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Functional Analysis of English Carriers and Related Resources of Cultural Communication in Internet Media

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Functional Analysis of English Carriers and Related Resources of Cultural Communication in Internet Media

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Abstract: In the Internet intelligent teaching platform, students' demand for English cultural content is increasingly obvious. To help students quickly locate the overall content of resources in online autonomous learning, this study constructs a video annotation model for online teaching. This method classifies text by designing an optimized BERT model, and designs a Text Rank keyword extraction model that integrates external knowledge and semantic feature weights. The extraction of knowledge points contained in audio and video resources can be realized. In the experimental dataset, a relatively complete video content summary can be obtained by combining the first three sentences with the last two sentences. The F1 value of the classification model is up to 91.3%. In addition, the BERT-T model proposed in this paper has the best effect in the experiment. Compared with the original BERT model, the macro-F1 is 0.8% higher, and 0.5% higher than the Ro BERTA model. In the keyword extraction experiment, B-TextRank is 2.19% and 2.85% higher than the traditional TextRank in the two datasets. The experiment shows that the BERT-TextRank network resource annotation model has excellent application performance in English online autonomous teaching and can guide students to learn.

Keywords: Online teaching; English culture; Video resources; Text classification; Keywords extraction; Dimension model

Introduction

Online English education has brought diverse learning methods to teachers and students. In the past, students and teachers can only obtain paper-based learning materials by purchasing books. Now, the emergence of various learning platforms enables teachers and students to obtain various types of learning resources such as video, audio, pictures, PPT et al. for free, creating a good environment for students' independent learning (Abdulrahman, 2022). The way of cultural teaching is therefore increasingly important on the Internet platform. However, the rapid expansion of digital education resources has not benefited everyone (Nartiningrum et al., 2021; Albiladi et al., 2019). Various schools and platforms are rich in teaching resources, but the storage method is relatively backward, and there is a lack of scientific and efficient organization of massive resources in the digital teaching resource database. This makes it difficult for users to retrieve and use knowledge resources. Therefore, this paper proposes an English network resource annotation model based on BERT-Text Rank. This method converts video files into text through speech recognition, and uses text classification method to classify resources. At the same time, a Text Rank keyword extraction model integrating external knowledge and semantic feature weights is designed. This can realize the extraction of knowledge points contained in audio and video resources, and use the classification label and keyword extraction results together as the label of audio and video resources. The significance of this study lies in the extension of the marking model to the marking methods of English teaching video resources. This method also solves the problem of English teaching and education informatization, and has important practical significance for realizing personalized and cultural content education. The contribution of the research is to help students achieve autonomous learning of English cultural knowledge and skills application on the online teaching platform.

1. Related work

Shijie Zheng (2022) put forward the application of English paradigm in the domestic English teaching scene. He explored the positive effects of English paradigm on students' English learning from the perspective of students' communicative competence and cultural cognitive level. He also proposed that multicultural textbooks should be used in English teaching. With regard to the measurement of teachers' implicit attitudes to communicative language in Chinese English teaching, Sun C et al. (2022) proposed an association test for evaluation. This evaluation result showed the advantages of communicative language and traditional language in modern English teaching and helped educators make teaching decisions. In the context of English blended learning, Richard Jegadiesan (2021) discussed the strategies of combining Internet technology factors with teachers. For example, the strategy content included applications such as increasing the richness of network knowledge teaching in the intelligent communication system, virtual classroom library of mobile devices, etc. The ultimate goal of the strategy is to improve students' learning enthusiasm. Bai B et al. (2021) conducted various experiments on English teaching among primary school students in Hong Kong, mainly exploring the relationship between students' interests, self-efficacy and other psychological factors and their motivation for English writing. Their results showed that the growth mentality had the strongest and most significant correlation with all students' SRL strategies. Turan Z et al. (2020) combined flipped classroom teaching method with computer statistics. They analyzed the data in the database and found that the mixed and quantitative methods are the most widely used in English teaching. Krysten et al. (2022) studied the advantages and disadvantages of distance teaching and content teaching in Australian universities in the context of COVID-19. Based on the analysis of examples, the mixed teaching model under such factors as students' privacy, students' teaching model tendency, and students' participation is obtained. Rahman M M et al. (2018) analyzed the state of English teaching in Bangladesh from the perspective of global economy and talent market. They also reviewed the development of communicative language teaching in the dilemma of English teaching from the point of teachers.

Gaurav Nanda (2021) focused on students' learning experience in the context of large MOOC. He proposed a LDA topic modeling to analyze the characteristics of MOOC subjects, so as to help students evaluate content and increase the accessibility of learning resources. Putri et al. (2021) constructed a neural network model to evaluate the quality of English teaching classroom. The authors designed a college ETE strategy based on BP network to calculate the curriculum indicators. Nie Wenyan et al. (2021) constructed a face recognition method suitable for online teaching through BERT model. This method helped teachers accurately identify students' learning state in the application, thus optimizing the classroom strategy of online teaching. HUJie (2022) considered combining mind mapping with foreign language teaching practice, and using numbers and keywords as branches to promote students' learning and memory. And color was also used to distinguish knowledge points for learners to build knowledge networks.

To sum up, although all countries have found the importance of oral training in English teaching, the solutions that scholars seek remain in the aspects of teachers' influence and students' psychology. There are few views on the combination of English culture teaching and skill teaching. In English online teaching, technology development mostly focuses on the recognition of students' state of attention and classroom quality in passive courses, but ignores students' ability of autonomous learning. Therefore, this study proposes an intelligent labeling model of online teaching resources from the perspective of autonomous learning of English culture.

2. The Role of Cultural Resources in English Teaching and Resource Labeling Model

2.1 The Explicit and Invisible Strategies of English Culture Teaching in the Network Platform

Since the reform and opening up, China's English education has been in the process of continuous development and continuous integration with international standards. But during the teaching, students and teachers pay less attention to communicative teaching. In addition, students are also in a real situation and social environment where English is not often used. The influence of these factors has led to the low oral English ability of Chinese students. Not only that, the cultural knowledge in the current English textbooks of all stages in China is dominated by the English-speaking countries, ignoring the communicative role of cross-cultural teaching. This leads to the insufficient ability of Chinese students to use English to express their local environment and culture.Therefore, students should be aware of the differences between Chinese and Western cultures and have a more thorough understanding when reading first-hand English materials. Mastering communication etiquette and taboos in life and work can effectively improve the ability of cross-cultural communication. The cultural aspect of English teaching usually includes the basic theories and knowledge of the history, politics, economy, diplomacy, social culture, literature and other aspects of British and American countries. In culture teaching, students can better accept the skills and knowledge of English listening, speaking, reading, writing and translating. Combining technical knowledge and cultural content, the ultimate goal of English teaching is to cultivate high-quality, high-level students with the ability to engage in translation, research, teaching and management work. The contents of English skills application teaching and cultural knowledge teaching are shown in figure 1.

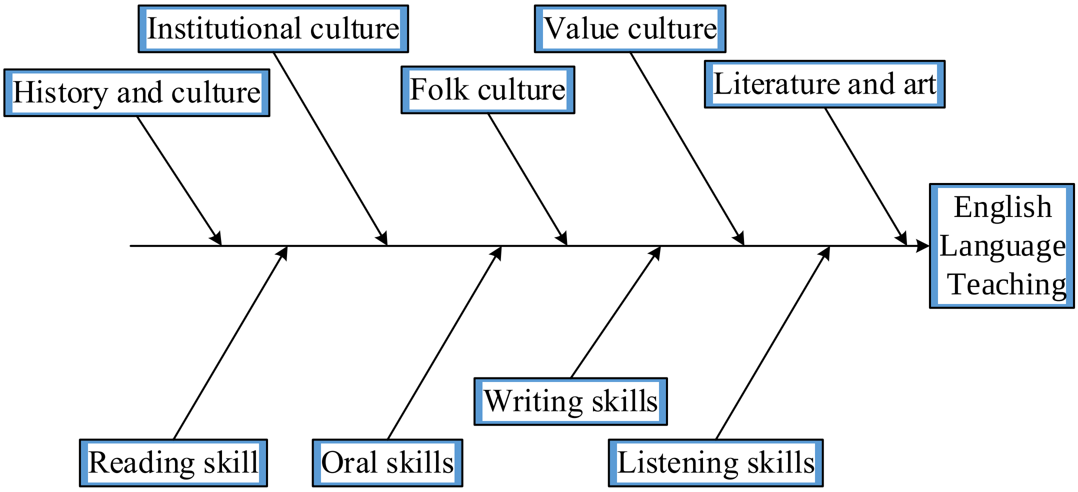

Fig.1 The content of English skill application teaching and cultural knowledge teaching

As shown in Figure 1, students should be able to understand some excellent Chinese and foreign cultures and ideas in teaching, and improve their humanistic, artistic and aesthetic qualities. To cultivate and improve the cultural quality of English majors, students should establish correct social and historical views and life values. From the dominant perspective, first of all, English education shows a trend of increasing knowledge application skills in the distribution of courses, while cultural and literature courses decrease. Secondly, English skill learning pays too much attention to grammatical structure analysis, which makes the content difficult and reduces the interaction between teachers and students. This also led to the inactive learning atmosphere in the classroom. Finally, there is a lack of hierarchy in English teaching. Students have insufficient time to sort out and understand the teaching content. If culture is divided into utensil culture, institutional culture and conceptual culture, the English culture teaching in China mostly stays on utensil and institutional culture. Its teaching rarely involves the content of the third stage. From the perspective of invisibility, first, it is difficult to give full play to students' advantages of online autonomous learning. Secondly, student-oriented English culture teaching activities show the characteristics of shallow content, simple form and passive acceptance by students. Finally, students tend to understand blindly in autonomous learning and have few opportunities to practice. The difficulties faced by English culture teaching at the present stage are shown in figure 2.

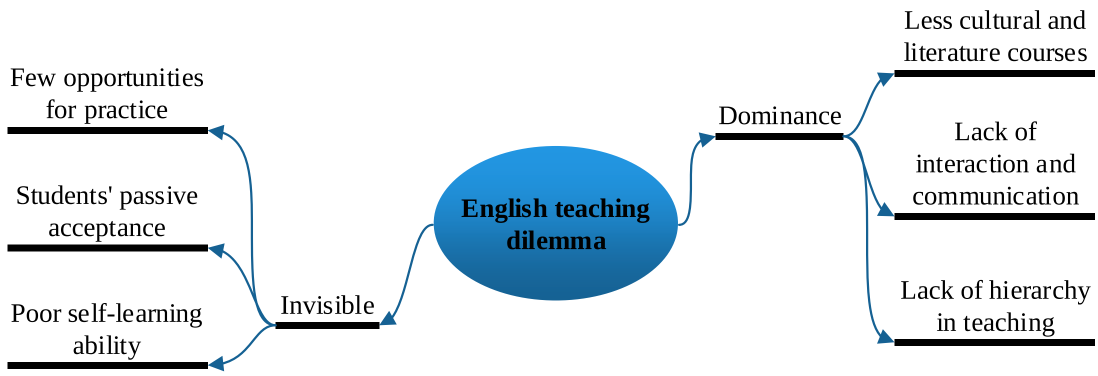

Fig.2 Difficulties in English culture teaching at the present stage

With the rapid development and popularization of the Internet in the new century, podcasts, blogs, MOOC, etc. provide new channels for digital and mobile English learning. This also brings new opportunities for English learning. Relying on the gradually developing network technology, teaching resources on the network show the characteristics of wide richness and high convenience, which plays an important role in English teaching. Internet English teaching supplements the cultural content that students learn in the classroom, and can ensure the complete transmission of teaching information. Secondly, there are many forms of network resources, such as text, voice, video and image. The presentation of network resources is more vivid and diverse. Knowledge is more easily accepted by students through this way. Teachers can arrange the teaching contents and steps in a more orderly way by relying on the network platform to improve the coherence and systematization of English teaching. Finally, the network platform can strengthen the interactivity of English teaching and activate the classroom atmosphere.

2.2Research on the Model of Educational Resources Labeling in English Online Media

Despite the growing importance of network resources for English culture teaching, the organization of teaching resource database is still in a low efficiency and slow query application mode. Knowledge atlas has become a hot spot to realize the structure of English teaching. Representing resource content information through tags is the basis of building knowledge map. This research will use the method of deep learning to build a label generation model of English online teaching resources. The process of generating resource annotations from this model is shown in figure 3.

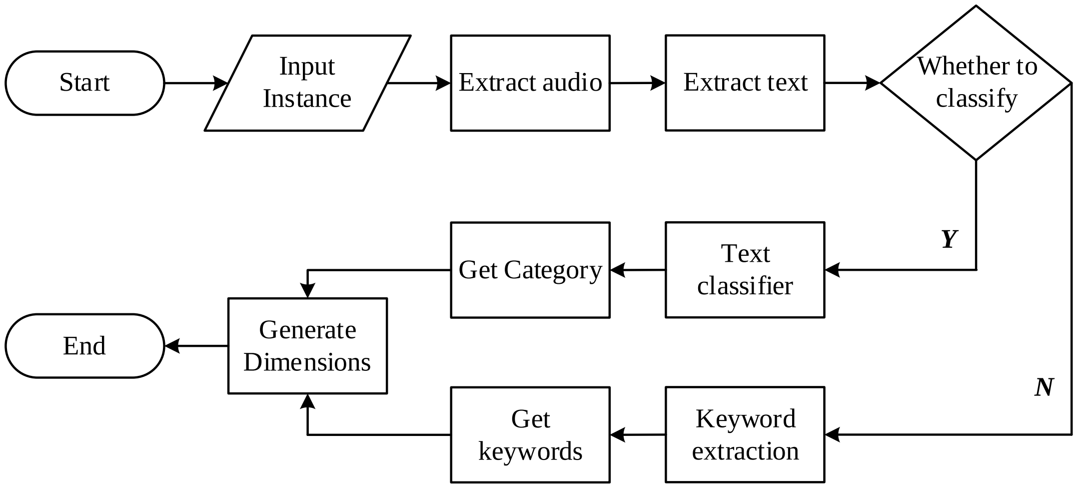

Fig.3 Model flow of tagging generation of English teaching network resources

Figure 3 shows that the educational resource annotation model built in this study mainly relies on two tasks: keyword extraction and classification, which are completed by Text Rank and BERT models respectively. BERT is a pre-training language model for two-way feature representation, which can simultaneously obtain the context feature representation of text. The core of BERT is the Transformer structure. The bidirectional transformer encoder is composed of multiple layers. The characteristics of the basic Transformer encoder enable BERT to better learn the context information in text data. The bidirectional network structure ensures that BERT can mine more semantic information. The structure of Transformer is shown in figure 4.

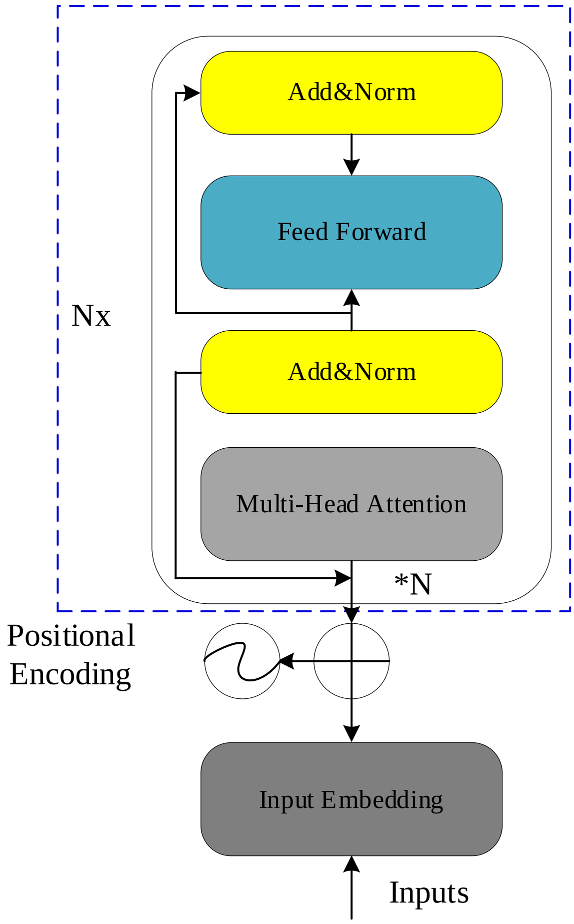

Fig.4 Transformer structure

As shown in figure 4, the Transformer encoder is composed of a Multi-head Attention Mechanism (MHAM) and a Fully Connected Feed-forward Network (FCFFN). Each layer has a residual connection and normalization layer. Assuming that the input of each sub-layer is x, the output of the sub-layer is expressed as equation (1).

$$Sublayer\_Output = LayerNorm(x + SubLayer(x)) \qquad (1)$$

The MHAM model is composed of multiple Scaled Dot Product Attention (SDPA) models, and its mathematical expression is shown in equation (2).

$$Attention(Q,K,V) = SoftMax(\frac{QK^T}{\sqrt{d_k}})V \qquad (2)$$

In equation (2), the input of Attention is Queries (Q) with dimension d_q, Keys (K) with dimension d_k, and Values (V) with dimension d_v. The mathematical expression of the MHAM model is (3).

$$MulitHead(Q,K,V) = Concact(head_1, head_1, ..., head_h)W^O \qquad (3)$$

First, a linear mapping is performed for the matrix with input dimension $d_{model} Q, K, V$. The parameters of the linear transformation matrix are $W_i^Q \in R^{d_{model} \times d_q}$, $W_i^K \in R^{d_{model} \times d_k}$ and $W_i^V \in R^{d_{model} \times d_v}$. $Q \in R^{d_{model} \times d_q}$, $K \in R^{d_{model} \times d_k}$ and $V \in R^{d_{model} \times d_v}$ are obtained after mapping. Then, the new matrix of SDPA is used to calculate, and the calculation results are obtained after performing the above steps for h times. Finally, the merged results are linearly transformed. The linear transformation matrix parameter is $W^O \in R^{hd_v \times d_{model}}$. The output result after linear transformation is matrix $M^{hd_v \times d_{model}}$. After the multi-head attention mechanism calculation, matrix M obtains the semantic features of different spaces of the text and captures the context information of each word. FCFFN is composed of two layers of linear fully connected network, and the linear transformation in the middle depends on ReLU activation function, i.e. :

$$FNN(x) = \max(0, xW_1 + b_1)W_2 + b_2 \qquad (4)$$

In the key word extraction of the tagging model of English online teaching resources, the TextRank model used in this study is essentially a weighted undirected graph model. Supposing any sentence in the sentence set $T = \{S_1, S_2, ..., S_n\}$ is expressed as $S_i = \{V_1, V_2, ..., V_m\}$. V represents the words in the sentence. Therefore, text can be represented by graph model $G = (V, E)$. V refers to the set of all word nodes in the word graph model. E refers to the weight set of edges between each word node in the word graph. The TextRank value of the word node V_i is expressed as equation (5).

$$S(V_i) = 1 - d + d \cdot \sum_{j \in In(V_i)} \frac{1}{|out(V_i)|} S(V_j) \qquad (5)$$

In equation (5), $S(V_i)$ is the importance score of word node V_i. d is the damping coefficient. $In(V_i)$ and $Out(V_i)$ represent the degree of entry and exit of word nodes in the word map. As a recursive formula model, the initial value of each word node in the original TextRank model is the same. In this paper, the research object in keyword extraction is educational text data. Educational texts contain subject-specific nouns, which are less likely to appear in ordinary texts. However, they may appear repeatedly in educational texts, and these proper nouns can reflect the main content of educational texts. If the unified initial weight is used to reconstruct the word map when performing the keyword extraction task of educational text, it will inevitably affect the importance ranking of proper nouns, and thus affect the whole keyword extraction result. Therefore, a method for calculating the initial weight of multi-domain words based on external proper noun database is proposed. This method improves the accuracy of the model by accurately assigning the initial weight of the word map. The optimized equation (5) is shown in equation (6).

$$S(V_i) = \lambda S_{com}(V_i) + (1-\lambda) S_{dom}(V_i) = \lambda \frac{N}{M1} + (1-\lambda) \frac{N}{M2} \qquad (6)$$

In equation (6), λ represents the thesaurus selection parameter. $S_{com}(V_i)$ refers to the weight of the current word node in the general thesaurus. $S_{dom}(V_i)$ is the weight of the current word node in the proper noun database. N represents the number of word nodes in the word map. $M1$ and $M2$ are the number of words appearing in the general vocabulary and special vocabulary in the current word map. TextRank model is essentially calculated on the basis of word graph. Although this model increases the importance of proper nouns through initialization weight, the importance of proper nouns also varies. Therefore, the research improves the probability transfer matrix of TextRank through the BERT pre-training model, and distinguishes the importance of words more accurately by integrating the meaning of words. First, the degree of semantic correlation between word vectors is calculated by the cosine similarity formula, and the equation (7) is obtained.

$$Similarity(V_i, V_j) = \frac{\bar{V_i} \cdot \bar{V_j}}{\left|\bar{V_i} \cdot \bar{V_j}\right|} \quad (7)$$

In equation (7), V_i, V_j represent two word nodes. $\bar{V_i}$ and $\bar{V_j}$ are two word vector expressions. In the weight allocation, the greater the semantic difference between two adjacent word nodes, the higher the transfer probability should be given. Therefore, the probability calculation formula of the transition from word node V_i to V_j is expressed as $P_{sim}(V_i, V_j) = 1 - sim(V_i, V_j)$. Then, the external knowledge weight and semantic weight are combined to comprehensively calculate the jump probability of nodes, i.e. :

$$P(V_i, V_j) = \alpha P_{sim}(V_i, V_j) + \beta P_{ext}(V_i, V_j) \quad (8)$$

The formula after improving the weight transfer matrix is equation (9).

$$M = \begin{bmatrix} P_{11} & \dots & P_{1m} \\ \dots & \dots & \dots \\ P_{n1} & \dots & P_{nm} \end{bmatrix} \quad (9)$$

After the probability transfer matrix is obtained, the TextRank value of the word node can be finally calculated, as shown in equation (10).

$$S_{B-TextRank}(V_i) = (1-d) + d \times \sum_{V_{i \in In(V_i)}} \frac{M_{ij}}{\sum_{V_{k \in Out(V_j)}} M_{jk}} S_{B-TextRank}(V_j) \quad (11)$$

Finally, when the research and construction of the English teaching network resource labeling method is applied to the online teaching platform, the relationship between administrators, teachers and students and the system functions are shown in figure 5.

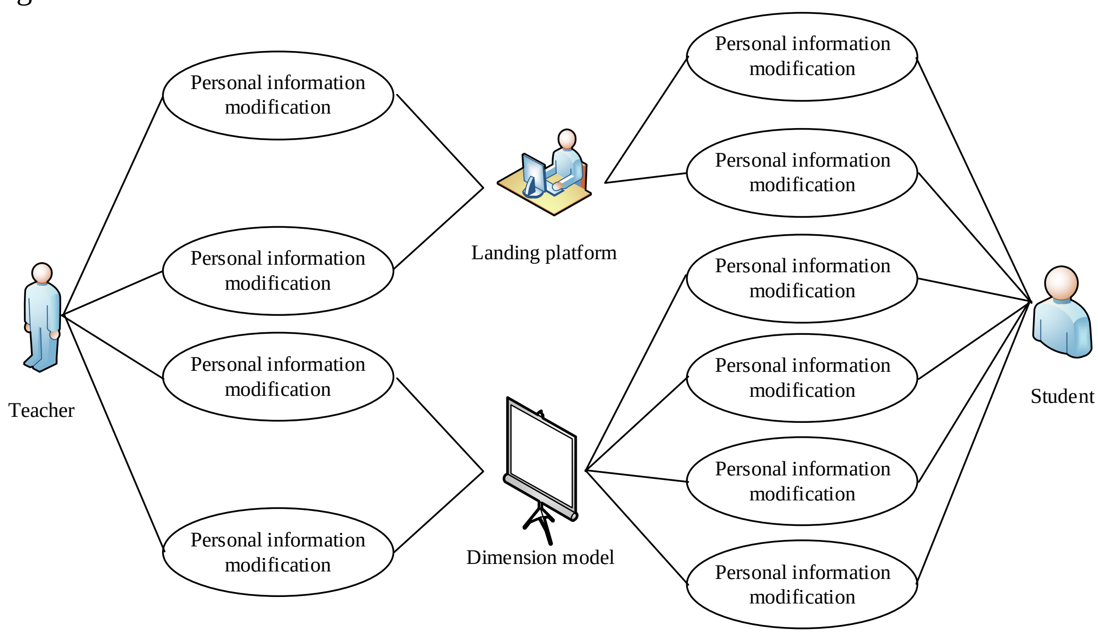

Fig.5 Application scenario of resource annotation model in online teaching platform

In Figure 5, the model built by the research takes into account the actual needs of teaching tasks. The design of educational video resource marking system can provide users with convenient educational video annotation, result display, data storage and other services. Thus, various personalized online teaching platforms can make better use of educational video data. The educational video resource tagging model includes module design and function construction, including data preprocessing, text classification, keyword extraction and result display functions.

3. Application and Analysis of Online English Teaching Resource Labeling Model

3.1 BERT Classification Model Experiment of Network Education Resources

To experiment the constructed annotation model of English teaching resources, the research takes all English course teaching videos in the online teaching resources platform of a university as raw data. The audio in the video is extracted and stored separately. The experiment will use the format factory audio and video conversion tool to save the audio track as a wav file. Intelligent speech recognition service is used to convert teachers' teaching content into text data. The model parameters of the experiment are shown in table 1.

Table.1 Model parameters of the experiment

Project	Parameter	Parameter name	Value
Pre-training covering method	Whole-word covering	Max_seq_len	510
Model type	Base	Batch_size	64
Pre-training word vector	5.4B	Learning_rate	5e-5
Optimizer	LAMB	Num_epoch	15
Cover vocabulary	11045	Num_labels	/

In this experiment, the structure of BERT classification model is composed of 12-layer bidirectional transformer decoder. Its hidden layer dimension is 768 with 12 attention mechanisms, and the overall parameter quantity is about 110M. The maximum length of the text sentence is 510 words, and the learning rate is $5e^{-5}$. The number of samples for each batch during training is 64. To verify the effectiveness of the BERT classification model in English teaching network resources, this experiment first set up the classification performance of the model in different teaching text interception. Since the length of text in the teaching video resources is generally more than 510 words, this study adopts three methods to obtain text data of different lengths. They are first segment interception method, the first and last combination interception method, and the direct interception method. The macro precision of the classification model under different interception methods is shown in table 2.

Table.2 Macro precision of classification model under different interception methods

Data interception method	Macro-P	Macro-R	Macro-F1
5 sentences in the Beginning	90.4%	89.7%	90.1%
First 4+last 1	90.6%	90.4%	90.5%
First 3+last 2	91.4%	91.1%	91.3%
First 2+last 3	91.0%	90.6%	90.8%
First 1+last 4	90.3%	89.5%	89.9%

The first 510 characters	90.5%	90.1%	90.3%
The last 510 characters	90.4%	90%	90.2%

Macro-P, Macro-R and Macro-F1 in the table represent the precision rate, recall rate and F1 value of performance indicators. The data in Table 2 shows that under the same model, different data interception methods directly affect the final effect of the model. From the two results of the direct interception method, both the beginning and the end of the document contain information that can summarize the document. The interception method combining the first three sentences and the last two sentences performs better, reaching the macro-F1 value of 91.3%. To sum up, this paper believes that in the text data of English education in a university, most of the course content is contained in the teacher's opening remarks. At the end of the course, the teacher will also review and summarize this lesson. The course content can be highly summarized by combining the first three sentences and the last two sentences. The number of text characters obtained varies from the original article, ranging from 200 to 350 words. After the experiment of text interception strategy, this study will compare the performance of different classification models.

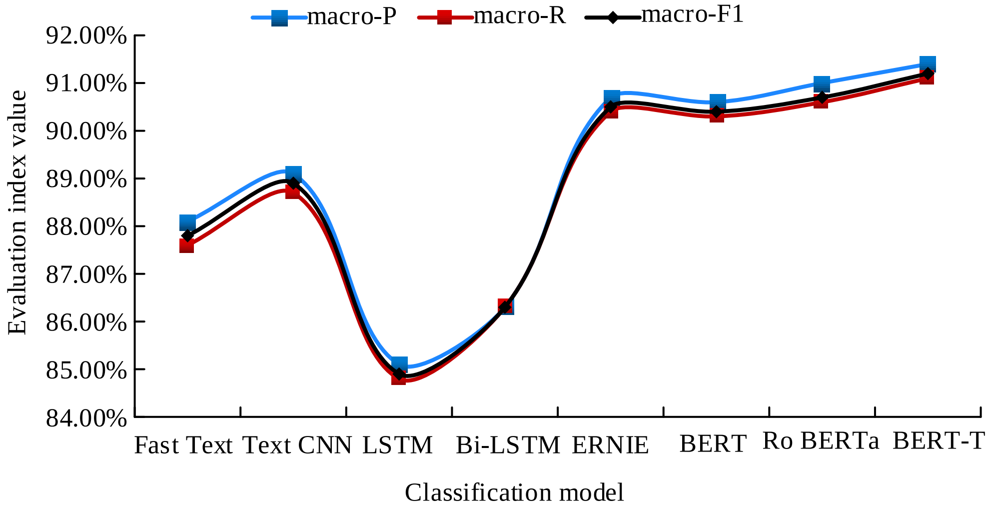

Fig.6 Performance comparison of different classification models

Figure 6 shows that the classification results of Fast Text model are only second to those of Text CNN and BERT series models. Its F1 value is 87.8%. The F1 value of Text CNN is only 0.5% different from the original BERT model. The LSTM model has the worst performance. The F1 value of Bi-LSTM is 1.4% higher than the original LSTM model, but still 4.1% lower than the original BERT model. The BERT-T model proposed in this paper has the best effect in the experiment, with the macro-F1 reaching 91.2%. It is 0.8% higher than the macro-F1 of the original BERT model and 0.5% higher than the macro-F1 of the Ro BERTA model. The reason is that the convolution neural network structure has excellent ability in local information extraction, which can more effectively extract the information in the BERT output word vector.

3.2 B-TextRank Keyword Extraction Application Experiment of Online Education Resources

This research takes Wiley InterScience (WIS) database and the English literature data of a university as the experimental objects, and validates the semantic weighted keyword extraction model. The WIS database contains social science and natural science journals in English. This experiment first compares the B-TextRank keyword extraction model built in the study with TF-IDF, YAKE, the original TextRank and EmbedRank models. Table 3 below shows the comparison of macro precision values of 3, 5 and 7 keywords extracted from two data sets by different models.

Table.3 Macro precision values of 3, 5 and 7 keywords extracted from two data sets by different models

Macro precision	College English Literature Database				Willey science database			
macro-P	Model	TOP3	TOP5	TOP7	Model	TOP3	TOP5	TOP7
	TF-IDF	23.60 %	20.30 %	16.70 %	TF-IDF	24.21 %	20.68 %	15.46 %
	YAKE	23.54 %	21.06 %	16.90 %	YAKE	23.71 %	20.36 %	15.31 %
	Text Rank	24.77 %	21.32 %	18.36 %	Text Rank	24.43 %	21.13 %	16.30 %
	Embed Rank	23.78 %	19.63 %	15.34 %	Embed Rank	23.84 %	20.45 %	15.73 %
	B-Text Rank	25.61 %	21.77 %	18.44 %	B-Text Rank	25.11 %	21.30 %	16.94 %
macro-R	Model	TOP3	TOP5	TOP7	Model	TOP3	TOP5	TOP7
	TF-IDF	23.60 %	20.30 %	16.70 %	TF-IDF	24.21 %	20.68 %	15.46 %
	YAKE	23.54 %	21.06 %	16.90 %	YAKE	23.71 %	20.36 %	15.31 %
	Text Rank	24.77 %	21.32 %	18.36 %	Text Rank	24.43 %	21.13 %	16.30 %
	Embed Rank	23.78 %	19.63 %	15.34 %	Embed Rank	23.84 %	20.45 %	15.73 %
	B-Text Rank	25.61 %	21.77 %	18.44 %	B-Text Rank	25.11 %	21.30 %	16.94 %

The comparison of macro recall rate values in table 3 shows that the more keywords extracted, the greater the value of each model. In the two datasets, the keyword extraction method with external knowledge weight proposed in this paper is superior to other baseline models in obtaining the macro-R value. When the number of keywords extracted is 7, the B-TextRank model proposed in this paper is 0.47% higher than the original TextRank model. The comparison results of macro precision in the table shows that the macro-P value of the keyword extraction method with external knowledge weight proposed on the two datasets is superior to other baseline models. When the number of keyword extraction is set to three, the TextRank model with external knowledge weight proposed is 0.84% higher than the original model. Finally, F1 value of different algorithms is shown in figure 7.

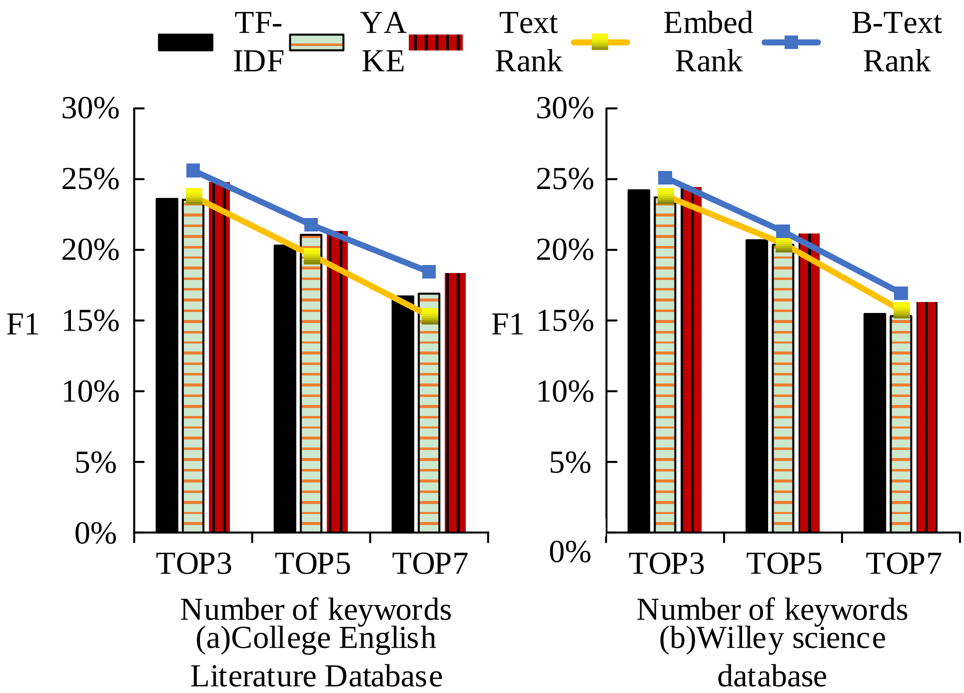

Fig.7 F1 Value of Different Algorithms

The two datasets in figure 7 show that the keyword extraction method with external knowledge weights is better than other baseline models. When five keywords are selected, the B-TextRank model is 0.56% and 0.69% higher than the TF-IDF and YAKE based on statistical methods, and 0.19% higher than the original TextRank model. This group of experiments set up two control groups to verify the feasibility and efficiency of the interception method proposed in keyword extraction. The setting purpose of control group 1 is to verify the feasibility and effectiveness of the text rank model integrating semantic weight. Control group 2 is to verify the impact of data interception methods on the keyword extraction process. The specific results are shown in table 4.

Table.4 Macro-F1 of models in different control groups on two data sets

Data set	Groups	Model	TOP3	TOP5	TOP7
College English Literature Database	Control group 1	TF-IDF	19.29 %	20.51 %	19.94 %
		YAKE	19.14 %	20.85 %	20.01 %
		Text Rank	20.28 %	21.39 %	21.17 %
		Embed Rank	19.08 %	19.87 %	18.71 %
	Control group 2	TF-IDF	19.70 %	20.56 %	19.79 %

		YAKE	19.53%	20.99%	19.97%
		Text Rank	20.58%	20.95%	20.65%
		Embed Rank	19.76%	20.69%	18.95%
		W2V-Text Rank	20.99%	21.97%	20.69%
		ELMO-Text Rank	21.75%	23.58%	21.68%
	Experimental group	B-Text Rank	21.81%	23.48%	21.56%
Willey science database	Control group 1	TF-IDF	19.58%	20.86%	18.99%
		YAKE	19.48%	20.73%	18.93%
		Text Rank	19.92%	21.23%	19.78%
		Embed Rank	19.24%	20.66%	19.12%
	Control group 2	TF-IDF	19.71%	20.30%	19.21%
		YAKE	19.85%	20.72%	19.64%
		Text Rank	20.38%	21.00%	20.27%
		Embed Rank	20.18%	20.76%	19.81%
		W2V-Text Rank	21.46%	21.99%	20.93%
		ELMO-Text Rank	22.24%	23.81%	22.11%
	Experimental group	B-Text Rank	22.60%	24.08%	22.29%

In Table 4, the performance of B-TextRank is improved compared with other baseline models in terms of macro-F1 value indicators. In the experiment of control group 1, B-TextRank was 2.19% and 2.85% higher than the traditional TextRank in the two models. This shows that the fusion of semantic weights is feasible and improves the performance of the model. In the control group experiment 2, this paper has the best effect in three key words extraction. In conclusion, B-Text Rank performs well under the comprehensive consideration of model extraction performance and efficiency. At last, the experiment applies the B-TextRank resource annotation model proposed in the study to the MOOC forum management of the university. It also analyzes satisfaction evaluation from the feedback of the teacher administrator. Details as following figure 8.

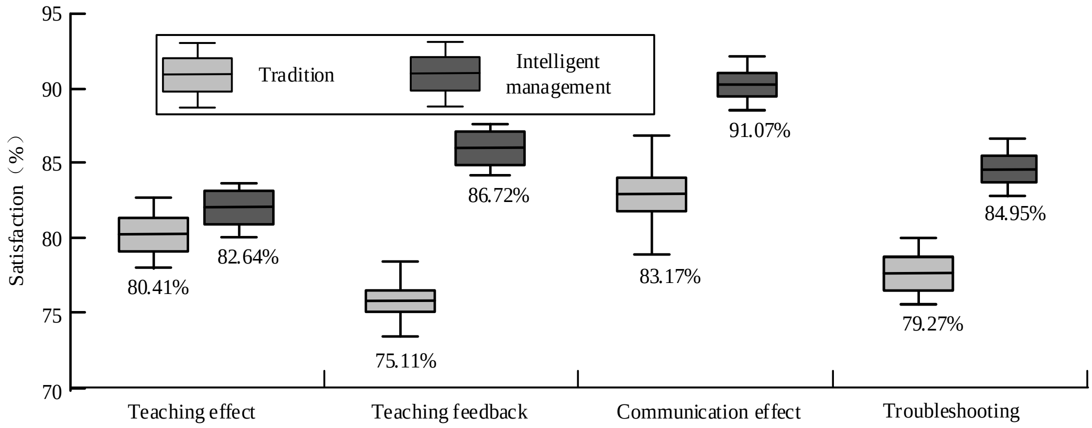

Fig.8 MOOC administrator's satisfaction evaluation on traditional classification methods and optimized management methods

The new MOOC intelligent management labeling method feedback its satisfaction evaluation through the administrator's scoring behavior. The average satisfaction of teachers' overall service is 84.95%, higher than 5.68% of the old system. It means that the staff generally recognized the effect of model classification on the classification of comments in MOOC forums. In terms of teaching effect, the satisfaction of teachers in the new system is 82.64% ± 1.86%, while that in the old system is 80.41% ± 0.79%. In terms of teaching feedback and communication effect, teachers' average satisfaction increased by 11.6% and 7.9%. In terms of fault resolution, the satisfaction of teachers in the new system is 84.95% ± 1.34%, and that in the old system is 79.27% ± 1.83%.

4. Conclusion

To realize the effective marking of educational video resources on the video resource platform, the BERT-TextRank video annotation model is proposed and applied in the English culture teaching and skill teaching. In the classification technology of video teaching resources, experiments on text interception methods and different classification models are studied. The conclusion is that the extraction method of the first three sentences+the last two sentences can better summarize the overall content of the English teaching video. In the comparison of classification models, BERT-T model has the best effect in the experiment. Macro-F1 reached 91.2%, 0.8% higher than that of the original BERT model and 0.5% higher than that of the Ro BERTA model. In addition, the performance of different extraction models is compared in the experimental video keyword extraction. When the number of keywords extracted is 7, the B-TextRank model is 0.47% higher than the original TextRank model. The comparison results of macro precision in the table found that the macro-P value of the keyword extraction method with external knowledge weight on the two datasets is better than other baseline models. When the number of keyword extraction is set to three, the TextRank model with external knowledge weight is

0.84% higher than the original model. The deficiency of this study is that the B-TextRank method is only applicable to English online teaching video resources. It cannot analyze audio files. As a result, computer vision model and multimodal educational video resource labeling model can be constructed to process such videos in subsequent research.

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