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A Text Analysis Method for Student Learning Feedback on Network Teaching Platform Based on Natural Language Processing

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Abstract. With the emergence and end of the COVID-19, online learning has become an irreplaceable way of learning. In order to promote the improvement and enhancement of online curriculum resources and increase the learning effect of students, the content of curriculum evaluation is an important reference for the direction of curriculum improvement. Therefore, this article focuses on the student learning feedback of course resources. Firstly, through data collection algorithms, effective evaluation information is crawled, and then based on the collected information, the course evaluation text is annotated and classified, forming a reasonable corpus. Finally, through feature collection and sentiment analysis algorithms, sentiment analysis is performed on the evaluation content, effectively distinguishing between positive and negative evaluations, and guiding teachers to improve the course content.

Keywords: smart vocational education, curriculum resource, sentiment analysis, lexicon classification

1 Introduction

Entering the 21st century, artificial intelligence technology has begun to play its greatest role in various industries. Deep learning technology has greatly improved the development level of various artificial intelligence directions, including natural language processing. In the continuous growth of online learning platform access and interactive information, we need to obtain useful information from dynamic changes and a large number of web pages, and then classify the text. The classified information can effectively help users quickly find the information they need. Therefore, this article categorizes and summarizes the learning situation of students on the campus teaching platform and the evaluation of courses during the learning process. Then, automatic analysis is performed on the classified comments to analyze the emotional direction of student evaluation. This effectively evaluates the learning status of students and the effectiveness of course content, assists the school's curriculum construction, and improves the teaching quality of mixed ownership classrooms. Therefore, in response to the above requirements, the work done in this article is as follows:

1) Firstly, an effective analysis was conducted on the online resource library of "Smart Vocational Education", including page structure, page programming, and page data composition. Subsequently, a targeted page data collection algorithm was proposed.

2) Course evaluation sentiment analysis requires targeted corpora, and the existing typical corpora are insufficient to cope with the scenarios in this article. Therefore, we have started to establish a specific corpus for this article.

3) In order to improve the recognition level of emotional evaluation for vocational college students, this article establishes an improved natural language recognition model to enhance recognition efficiency.

In order to provide a detailed description of the content of this article, the structure of this article is as follows: Chapter 2 discusses the relevant research results to guide the research direction of this article; Chapter 3 is data processing, which discusses the process of data collection, annotation, classification, and corpus construction; Chapter 4 is data analysis, which explains the method of establishing a data analysis model; Chapter 5 is experimental simulation, which takes a specific course as an example to conduct data analysis, And provide reasonable suggestions for curriculum construction, Chapter 6 is the conclusion section.

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2 Related Work

Alpert Jordan conducts text screening and categorization of patient electronic health records to summarize the social determinants of health, and then explores the use of this factor to guide patient health management [1]. Jie Hu conducted a case study based on the “Voice of Users” dataset of SAIC-GM Wuling. Firstly, the text data was preprocessed and a professional dictionary in the automotive field was constructed. Then, the semantic features obtained through word vector training were input into the machine learning model in the cloud algorithm pool for prediction and classification, ultimately serving various scenarios and task objectives in the application layer business process [2]. Lin Zhang, the research object is the evaluation of tourists in the ancient town of Jiangnan. Using text analysis methods such as natural language processing, a comprehensive analysis was conducted on the online review data of Tongli Ancient Town in different years and seasons, and finally strategic suggestions were given for the tourism planning of the ancient town [3]. Xinkai Huang designed a product review analysis system for online consumers based on natural language processing methods. The system can preprocess post purchase reviews, extract keywords, and analyze emotional features, providing online consumers with a more convenient product selection experience and improving the shopping experience [4]. Hongchun Zheng, based on natural language processing technology, used algorithms such as K-Means and Classification for regression, classification, and clustering analysis to provide analysis for petition cases throughout the province. The trial results showed that after the system was launched, the processing cycle of cases was reduced, and the quality and efficiency of petition work were improved [5]. Xiuhui Hao, for campus news data, uses custom functions of algorithms to extract keywords from campus news, label news for classification, and achieve the goal of quickly identifying campus events, which has a positive effect on campus management and public opinion control [6].

3 Related Work

This article takes the course resource website “Smart Vocational Education” as an example to collect data from web pages. Firstly, it is necessary to observe the page structure, data structure, and the distribution of data in Javascript. The text data to be collected by this research institute is distributed in two modules. Course evaluation texts can be directly viewed on the course homepage, while question answering and questioning communication texts need to be accessed in the “Learning Center” to be viewed.

3.1 Page Structure

The discussion area consists of three sections: teacher’s Q&A section, classroom communication section, and comprehensive discussion section. The teacher’s Q&A area mainly gathers learners’ questions about the course content, the classroom communication area records learners’ answers to classroom questions, and the comprehensive discussion area is a section for learners to express broad topics. The page structure is shown in Fig. 1.

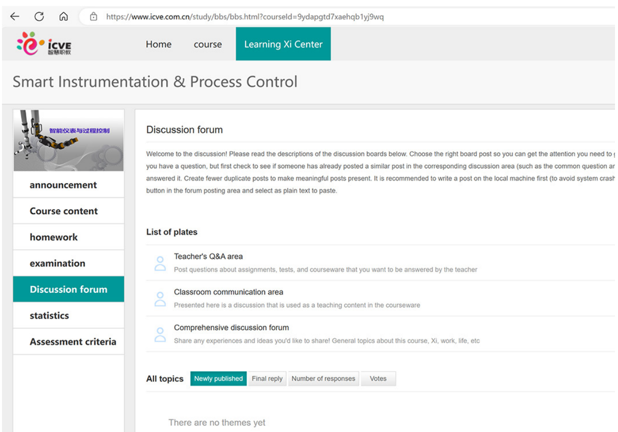

Fig. 1. Page structure

3.2 Data Composition

The data mainly consists of unit questions posted by teachers, learner response texts, learner IDs and comment times, and number of likes. The learner's response text is the core data in the data structure. By diagnosing the learner's response to questions, teachers can understand their level of knowledge mastery and improve subsequent teaching accordingly. Learner ID can be used to label text data, and comment time is an important data for understanding the distribution of learner response time. The number of likes indicates the recognition of a text by other learners, and generally speaking, a text with a higher number of likes can represent the opinions of more learners. The data composition is shown in Fig. 2.

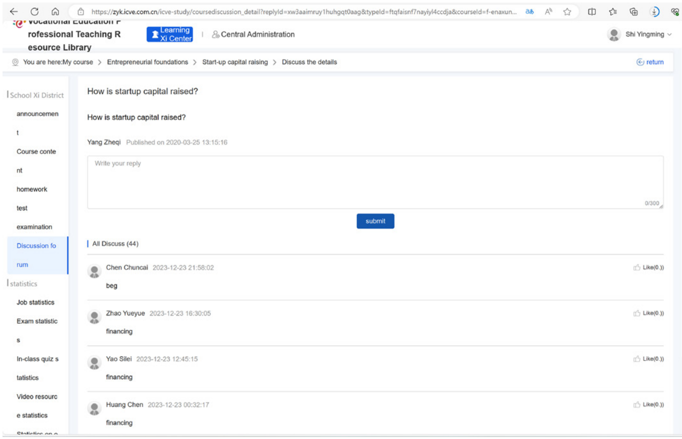

Fig. 2. Page data composition

3.3 Website Source Code

The "Smart Vocational Education" website is developed based on Javascript, and the collection of webpage data can be matched with rules through Javascript code to locate effective data and remove redundant information. The logic and specific data of learner feedback texts can be classified according to the course institution. Question answering texts are collected from the classroom communication area in the discussion area, while questioning and communication texts are collected from other sections in the discussion area. The website backend code is shown in Fig. 3.

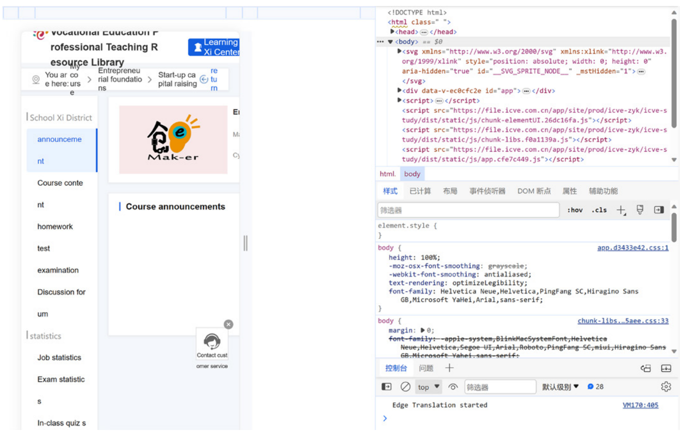

Fig. 3. Website backend code

3.4 Design of Web Data Programs

This article uses Webdriver from Selenium 2.0 library to build a development environment, uses Chrome browser as a webdriver login tool, and configures the correct XPath. Assign a string corresponding to the username and password in Python, then use Webdriver's element localization function to find the username and password input box, clear the original content, and pass in the string. Finally, simulate clicking the login button. In order to collect typical multiple courses on campus, the crawler program executes the data collection task for a course, returns the corresponding tag to the console, packages and stores the course data, and then collects the data for the next URL [7]. This is a phased series collection scheme.

For course evaluation texts, the beautifulsoup and Webdriver in the BS4 library can be directly called Collaborating with page parsing and data localization, the core steps of this stage include:

1) In the order of "iFrame framework → <div>...</div> → <a>...or<p>...</p>, etc.", Locate the lowest level structure where different field data is located.

2) Use the "find all" function to filter out all the content of a certain field data on the page.

3) Flip the page and repeat the above two steps.

3.5 Annotation of Course Evaluation Text Types

Course evaluation texts only need to be annotated with emotional attitude tendencies, that is, based on the emotions expressed in the text, they are labeled as positive, neutral, or negative evaluations. This article collected a total of 3452 evaluation results, among which the effective evaluations were mainly positive and neutral, with fewer negative evaluations. The classification of text annotations is shown in Table 1.

Table 1. Text annotation for course evaluation

Course evaluation text	Plate to which it belongs	Emotional tendencies
The course content is excellent. The teacher explained the principles of electricity clearly and provided an intuitive demonstration, which resulted in a lot of learning.	Content	Positive evaluation
The website is very slow, and the controllers used in the course are outdated. It is recommended to study the current technical situation carefully and adjust the content!	Content	Negative evaluation
I am following the learning process and sharing the learning outcomes and resource quality with everyone in the future.	Content	Neutral evaluation

3.6 Participle Operation

The main process of constructing a vocabulary based on evaluation content feedback for course content is to [8]:

1) Delete unnecessary information from the corpus, only retain sentences separated by commas or question marks, and store them in an array.

2) Create a new array, for each length 3 string XYZ in the original array, divide it into two strings XY and YZ, and store these two strings in the new array.

3) Delete strings with a length greater than 2 from the new array. Perform frequency statistics on the extracted strings and remove strings that appear less than 3 times.

4) Calculate the mutual information value of each string and store strings with mutual information values greater than or equal to 3.5. The calculation method for mutual information is as follows:

$$I(ab) = \ln \frac{p(ab)}{p(a) \cdot p(b)} . \quad (1)$$

Among them, $p(a)$ represents the probability of Chinese character a appearing in the dataset, $p(b)$ represents the probability of Chinese character b appearing in the dataset, and $p(ab)$ represents the probability of Chinese characters a and b appearing in the dataset. After calculating the mutual information of character combinations, it is also necessary to examine the left and right degrees of freedom of the combinations, that is, whether there are enough changes in the context when the character combinations as words appear at different positions in the corpus. The expression for information entropy is:

$$H\left(left\right) = -\sum_{x \in X} p\left(x\right)\log_2 p\left(x\right). \tag{2}$$

After segmenting the 3542 texts extracted from Smart Vocational Education, the segmentation results of each entry are stored in a list. Table 2 shows examples of segmentation representations.

Table 2. Comparison of examples before and after word segmentation

	Before word segmentation operation	After word segmentation operation
Example 1	The teacher spoke very clearly and easily, and I finally understood the meaning of Kirchhoff's law. I hope the specialized course will go smoothly.	"Teacher," "explained," "understood," "easy to understand," "finally," "understood," "Kirchhoff," "law," "meaning," "hope," "specialized textbook," "smooth progress."
Example 2	Understand the true meaning and usage of computer memory, variables, and microcontroller pins.	"Understand", "Computer", "Memory", "Variable", "Microcontroller", "Pin", "True", "Meaning", "Usage"

4 Feature Extraction and Sentiment Analysis for Course Evaluation

4.1 Feature Extraction

The main analysis objective of this study is to use natural language processing techniques to classify positive, neutral, and negative attitudes towards course evaluation texts, and to extract evaluation texts that provide feedback on certain shortcomings in the "Smart Vocational Education" course resources [9]. This article uses the TFID method that can calculate weights. In the calculation process, only two factors are considered: the frequency of TF words and the frequency of inverted documents with IDF words. The calculation method is as follows:

$$w_{ik} = tf_{ik} \times \log\left(N / n_k + 0.01\right). \tag{3}$$

The number of documents is N, and the number of texts where this word appears is represented by n_k. Considering the influence of text length on weights, the weight formula for each item is normalized to between [0,1]. The formula is as follows:

$$w_{ik} = \frac{tf_{ik} \cdot \log\left(N / n_k + 0.01\right)}{\sqrt{\sum_{k=1}^{n} tf_{ik}^2 \cdot \log^2\left(N / n_k + 0.01\right)}}. \tag{4}$$

By balancing the calculated word frequency appropriately, the weights of each item can be calculated. A relatively simple method is to square the calculated weights. The formula for calculating the weight of TFIDF after word frequency balancing is:

$$w_{ik} = \frac{\sqrt{tf_{ik} \cdot \log\left(N / n_k + 0.01\right)}}{\sqrt{\sum_{k=1}^{n} tf_{ik} \cdot \log\left(N / n_k + 0.01\right)}}. \tag{5}$$

The larger the TF, the wider the distribution range of feature items in the document set, and the higher their importance; The larger the IDF, the greater the ability of feature items to distinguish document content attributes and the distribution range in the document. Therefore, feature items that are assigned higher weights will only appear in fewer documents in the document set.

4.2 Sentiment Analysis

This article combines BERT language model and CNN. BERT's encoder is bidirectional and adds two pre training tasks, namely masking language models and next sentence prediction, thus possessing good bidirectional language features and universal adaptability. CNN is responsible for extracting features, and pooling layers can improve the model's expressive power [10].

BERT randomly selects 15% of the word elements in each pair of sentences for covering actions. Among them, 80% are directly replaced with<mask>, 10% are replaced with random word elements, and 10% maintain the original word elements. This allows BERT to focus on predicting bidirectional contextual information, with functions similar to cloze tests. In NSP tasks, during pre training sample sampling, there is a 50% probability of selecting a sentence that happens to be the adjacent next sentence, and a 50% probability of randomly selecting any sentence.

The formula for representing text features in convolutional layers is as follows:

$$d_j = f\left(t \cdot S_{j:j+n-1} + h\right). \tag{6}$$

In the formula, j represents the j -th feature, d_j represents the feature vector generated by the j -th feature value, f is the nonlinear activation function, h is bias, t represents the size of the convolution kernel, n represents the size of the sliding window, and $S_{j:\,j+n-1}$ represents the feature matrix generated by matrix S from the j -th to $j+h-1$-th rows. The final feature vector d is represented as follows:

$$d = \left[d_1, d_2, \cdots, d_{n-h+1}\right]. \tag{7}$$

The pooling layer only retains the feature value with the highest weight in each pooling kernel, and discards the rest. The formula is as follows:

$$p_i = \max\left(d_i\right). \tag{8}$$

For the convenience of description, the model in this article is referred to as the BERT-CNN model, and the model results are shown in Fig. 4.

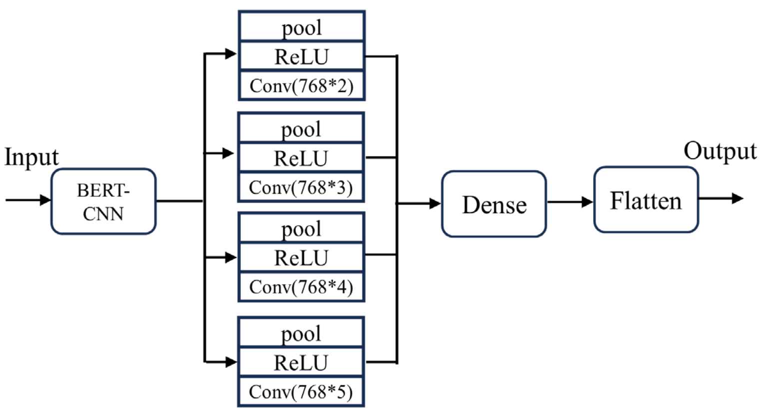

Fig. 4. Model diagram

5 Experimental Results and Analysis

By visualizing the classification results through Matplotlib, it can be found that all “smart vocational education” course evaluations have reached over 60%, and some learners have made negative evaluations of the courses, while the evaluation of expressing a neutral attitude towards the courses is the least. The course evaluation results are shown in Fig. 5.

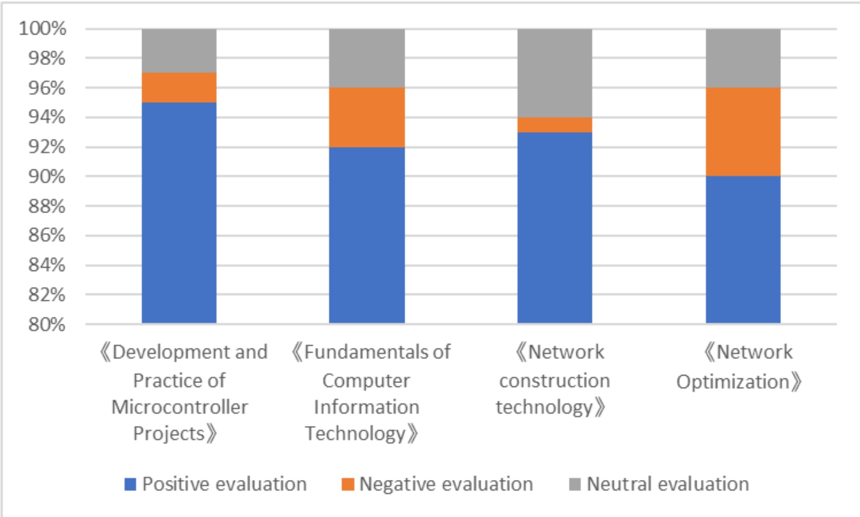

Fig. 5. Course evaluation text inclination

After conducting attitude analysis on course evaluation texts, when the data volume is large, clustering is necessary to facilitate teachers to understand which aspects of the current course resource construction learners are dissatisfied with. Cluster negative evaluations based on the three dimensions of course resource quality evaluation pointed to by negative evaluations. The clustering results are shown in Fig. 6.

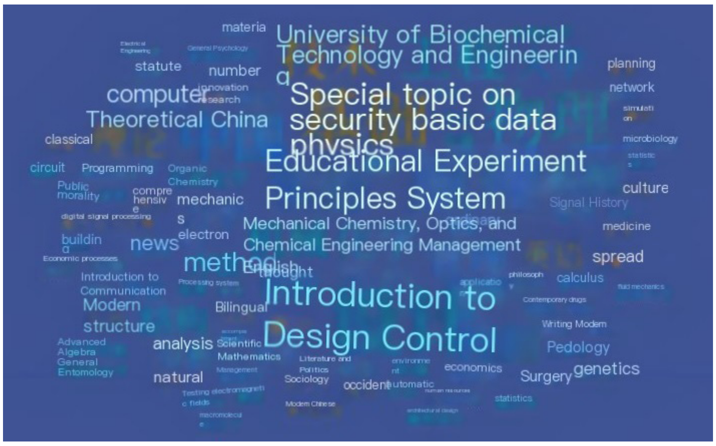

Fig. 6. Course category word cloud

Therefore, based on the above emotional analysis process, corresponding recommendations and results are obtained. Teachers should attach importance to the evaluation of “smart vocational education” course resources by learners, especially the common issues reflected by most learners in negative evaluations. Based on the dimensions that negative course evaluations mainly gather, improvements should be made in subsequent course design. In terms of teaching skills and teaching methods, it is also necessary to shift from the traditional classroom teaching mode to a teaching mode that adapts to online resources.

6 Conclusion

This article proposes a BERT-CNN recognition algorithm based on precise analysis of the target website during the process of emotional feedback on student learning in online course resources. The experiment shows that the BERT-CNN algorithm has significantly improved accuracy, and the course resources analyzed through sentiment analysis can guide teachers to play an important role in course improvement, which has high practical significance.

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