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# Construction and Application of Knowledge Graph Based on Artificial Intelligence Algorithm in English Learning in Colleges and Universities

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**Abstract** In recent years, with the rise of artificial intelligence and deep learning technologies, knowledge graphs can bring more efficient and intelligent solutions to different fields. In this paper, we mainly propose the BiLSTM-Attention-CRF model and the model of BERT-BiLSTM-Attention for entity recognition and relationship extraction of text data. Entities and relationships can be recognized by these two models. The entities obtained by knowledge fusion are then utilized to complete the construction of the knowledge graph of English learning in higher vocational colleges. The results show that the attention module added to the BiLSTM-CRF model improves the precision rate, recall rate and F1 value by 2.81%, 3.36%, and 3.63, respectively.The introduction of the BiLSTM-Attention model into the BERT layer also improves the effectiveness of the model. It can be found in the knowledge graph of English learning in higher vocational colleges and universities, and its research hotspot is the Internet. The application of knowledge mapping to the practice of English teaching in higher vocational colleges can significantly improve the English performance and learning attitude.

**Index Terms** BiLSTM-Attention-CRF, BERT-BiLSTM-Attention, knowledge graph, English teaching, entity recognition

## I. Introduction

With the rapid progress of science and technology, online teaching occupies a pivotal position in higher education. At the same time, the booming development of mobile Internet, big data, artificial intelligence, cloud computing and other technologies is profoundly changing the learning method, promoting the learning method to the direction of wisdom and intelligence [1]. In this process, the concepts of "focusing on the individual needs of learners" and "customizing appropriate educational programs for each learner" have gradually become a consensus [2], [3]. In such a context, knowledge mapping, as a way of presenting knowledge in a graphical structure, has the potential to promote the quality of teaching and learning in higher vocational English education, which cannot be ignored [4]. It is widely recognized by scholars that knowledge mapping has a strong potential for critical thinking about educational change and curriculum design, and can help students understand subject matter more effectively and better master what they have learned [5]-[8]. The application of knowledge graphs in the field of education not only saves time and effort, but also enhances student learning and improves the quality of education and teaching [9]-[12]. In the field of education, knowledge mapping technology is commonly used in the categories of constructing subject knowledge system, optimizing teaching content and curriculum design, and improving students' independent learning and innovation ability [13]-[15].

Some researchers, both domestic and foreign, have carried out research on applications related to knowledge graphs in the field of education several years ago. Martin, A. J. and Dominic, M. M. proposed a knowledge graph system for online education, which is able to build a knowledge network from heterogeneous pedagogical data in the field of education, and provide personalized pedagogical content matching the abilities of students at different levels [16]. Duan, S. et al. constructed a personalized teaching resource recommendation system consisting of models such as subject knowledge graph and learner portrait to provide students with accurate and effective educational resources in large-scale learning environments based on their individual characteristics and learning feedback [17]. Yan, Z. et al. studied the exercise recommendation system in online learning resources recommendation, constructed the motion recommendation framework based on knowledge graph, and recommended personalized exercises for students based on students' answer records and course knowledge structure map, which provided an effective path to realize accurate teaching [18]. Baig, D. et al. used knowledge graph to process massive student online learning data and extract the implicit knowledge entities and relationships, which can be used to recommend resources without the historical data of the target learners, effectively solving the cold-start problem [19]. Guan, H. designed a joint extraction method of course knowledge entities and relationships in the education domain by integrating knowledge graph and deep learning techniques, aiming to provide learners with recommendations of course resources based on relevance and accuracy, and to improve their learning efficiency and satisfaction [20]. Wang, F. et al. established a knowledge graph within the subject area, and on this basis constructed a model of the learner's knowledge structure based on his existing knowledge and target knowledge, combined with the improved Portfolio ST algorithm to fully excavate optimal learning paths with personalization, which in turn enhances the learner's learning efficiency [21]. Troussas, C. and Krouska, A. examined a knowledge graph-based student activity recommendation system that enhances the effectiveness of teaching and learning approaches by mining students' behavioral patterns and learning preferences in order to analyze the path-level commonalities in the way students carry out their learning activities and, as a result, recommending knowledge-graph-based learning activities to students [22]. It can be seen that the teaching system based on knowledge graph can automatically adjust the learning path and recommend learning resources according to the students' learning progress and comprehension level, so as to improve the students' learning effect.

Similarly, in English teaching in higher vocational colleges and universities, knowledge graph technology can be used to build an English knowledge system and a personalized knowledge recommendation system for students [23], [24]. Knowledge graph can not only store knowledge nodes, but also establish connections between multidimensional knowledge points in the form of edges, so that the teaching content can become a kind of organized and structured knowledge network [25]-[27]. This can not only meet the individualized needs of students, but also achieve the sharing of teaching resources and promote the efficient delivery of lectures [28], [29]. Therefore, it is of great significance to study the combination of knowledge mapping and English teaching in higher vocational colleges and universities to improve the quality and effect of college English education.

In this paper, we take the data included in China Knowledge Network database as the research object, and use higher vocational colleges and universities + English language learning as the search keywords, and use crawler technology to crawl the relevant data. Taking this as the data base, artificial intelligence deep learning techniques, i.e., BiLSTM-Attention-CRF model and BERT-BiLSTM-Attention model, are used for named entity recognition and relationship extraction. This improves the model named entity recognition accuracy and strengthens its classification ability. The knowledge information and relationships extracted by the above two models are combined with the processes of knowledge fusion and knowledge storage to complete the construction of the knowledge graph of English learning in higher vocational colleges. Comparison experiments are conducted in terms of precision rate, recall rate and F1 value to verify the superiority of the model in this paper. Finally, the reliability of knowledge mapping in English teaching practice is tested.

## II. Construction of knowledge graph examples

### *II. A. Literature analysis*

Knowledge graph analysis software CiteSpace is a powerful visualization literature analysis software [30]. The information visualization software uses co-citation analysis and path-finding network and other methods to visualize the literature data, and it can present the relationship between the author, the issuing institution and the keywords of the literature through the visual mapping, which can clearly show the evolution of a certain subject area. The research hotspot of a certain discipline is always the hot topic of the discipline, which is closely watched by researchers and research organizations, and plays a key role in promoting the innovation and development of the discipline. The use of CiteSpace software can help researchers to understand the past research trajectory and research status of a certain discipline, grasp the research hotspots, grasp the most concentrated research problems and the latest research dynamics in the field, and predict the future development direction of the discipline. Meanwhile, in a literature, keywords are the words reflecting the author's core idea or core point of view, which are highly condensed to the research content. Therefore, this subsection utilizes CiteSpace software to analyze the keywords of the literature data in this paper, to grasp the research hotspots and research themes, and to provide key research directions for further improving the knowledge map.

### *II. B. Knowledge graph construction process*

Knowledge graph construction methods are divided into two main categories: top-down and bottom-up methods. The top-down approach first defines an ontology and data schema for the knowledge graph, and then extracts entities to be added to the knowledge base [31]. This construction method needs to utilize some existing structured knowledge bases as its base knowledge base and requires high data quality, this method is suitable for small-scale knowledge graph construction and is usually applied in the construction of domain knowledge graphs. At present, the most widely used is the bottom-up construction method, which extracts information such as entities, relationships, attributes, etc. from open data sets with the help of machine learning, natural language processing and other technologies, and then finally constructs a complete knowledge graph after knowledge fusion and other stages.

The construction process of knowledge graph mainly contains four stages: data acquisition, information extraction, knowledge fusion and knowledge storage. Among them, data acquisition is to obtain text data from academic paper databases, public government data, professional websites and other channels, and after machine learning, natural language processing and other technologies for data cleaning and processing; information extraction process extracts entities, attributes, and inter-relationships between entities from the processed data through named entity recognition and entity relationship extraction technologies. Knowledge fusion can standardize and integrate knowledge from different sources, and after obtaining new knowledge, it needs to be integrated to eliminate entity ambiguity, for example, some entities may have multiple expressions, and a particular title may correspond to multiple different entities. The knowledge storage process is to store the processed triplet "entity-relation-entity" through a graph database such as Neo4j. Figure 1 shows the process of building a knowledge graph.

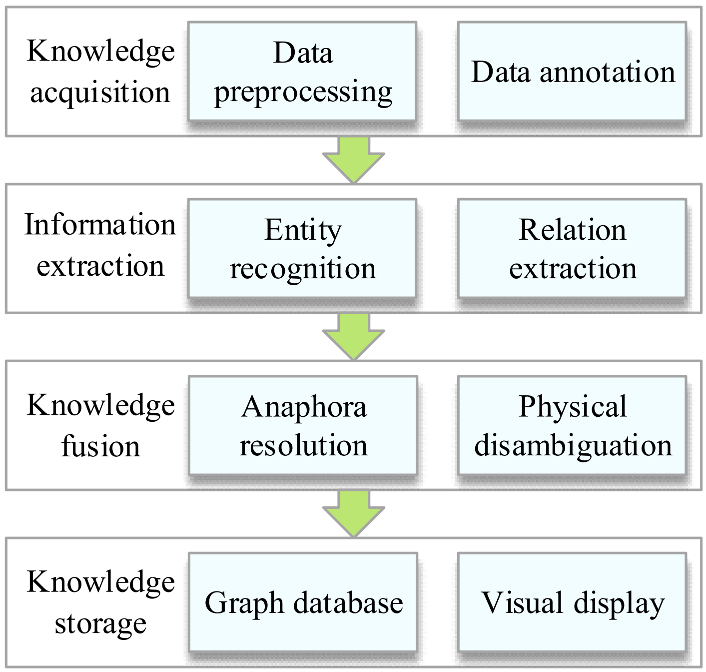


Figure 1: Flowchart of knowledge graph construction

Knowledge graphs are mainly stored in RDF storage and Neo4j and other graph databases storage. Resource Description Framework is used to describe the network resources W3C standard, RDF storage will be stored in the form of ternary data, through the ternary description of the association between resources. Figure database is a mathematical graph theory as the theoretical foundation of the non-relational database, in addition to supporting the storage, analysis, processing of data, but also more adept at the analysis of complex relationships between large amounts of data, the figure database Neo4j is currently the most popular knowledge graph storage tool. Neo4j is a Java programming language development and implementation of open source non-relational graph database, in 2007. Formally released, in addition to supporting the needs of Java language development, but also through the inner driver py2neo Python language development. Neo4j was born specifically for the graph data storage, for which the nodes, edges, attributes and other attributes of the graph structure part of the specialized storage plan, Neo4j can be a simple and clear description of the complexity of the inter-entity relationships. In the Neo4j graph database can use Cypher query language to quickly and effectively query the knowledge graph of relevant information, and its visual interface makes the user can be more convenient and intuitive to analyze and process the data.

### *II. C.Research on Named Entity Recognition Methods*

The main steps of the model used in this paper are as follows: 1. Firstly, the labeled data is vectorized using word embedding; 2. The vectorized data is input to the BiLSTM network, which captures the information dependency of the context to obtain the corresponding semantic features. 3. The acquired bidirectional features are input into the attention mechanism, which is utilized to focus on the features related to the current output and suppress the useless features. 4. finally, they are input into the conditional random field to extract the corresponding entities [32]. The overall architecture of the model used in this paper is shown in Figure 2.

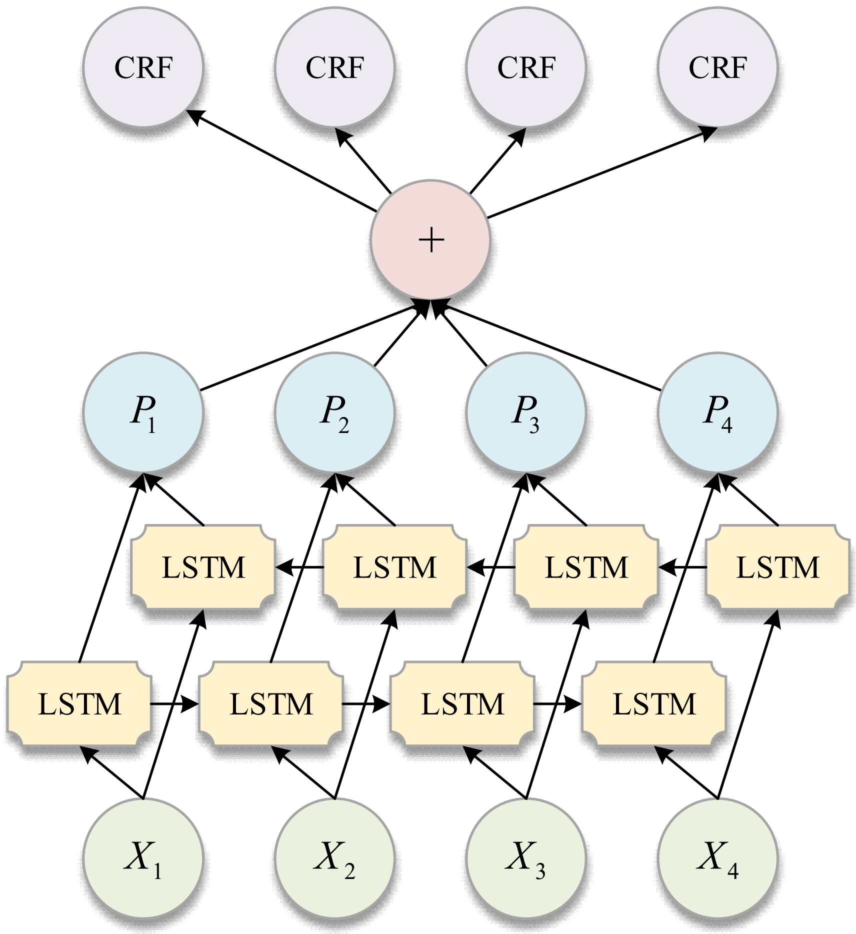


Figure 2: Overall architecture of the BiLSTM-Attention-CRF model

Long Short-Term Memory Network is a kind of recurrent neural network, LSTM network effectively solves the gradient vanishing problem of RNN network through the gate mechanism.LSTM network adds memory cells, input gates, forgetting gates, and output gates compared to RNN network. Among them, the horizontal line above in the memory block is called the unit state, and the LSTM network utilizes the unit state to pass the hidden layer information of this moment to the hidden layer of the next moment. The main role of the forgetting gate is to decide what information can be used to discuss the state of the unit, the ISTM network can use the forgetting gate to selectively filter the information of the hidden layer legend in the previous moment. The main role of the input gate is to generate the information that needs to be updated, the LSTM network uses the input gate to decide the generation of new information, which mainly uses the sigmoid function to decide the values that need to be updated, and then uses the tanh layer to sum the values that need to be updated. The main role of the output gate is to decide the output of the model.

Since this paper needs to make better use of contextually relevant information, this paper uses a bidirectional long short term memory network in this layer of the neural network. The sentences in the dataset are computed according to left-to-right as well as right-to-left, and then the vector passes obtained from both of them are spliced to obtain the vector representation of the hidden layer of the BiLSTM network, and the relevant formulas for the BiLSTM layer are shown in Eqs. (1) to (6):

$$f_t = \sigma(w_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = tanh(w_c \cdot [h_{t-1}, x_t] + b_c) \tag{3}$$

$$S_t = f_f \cdot S_{t-1} + i_t \cdot \tilde{C}_1 \tag{4}$$

$$O_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = O_t \cdot tanh(S_t) \tag{6}$$

$\sigma$ is the sigmoid activation function, tanh is the hyperbolic tangent function, $f_t$ represents the forgetting gate, $i_t$ represents the input gate, $O_t$ represents the output gate, and $x_t$ represents the input of the BiLSTM network $t$ moment. $b$ is the associated offset vector, $w$ is the associated weight matrix. $c_t$ represents the state at moment $t$, which is the new candidate value vector created by the tanh layer, $S_t$ represents the new unit state updated by state $S_{t-1}$, $h_t$ represents the final output at moment $t$, and $h_{t-1}$ represents the output at moment $t-1$.

The principle of the attention mechanism is similar to that of the human brain in allocating limited energy to important information, and the model used in this paper adds the attention mechanism after the bi-directional long and short-term memory network. The attention mechanism can focus on the features related to the current output and suppress the features not related to the current output. It can better capture the contextual information dependence to obtain the corresponding semantic features. The formula of the model used in this paper in Attention layer:

$$V_t = tannh(h_t) \tag{7}$$

$V_t$ represents the attention weight, which is equivalent to the semantic relationship between the current entity and the context, tannh in the formula is the hyperbolic tangent function, and $h_t$ is the contextual feature vector obtained from the bi-directional long and short-term memory network. For the acquired attention weights are not directly used, but also need to probabilize the attention weights, the relevant formula is shown in Equation (8):

$$P_t = exp(v_t) / \sum_{t=1}^{m} exp(v_t) \tag{8}$$

The weight probabilistic is mainly obtained by using softmax calculation function, the obtained attention weights. After obtaining the corresponding weight probabilistic also have to carry out the attention weight configuration, according to different semantic correlation degree to give different semantic weight configuration, so as to achieve the purpose of enhancing the relevant semantic features. The relevant calculation formula (9) is shown:

$$a_t = \sum_{t=1}^{m} p_t h_t \tag{9}$$

$p_t$ is the weight probabilistic, and $h_t$ is the contextual feature vector obtained from the bi-directional long short-term memory network.

Although the use of BiLSTM network in the named entity recognition task can well consider the contextual features of the textual information, but because BiLSTM network is individually labeling and classifying each token, the use of BiLSTM network only cannot well consider the overall situation of the text, and the prediction results may not match the naming of the entity. In order to address this shortcoming in BiLSTM and Attention based on the addition of Conditional Random Fields (CRF), the addition of Conditional Random Fields can make the model in the text at the overall height of the text of the overall overview of the text of the information, to avoid the prediction of the results do not meet the entity naming, so that the accuracy of the named entity recognition will be improved accordingly, the relevant formula for the CRF layer is shown in Equation (10):

$$\mathrm{Score}(x, y) = \sum_{i=0}^{n} T_{yi,yi+1} + \sum_{i=0}^{n} P_{i,yi} \tag{10}$$

### *II. D.Relationship Extraction Model*

The model used in this paper for relationship extraction is BERT-BiLSTM-Attention model, compared with the classical BiLSTM-Attention model, this paper adds BERT before the bidirectional long and short-term memory network and the attention mechanism, which can better classify the relationship through the feature extraction module in BERT [33].

The main steps of the model used in this paper are as follows: 1. Firstly, the feature extraction module in the BERT model is used to process the textual information and obtain the corresponding feature vectors. 2. The obtained feature vectors are used as inputs into the BiLSTM network, which captures the contextual dependencies and obtains the corresponding semantic features. 3. The obtained bi-directional features are inputted into the attention mechanism, and the word-level features are classified into the word-level features by using the attention mechanism. The attention mechanism integrates the word-level features into sentence-level features. 4. Finally, the feature information is classified to achieve the purpose of relationship classification.

# III. Research on the Construction and Application of Knowledge Mapping for English Learning

## III. A. Evaluation of Deep Learning Models

This paper proposes a named entity recognition model architecture based on BiLSTM-Attention-CRF, which effectively improves the relevance of contextual entity knowledge. Finally, experimental analysis is conducted to prove the effectiveness of this method for knowledge mapping of English learning in higher vocational colleges.

In order to verify the goodness of the model used in this paper, corresponding experiments are carried out in this paper, and the specific experimental design as well as the experimental results are analyzed as follows:

Named entity recognition task needs to judge the accuracy of recognition, when the model predicts both the boundary and type of the entity correctly to prove that the prediction is accurate. Based on the results of the predicted types and the specifics of the real types, four different cases will be determined: $Tp$ denotes the number of positive samples that will be predicted as positive samples, $Fp$ denotes the number of positive samples that will be predicted as negative samples, $Fn$ denotes the number of negative samples predicted as positive samples, and $Tn$ denotes the number of negative samples predicted as negative samples. According to the statistical results of the above four different cases, the experiment sets three evaluation indexes. Precision rate can reflect the accuracy of named entity recognition. Recall rate can reflect the coverage rate of named entity recognition.F1 value can reflect the experimental effect relatively balanced according to precision rate and recall rate.

Based on the English course dataset obtained from the data preprocessing part as the input to the model, this dataset is randomly divided into 80% training set, 10% testing set, and 10% validation set. The dataset contains 177028 utterances and 3584 labeled entities. The results under different number of iterations are shown in Table 1. According to the results in the table, it can be seen that the number of iterations gradually grows from 10 to 30, the evaluation indexes all grow gradually, and the model learning effect is improved, while after growing to 50, the indexes have a small decrease, and there are problems such as overfitting, so 30 is selected as the final parameter.

Table 1: results of different iterations

| Iteration number | Exact rate (%) | Recall rate(%) | F1 value(%) |
|---|---|---|---|
| 10 | 71.12 | 72.45 | 71.78 |
| 20 | 77.41 | 78.56 | 77.32 |
| 30 | 81.47 | 83.59 | 82.48 |
| 40 | 80.11 | 83.27 | 82.69 |
| 50 | 81.36 | 84.79 | 81.94 |

In order to verify the effect of dropout on the model effect, this paper was tested at dropout of 0.3,0.4,0.5 and 0.6,the results are shown in Table 2. According to the results in the table, it can be seen that with the increase of dropout, the precision rate,recall rate and F1 value are increased accordingly.When the dropout is 0.5 and 0.6,the effect decreases instead.Therefore,the dropout of 0.4 is selected as the final parameter setting.

Table 2: Different dropout experiment analysis

| dropout | Exact rate (%) | Recall rate(%) | F1 value(%) |
|---|---|---|---|
| 0.3 | 79.14 | 81.74 | 80.46 |
| 0.4 | 81.32 | 83.51 | 82.44 |
| 0.5 | 78.63 | 80.57 | 79.58 |
| 0.6 | 79.25 | 80.15 | 81.89 |

In order to verify the effectiveness of the model used in this paper,this paper conducts the following comparative experiments between the BiLSTM-Attention-CRF model of this paper and the CRF model,BiLSTM-CRF model.The results of the experiments are shown in Table 3.

According to the results in the table, the BiLSTM-Attention-CRF model used in this paper achieves the best results among the three models.The added Attention module effectively improves the precision rate by 2.81%, the recall rate by 3.36%,and the F1 value by 3.63.It proves that the addition of the Attention layer in BiLSTM-CRF can effectively learn the utterance's semantic features and improve the model performance.

Table 3: Naming entity recognition comparison experimental results

| Algorithm model | Exact rate (%) | Recall rate(%) | F1 value(%) |
|---|---|---|---|
| CRF | 60.23 | 61.35 | 61.42 |
| BiLSTM-CRF | 78.53 | 80.19 | 78.78 |
| BiLSTM-Attention-CRF | 81.34 | 83.55 | 82.41 |

In order to verify the effectiveness of the BERT-BiLSTM-Attention model proposed in this paper, the model is compared with the BiLSTM-Attention model in a comparison experiment, and the specific experimental results are shown in Table 4. According to the three evaluation metrics shown, BERT-BiLSTM-Attention improves in all three metrics. The model with the introduction of the BERT layer improves 2.26% in precision rate, 2.29% in recall rate, and 2.56 in F1 value.The effectiveness of introducing BERT before BiLSTM is effectively demonstrated through the comparison experiments.

Table 4: The relationship was compared to the experimental results

| Algorithm model | Exact rate (%) | Recall rate(%) | F1 value(%) |
|---|---|---|---|
| BERT- Attention | 81.25 | 82.35 | 81.36 |
| BERT-BiLSTM-Attention | 83.51 | 84.64 | 83.92 |

### *III. B. Construction of English Knowledge Map*

In this study, the literature included in the China National Knowledge Infrastructure (CNKI) database was taken as the research object. According to the research content, "Higher Vocational Colleges" and "English Learning" were used as the "themes" to conduct advanced searches in CNKI, with no restriction on "time" and "All Journals" as "Source Category". A total of 976 articles were retrieved (4 January 2024). All the retrieved literature was manually screened and screened one by one: the first round of screening eliminated retracted or invalid literature, and 954 pieces of data were obtained. In the second round of screening, the literature that only focused on "vocational colleges" or "English learning" was eliminated, and finally 871 valid literature were obtained.

After integrating the time of issuance of valid literature, the annual change of issuance was plotted using EXCEL as shown in Figure 3. This figure visualizes the research trends and development trends in this field. Overall, the number of research papers on English language learning in the context of "higher vocational colleges and universities" has been steadily increasing, and reached a peak of 175 papers in 2019.

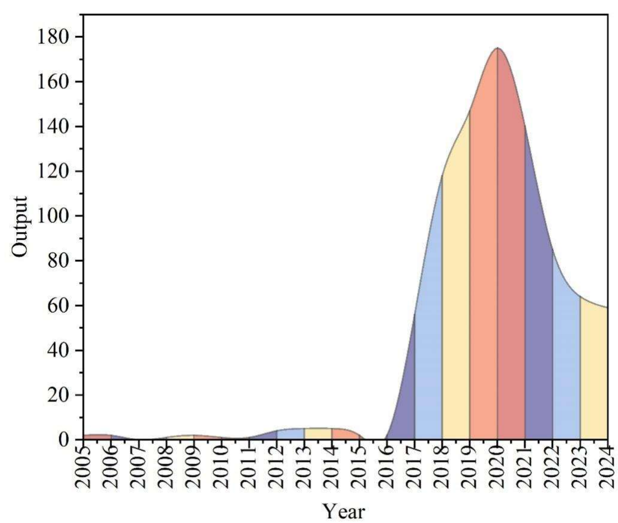


Figure 3: The number of literature changes

Table 5 shows the top 20 keywords ranked by frequency and their centrality. "Teaching mode" ranked first with 224 occurrences. Keywords such as "College English", "Internet", and "Higher Vocational English" followed. From the perspective of the centrality of keywords, a total of 8 keywords have a centrality higher than or equal to 0.3, namely "higher vocational", "English", "classroom teaching", "English teaching" and "Internet", which indicates that these keywords are the hot spots and core of research in the field of English teaching mode in the context of the

"Internet" era. It's important to note that while there is a correlation between keyword frequency and centrality, high frequency does not necessarily mean high centrality. For example, although "teaching reform" appeared 35 times, its centrality was only 0.09.

Table 5: Keyword frequency and central table

| Serial number | Key words | Frequency | Centrality |
|---|---|---|---|
| 1 | Teaching model | 224 | 0.32 |
| 2 | College English | 212 | 0.40 |
| 3 | Internet + | 198 | 0.22 |
| 4 | Higher vocational English | 95 | 0.30 |
| 5 | The Internet | 79 | 0.92 |
| 6 | Flip class | 68 | 0.18 |
| 7 | English teaching | 54 | 0.78 |
| 8 | Teaching reform | 35 | 0.09 |
| 9 | Innovate | 27 | 0.09 |
| 10 | Business English | 24 | 0.24 |
| 11 | Microclass | 20 | 0.08 |
| 12 | Higher vocational colleges | 18 | 022 |
| 13 | English | 16 | 0.08 |
| 14 | Higher vocational college | 15 | 0.18 |
| 15 | anthology | 14 | 0.40 |
| 16 | Classroom instruction | 12 | 0.38 |
| 17 | Autonomous learning | 11 | 0.29 |
| 18 | Writing teaching | 11 | 0.50 |
| 19 | Translation teaching | 10 | 0.20 |
| 20 | Information technology | 10 | 0.12 |

The data layer can be regarded as the flesh and blood of the knowledge graph, which is the concrete presentation of the content and knowledge. Based on the schema layer, the data layer represents the instantiated knowledge and relationships of the knowledge graph. We mainly introduce the specific process of constructing the data layer and the specific construction methods involved. The first is data acquisition, i.e., obtaining structured and unstructured data about the courses from open source websites through crawler technology, completing the corresponding pre-processing, and then automatically extracting information from heterogeneous data sources, mainly including named entity recognition and relationship extraction. This chapter details two deep learning-based knowledge extraction subtask models. After obtaining specific entity-entity relationship pairs, it is also necessary to perform some auxiliary operations on them to further improve the accuracy of the data layer, which mainly involves knowledge fusion and processing such as entity disambiguation. Finally, the processed knowledge is stored in the graph database Neo4j for efficient storage management, this step introduces the data conversion and import methods used, as well as the visualization effect of the graph data natively. The partial knowledge graph is shown in Figure 4, where the larger the keyword node, the higher the frequency of its occurrence. Frequency and centrality are the main indicators of the importance of keywords. The larger the centrality value of a node means that the keyword is more strongly associated with other keywords and plays a more significant role as a mediator in the whole knowledge graph, indicating that the node has a higher research value.

Keyword clustering refers to the aggregation of words with similar word meanings into relatively independent conceptual clusters. In this study, keyword clustering analysis was conducted on the selected valid literature and the clustering results are shown in Figure 5. The analysis results show that Modularity Q=0.8579 (>0.3). It shows that the clustering result is significant.Mean S=0.9241(>0.5), which shows that the clustering result is reasonable. As can be seen from the figure, there are 11 keyword clusters.

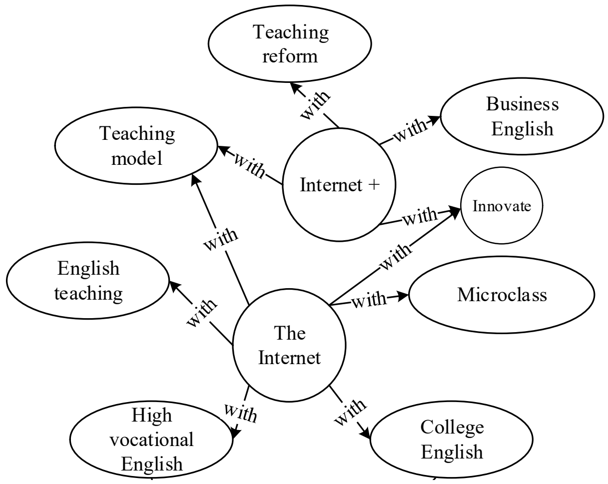


Figure 4: Partial knowledge map

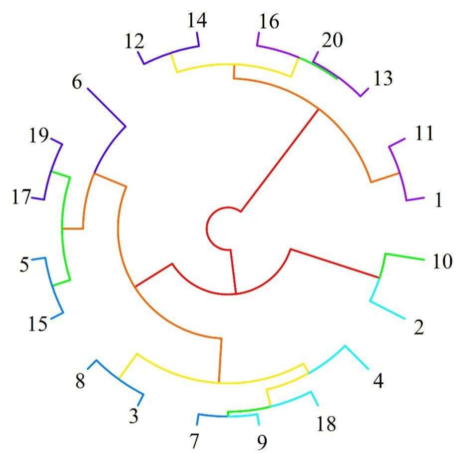


Figure 5: Keyword cluster map

### *III. C. Application of Knowledge Mapping in English Teaching and Learning*

With the rapid integration and development of knowledge graph in the field of education, the concepts of educational knowledge graph and subject knowledge graph have gradually emerged, and the courses of educational knowledge graph and subject knowledge graph are collectively referred to as "knowledge graph in the field of education", which includes the organizational representation of knowledge, resources, and learning activities in the field of education under the scope of knowledge graph in the field of education. With the development of the information revolution, knowledge mapping has gradually become an emerging knowledge management method, and its own essential attribute of “knowledge structuring” determines that it can play a significant role in knowledge acquisition and education and teaching. The process of human knowledge learning can fully draw on the path of knowledge map construction, through the analysis and summarization of dispersed knowledge, to form a highly structured and logical knowledge system, and then deduction and reasoning, so as to obtain new knowledge.

This study adopts quasi-experimental research method to select two classes in H College of G City to carry out teaching experiments, setting up an experimental class (Knowledge Graph-based English Teaching Methods in Higher Vocational Colleges and Universities) and a control class (Traditional Teaching) with a total of 100 students. The data and information of the experiment were collected through questionnaire survey, test paper examination, classroom observation and interviews with teachers and students, etc. Based on the results of the statistical analysis of the experimental data, the effectiveness of knowledge mapping in English learning in higher vocational colleges and universities was verified in terms of the degree of improvement in the students' academic performance and their attitudes to learning. As can be seen in the results of the multiple comparison analysis of the pre-test of the two classes, the P-value between any two groups is greater than 0.05, indicating that there is no significant difference between any two classes.

The significant analysis of differences in learning achievement is shown in Fig. 6, the mean of English posttest scores of students in the experimental class is 72.96, and the mean of English posttest scores of students in the control class is 65.14, and the difference in the mean of English posttest scores between the two classes is as high as 7.82. The significance (two-tailed) is 0.021, which satisfies P<0.05, indicating that there is a significant difference between the two classes in terms of their scores on the English posttest. And the English post-test scores of the experimental class are significantly higher than the English post-test scores of the control class. After nearly two months of teaching experiments, the knowledge mapping-based English teaching method in higher vocational colleges and universities presents a significant positive effect on the English scores of students in the experimental class, and it can significantly improve students' English learning achievements.

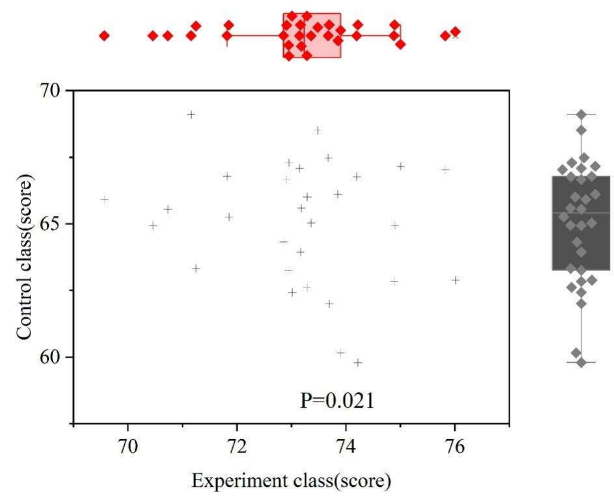


Figure 6: Analysis of the difference between learning scores

In order to understand the degree of change in the learning attitude of the students in the experimental class before and after the teaching experiment after the implementation of the English teaching method based on knowledge mapping in higher vocational colleges and universities, this study analyzed the questionnaire data of the pre-test and post-test of the experimental class's learning attitudes for the significance of differences by using a paired-sample t-test, and the results of the test are shown in Table 6. The data results show that the posttest mean of learning attitude of the experimental class is greater than the pretest mean at the overall and dimensional levels, and the P-value of the paired-sample t-test for the four comparative items mentioned above is less than 0.001, and at the same time satisfies P<0.05, which indicates that there is a significant difference between the pre-test level and the post-test level of the experimental class's attitude toward learning at the overall level and in the three attitudinal dimensions. This indicates that the English teaching method of higher vocational colleges and universities in this study's knowledge mapping has a significant positive effect on subjects' attitudes toward learning.

Table 6: Study attitude matching sample T test results

| Dimension | Order | N | M | SD | T | P | Sig. |
|---|---|---|---|---|---|---|---|
| Inventory of total | Pretest | 50 | 3.35 | 0.812 | -7.582 | <0.001 | Significant difference |
| | Posttest | 50 | 4.12 | 0.564 | | | |
| Learning emotion | Pretest | 50 | 3.14 | 1.023 | -6.774 | <0.001 | Significant difference |
| | Posttest | 50 | 4.25 | 0.638 | | | |
| Learning cognition | Pretest | 50 | 3.46 | 0.884 | -6.672 | <0.001 | Significant difference |
| | Posttest | 50 | 4.22 | 0.776 | | | |
| Learning behavior | Pretest | 50 | 3.38 | 0.638 | -5.748 | <0.001 | Significant difference |
| | Posttest | 50 | 4.02 | 0.789 | | | |

## IV. Conclusion

In this paper, we use BiLSTM-Attention-CRF model for entity recognition, BERT-BiLSTM-Attention model for relationship extraction, combined with knowledge storage and knowledge fusion, to finally complete the construction of the knowledge graph instance of English learning in higher vocational colleges. Through comparison experiments with other base models, it can be found that introducing the Attention layer into the BiLSTM-CRF model can improve the accuracy of model entity recognition and enhance the model performance. Introducing BERT before BiLSTM in BiLSTM-Attention model improves the performance of relationship extraction. In the knowledge graph of English learning in higher vocational colleges and universities, “Internet” has the strongest relevance and plays a more significant role as a mediator, indicating that this node has the highest research value. After nearly two months of teaching experiments, the knowledge graph-based English teaching method in higher vocational colleges has a significant positive effect on English performance and learning attitude.

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