features than the reference model and had a text classification accuracy of 99%. Pan et al. [13] proposed an emotion recognition algorithm based on synchronized time comments as the basis for video clip recommendation and found that the model could effectively analyze the complex emotions of different types of text information.

III. METHODS

A. Basic Process of the CNN+LSTM Algorithm

This paper analyzed the sentiment in the comments of online courses with the CNN and LSTM algorithms [14]. The CNN algorithm was used to extract features from comment texts. The LSTM algorithm analyzed the sentiment in the extracted features based on its feature of capable of contacting the context. The flow of the combined algorithm is shown in Fig. 1.

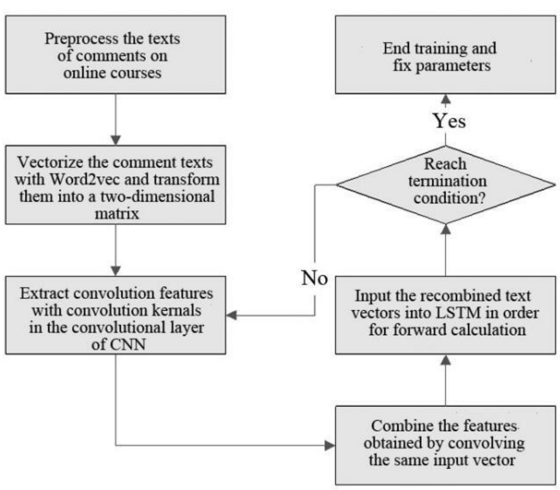

Fig. 1. Training Process of the CNN+LSTM-Based Sentiment Analysis Algorithm for Comments on Online Ideological and Political Courses.

1) The comment text about online ideological and political courses is pre-processed by denoising, filtering, and word segmentation [15]. Denoising refers to removing meaningless characters such as numbers and punctuation from the comment text; filtering means removing comments that are irrelevant to the course topic with a clustering algorithm; word segmentation means dividing sentences into phrases or words [16] for later text vectorization.

2) The pre-processed comment text is vectorized to transform natural language into a text vector that computers can understand. The skip-gram model [17] in Word2vec is used for text vectorization. The dimensionality of the text vector is determined according to the computational requirements, and usually, the larger the dimensionality, the more accurate the distribution of semantic features of the words that the vector can reflect, but the more difficult the computation. Then, the vectorized text is transformed into a two-dimensional matrix. Taking a five-dimensional text vector as an example, it is assumed that there are only four words in the short comment. The two-dimensional matrix of the text vector of the comment is shown in Fig. 2, where every row represents a five-dimensional text vector of one word.

3) After transforming the text vector of the comment into a two-dimensional matrix, the text vector of the comment is regarded as an image, and every dimensional vector of words is regarded as a pixel point in the image. The two-dimensional matrix is input into the CNN, and plural convolution kernels slide on the two-dimensional matrix in a certain step length in the convolutional layer, and convolution operation is performed using the convolution kernel in every slide [18]. The convolution formula is:

$$Y_i = f(X_i \otimes W_i + b_i), \tag{1}$$

where Y_i is the convolutional output eigenvalue of the i-th convolutional kernel, X_i is the input vector of the i-th convolutional kernel, W_i is the weight of the i-th convolutional kernel, and b_i is the bias of the i-th convolutional kernel.

4) Several convolutional characteristic faces of the two-dimensional matrix are obtained by the convolutional operation of the CNN convolutional layer. The characteristic part obtained by convolving the same input vector is selected from the convolutional characteristic faces extracted by every convolutional kernel and joined in rows to obtain a new vector [19].

$$\begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} \end{bmatrix}$$

Fig. 2. Schematic Diagram of the Two-Dimensional Matrix of Text Vectors.

5) The new combined vector obtained is input to the LSTM for forward computation by the input gate, forgetting gate, and output gate [20]. The equations are as follows:

$$\begin{cases} i_t = g(\omega_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t = \tanh(\omega_C \cdot [h_{t-1}, x_t] + b_C) \\ C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \\ f_t = g(\omega_f \cdot [h_{t-1}, x_t] + b_f) \\ o_t = g(\omega_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t = o_t \cdot \tanh(C_t) \end{cases}, \quad (2)$$

where the current cell input is x_t, the previous hidden layer state is h_{t-1}, the last cell state is C_{t-1}, i_t is the proportion that determines the newly added information that can be remembered, $\tilde{C}_t$ is the cell state of the newly added information, C_t is the current cell state after the new information is added, ω_i and ω_t are the corresponding weights [21], b_i and b_C are the corresponding biases, f_t is the weight of the information not to be forgotten in C_{t-1}, ω_f is the corresponding weight, b_f is the corresponding bias, o_t is the proportion that determines the final output information volume, and h_t is the final output or the next hidden state[22]. The output result of the output gate of the LSTM is calculated using the softmax function [23] in the fully connected layer to obtain the sentiment classification result.

The actual results obtained from the forward calculation are compared with the expected results of the training samples. Cross-entropy is used to calculate the error between them. Then, whether the training of the algorithm reaches the termination conditions, including the number of iterations reaching the set number and the error converging to the set range, is determined. If the algorithm reaches the termination condition, the training will be stopped, and the algorithm's parameters will be fixed; if the algorithm does not reach the termination condition, the parameters in the algorithm will be adjusted reversely, and then it returns to step *3)*.

B. Simulation Experiment on the CNN+LSTM Algorithm

1) Experimental Data and Setup

The comment text data used in the experiment came from the China University MOOC website. Twelve thousand comments were crawled from the comment area of ideological and political courses using crawler software. After identification, the emotional tendency of these comments was divided into positive and negative, and their numbers were close. Then, 60% of the comments were used as training samples, and the remaining 40% was used as testing samples.

The parameters of the CNN+LSTM-based sentiment analysis algorithm [24] are as follows. The dimension number of the Word2vec vector for vectorizing the comment text was set as 100. The parameters of the CNN part are as follows. There was a convolutional layer with 64 convolutional kernels. The specification of every convolutional kernel was 2 × 100, and the moving step length of the convolutional kernel was 1. The specification of the input data in the input layer, i.e., the size of the two-dimensional matrix, was $M \times 100$, where M is the maximum number of the segmented words. The parameters of the LSTM part are as follows. There were 64 hidden neurons. The weights were initialized using glotot_normal. The bias was set as 0. Training stopped after a maximum of 1,000 iterations.

In order to further verify the effectiveness of the CNN+LSTM algorithm, it was compared with a machine learning algorithm, SVM, and a deep learning algorithm, LSTM, by experiments. As to the relevant parameters of the SVM algorithm, the sigmoid function was used as the kernel function, and the penalty parameter was set as 1. The relevant parameters of the LSTM algorithm were the same as the LSTM part of the CNN+LSTM algorithm.

2) Experimental Project

a) The Impact of Comment Text Vectorization Methods on Sentiment Analysis Algorithms

The Word2vec method was used to vectorize the comment text, but the one-hot method was also applicable in addition to this method. The CNN+LSTM algorithm used the one-hot method and the Word2vec method, respectively, and the recognition performance of sentiment analysis algorithms under these two text vectorization methods was compared.

b) Performance Differences between Different Sentiment Analysis Algorithms

All three sentiment analysis algorithms used the Word2vec method for text vectorization. Then, they were trained using the same training set and tested by the same training set.

The evaluation indexes used to compare the performance were precision [25], recall rate, and F-value, which were calculated by the following formulas:

$$\begin{cases} P = \dfrac{TP}{TP + FP} \\ R = \dfrac{TP}{TP + FN} \\ F = \dfrac{2PR}{P + R} \end{cases}, \quad (3)$$

where P is the precision, R is the recall rate, F is a combination of the precision and recall rate, TP is the number of positive samples that are predicted as positive, FP is the number of negative samples that are predicted as positive, and FN is the number of positive samples that are predicted as negative.

(3) Analysis of comments on online ideological and political courses with the validated sentiment analysis algorithm

The CNN+LSTM-based sentiment analysis algorithm performed sentiment analysis on online ideological and political courses on the Chinese University MOOC website.

The top ten ideological and political courses with the highest number of plays were selected from the corresponding classification in the MOOC platform. Comments on these ten courses were crawled using crawler software. The sentiment analysis algorithm identified the sentiment classification of the collected comments, and relevant course improvement suggestions were given based on the negative comments.

IV. RESULTS

Fig. 3 shows the recognition performance of the CNN+LSTM sentiment analysis algorithm under different text vectorization methods. It was seen from Fig. 3 that the sentiment analysis algorithm using the one-hot method for text vectorization had a precision of 84.48%, a recall rate of 84.57%, and an F-value of 84.52%; the sentiment analysis algorithm using Word2vec for text vectorization had a precision of 94.26%, a recall rate of 95.24%, and an F-value of 94.75%. The comparison of the performance between the algorithms under the two text vectorization methods revealed that the sentiment analysis algorithm using Word2vec had a more excellent sentiment recognition performance.

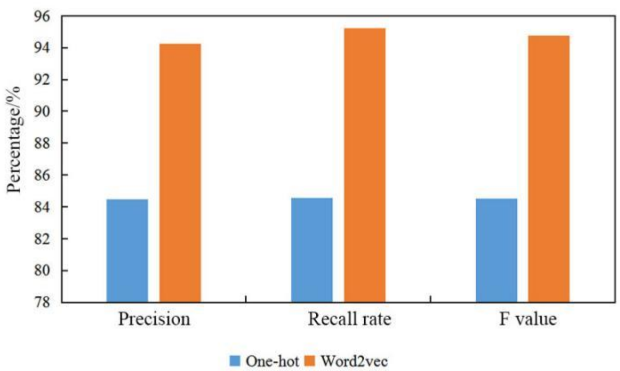

Fig. 3. Recognition Performance of the CNN+LSTM Sentiment Analysis Algorithm under Different Text Vectorization Methods.

Fig. 4 shows the comparison of the recognition performance of three sentiment analysis algorithms, SVM, LSTM, and CNN+LSTM algorithms. It was noticed in Fig. 4 that the precision, recall rate, and F-value of the SVM algorithm were 77.36%, 76.58%, and 76.97%, respectively; the precision, recall rate, and F-value of LSTM were 90.12%, 89.63%, and 89.87%; the precision, recall rate, and F-value of the CNN+LSTM algorithm was 94.26%, 95.24%, and 94.75%, respectively. It was intuitively seen that the SVM algorithm had the worst recognition performance, the LSTM algorithm had the medium performance, and the CNN+LSTM algorithm performed the best.

Fig. 5 shows the results of sentiment identification using the CNN+LSTM-based algorithm for the ten comments selected from the comment section of ideological and political courses. It was seen from Fig. 5 that 86.36% of the comments in the comment section contained positive sentiment and 13.64 % contained negative sentiment. For students, positive comments can help them understand the advantages of the course, while negative comments can make students view the online ideological and political course as objectively as possible; for teachers, positive comments can encourage teachers, but more importantly, negative comments can help them search for defects in online ideological and political courses and make better improvements. Due to space limitation, this paper only presented some comments containing negative sentiment and the corresponding key negative words, as shown in Table I. It was seen that users' negative comments on online ideological and political courses were "boring content," "lack discipline in online courses," "lack of interactivity in online ideological and political courses," "one-size-fits-all," etc.

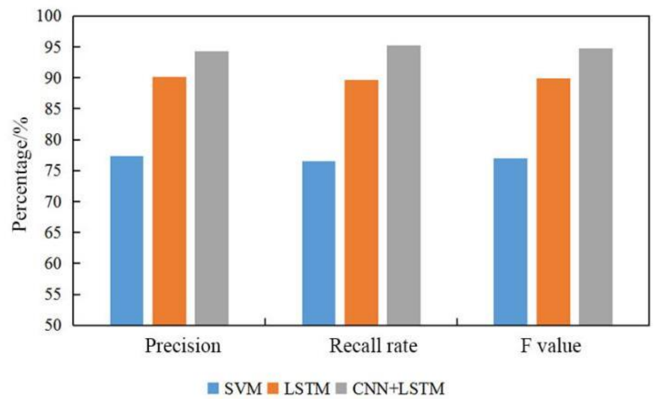

Fig. 4. Recognition Performance of Three Sentiment Analysis Algorithms.

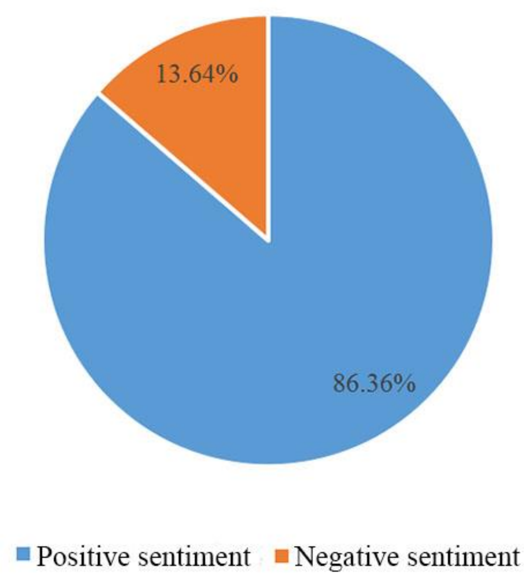

Fig. 5. Sentiment Recognition Results of Comments on Online Ideological and Political Courses by the CNN+LSTM-Based Sentiment Analysis Algorithm.

TABLE I. SOME NEGATIVE COMMENTS AND THEIR KEY NEGATIVE WORDS

Part of the original texts of some negative comments	**Key negative words**
The course content is straightforward and boring	Boring content
Online courses lack discipline, and students have low autonomy	Lack discipline
Lack of interactivity between teacher and students in online courses	Lack of interactivity

V. Discussion

Online teaching courses are gradually increasing with the popularity of the Internet. Compared with traditional offline teaching courses, online teaching courses have advantages of not constrained by time and space and a higher degree of autonomy for students. However, online teaching courses also have disadvantages such as difficulties in teacher-student interaction and students' difficulties in choosing due to the variety of teaching resources in the platform. The platforms where online teaching course resources are located often have comment areas. These comments on online courses can, to a certain extent, alleviate the problems of communication difficulties and diversification of choices for teachers and students, but the number of comments in the comment areas is so large that it is difficult for them to quickly obtain the emotional tendency from these comments. In order to solve the above problems, this paper combined two deep learning algorithms, CNN and LSTM, and then used them for sentiment analysis of online course reviews. In the simulation experiment, the effects of different text vectorization methods on the CNN+LSTM algorithm were tested, and it was compared with SVM and LSTM algorithms. Finally, the CNN+LSTM algorithm was applied to the actual MOOC platform to recognize the sentiment of comments in ten online ideological and political course comment areas in the platform. The final experimental results have shown in the last section.

The CNN+LSTM algorithm that adopted Word2vec performed better in sentiment recognition than the CNN+LSTM algorithm that adopted the one-hot method. The reason was analyzed. The one-hot method sets the length of the text vector according to the total number of words in the coding dictionary. The position of the word to be transformed in the dictionary determines that its corresponding position in the vector is one and the other positions are zero. This method is simple and intuitive, but in practice, the number of words in the dictionary is huge, resulting in a high dimensionality of the text vector, and only one position in the text vector is 1, making the text vector very sparse, so the algorithm wastes much computational power when training. In addition, the one-hot method encodes the words independently and does not contact the context. The Word2vec method vectorizes words by mapping them into a word space. Semantically similar words are clustered, i.e., the distribution expression of words is realized based on the context. In this paper, the skip-gram model of the Word2vec method predicted the probability distribution of the context based on the intermediate word and used it as its vector representation. Compared with the one-hot method, Word2vec made full use of the context of the words to be transformed and used a smaller word space dimension, so the sentiment analysis algorithm using Word2vec was better in terms of recognition performance.

The results of the comparative experiment on SVM, LSTM, and CNN+LSTM algorithms showed that the CNN+LSTM algorithm had better sentiment recognition performance. The reason is as follows. The SVM algorithm used the kernel function to map the text vector to a high-dimensional space, then searched for the hyperplane that could divide the space in the high-dimensional space, and used the hyperplane to classify the comment text. The SVM algorithm was still difficult to fit completely though it used the high-dimensional mapping of kernel functions to linearize the nonlinear laws in the text as much as possible. The LSTM algorithm is a derivative of the RNN algorithm. The activation function in the hidden layer effectively fit the nonlinear law, and the LSTM algorithm contacted the context based on the historical information, so its recognition performance was much stronger than the SVM algorithm. The CNN+LSTM algorithm is a combination of CNN and LSTM algorithms. The convolutional kernel of the CNN algorithm extracted local features from text vectors, and then the features were reorganized in text order. The LSTM algorithm identified the sentiment from the reorganized text features. The local features provided by the CNN algorithm made up for the defect that the LSTM algorithm could not utilize local features; thus, the CNN+LSTM algorithm was better than the LSTM algorithm in recognition.

The results of the sentiment recognition of the ten comment areas in the actual MOOC platform using the CNN+LSTM algorithm showed that most of the comments were positive. The following suggestions are given according to the negative comments in the comment areas.

1) Teachers should not use too many text descriptions when making online ideological and political courses but can combine teaching contents with pictures and videos.

2) For the lack of discipline when students take online courses, teachers can assist by setting hard targets and focusing on cultivating autonomy in the daily teaching process.

3) Teachers can enhance the interactivity of online ideological and political courses through the live streaming function in the MOOC platform.

VI. Conclusion

This paper combined two deep learning algorithms, CNN and LSTM algorithms, to identify and analyze the sentiment tendency of comments on online ideological and political courses and then simulated the CNN+LSTM-based algorithm in MATLAB software to test the recognition performance difference under two different text vectorization methods, one-hot and Word2vec methods. The following results are obtained. Moreover, the CNN+LSTM-based algorithm was compared with SVM and LSTM algorithms, and the comments on online ideological and political courses were also analyzed. The following results are obtained. The CNN+LSTM sentiment analysis algorithm using Word2vec for text vectorization had better sentiment recognition performance than the algorithm using the one-hot method. The SVM algorithm had the worst recognition performance, the LSTM algorithm had the medium performance, and the CNN+LSTM algorithm had the best performance. 86.36% of the selected comments on the ideological and political courses contained positive sentiment, and 13.64% contained negative sentiment. Relevant suggestions were given based on the negative comments.

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