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Article

# Research on Data Fusion and Big Data Analysis Methods in the Optimization of College Students' Innovation and Entrepreneurship Education Curriculum System

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**Abstract:** Knowledge mapping provides an effective solution to the problem of how to effectively and automatically integrate multimodal curriculum resources, as well as to better organize and present knowledge. In this paper, for the problem of optimizing the curriculum system of innovation and entrepreneurship education for college students, a named entity recognition model based on CNN+BiLSTM-CRF and an entity alignment model with fine-tuned BERT word embeddings are proposed to integrate the multimodal curriculum knowledge and visualize and analyze it. Experiments show that the Precision, Recall, and F1 values of the CNN+BiLSTM-CRF model in this paper reach 96.90%, 96.49%, and 96.69%, respectively, which are all better than those of other comparative models, which fully demonstrates that the proposed model in this paper has a considerable generalization ability. Meanwhile, the entity alignment model BERT+softmax proposed in this paper outperforms other models on each dataset, indicating that its design is more reasonable and can better serve the entity alignment task. In addition, the hot content of innovation and entrepreneurship curriculum research is innovation and entrepreneurship education, entrepreneurial ability and innovation, which can be the main direction of curriculum system optimization.

**Keywords:** CNN+BiLSTM-CRF; curriculum knowledge graph; multimodal; BERT; visualization; innovation and entrepreneurship education

## 1. Introduction

Nowadays, innovation and entrepreneurship education has become an important initiative for colleges and universities to promote their own development, and the practice of innovation and entrepreneurship of college students has entered a new stage, in order to comprehensively improve the level of innovation and entrepreneurship of college students, most of the colleges and universities have strengthened the research and exploration of this issue, in the hope that it can be truly implemented on the entrepreneurship and employment guidance for students, and to promote the success of students' employment and entrepreneurship [1-4].

Innovation and entrepreneurship education is a long-term and complex project, which requires schools and teachers to work hand in hand, follow the corresponding principles, combine the social market orientation and the actual situation of the school to set more accurate talent training objectives, penetrate the modern education and teaching concepts, to ensure that the construction of their own curriculum system and specific teaching practices in line with the laws of modern education and teaching, and thus the construction of the curriculum system should be gradual and comprehensive [5-8]. However, the theory and practice of the innovation and entrepreneurship education curriculum system of most universities are disconnected, failing to integrate with the professional curriculum in depth, lacking the integration with modern science and technology and emerging disciplines, emerging industries, the innovation and entrepreneurship education curriculum system is outside the professional education, more like a quality development course, and the degree of attention and participation of students are not ideal [9-11]. In addition, although some schools have set up college students' entrepreneurship incubation bases and incubators, there are not many real opportunities to use them, and basically all the initiatives taken by colleges and universities can be attributed to the above forms, failing to be truly based on the actual situation of the region and the school, resulting in the fact that the practical training courses are not prominent and perfect, and thus it is difficult to realize targeted innovation and entrepreneurship education and enhance the innovation and entrepreneurship literacy of students [12-13].

The development concept and model of big data and Internet openness, sharing, innovation and integration generate diversified educational data, which brings new impetus and direction to the adjustment and innovation of the current education model in colleges and universities [14-15]. In order to better adapt to the development trend of education and the whole society, colleges and universities are bound to make fundamental changes and innovations to the traditional talent cultivation mode by combining data, and it is imperative to vigorously carry out innovation and entrepreneurship education [16-17]. Therefore, the use of data fusion to improve the curriculum system can explore a more distinctive and advantageous path for colleges and universities to cultivate innovative and entrepreneurial and composite talents.

Based on the knowledge graph, this paper explores the data fusion and big data analysis in the optimization of college students' innovation and entrepreneurship education curriculum system, proposes a named entity recognition model based on CNN+BiLSTM-CRF and an entity alignment model with fine-tuned BERT word embedding, realizes the fusion of multimodal curriculum knowledge, and carries out a big data visualization analysis based on the knowledge graph. In order to verify the effectiveness of the proposed model, comparative experiments are conducted with other models, and the visualization and analysis results are used to realize the exploration of the direction of the optimization of college students' innovation and entrepreneurship education curriculum system.

## 2. Construction of a Curriculum Knowledge Map Incorporating Multimodal Resources

In order to realize the optimization of the curriculum system of innovation and entrepreneurship education for college students, this chapter proposes a curriculum knowledge graph construction method that integrates multimodal resources, which mainly includes a named entity recognition model based on CNN+BiLSTM-CRF, as well as a multimodal curriculum resource fusion method.

### *2.1. Related Machine Learning Algorithms*

#### 2.1.1. Convolutional Neural Networks

The convolutional neural network model (CNN) [18] generally includes a convolutional layer, a pooling layer, and a fully connected layer.

(1) Convolutional layer: the word embedding model obtained from the embedding layer is used as the input to the convolutional layer to capture the character vectors corresponding to multiple words, different convolutional window sizes are set for the convolutional layer, and in order to keep the boundary information and the length of the input consistent, the length of the vectors after the convolution is controlled by zero-padding the first and last ends of 1D inputs through Padding, and the number of convolutional kernels is set, and the strategy for complementing 0 is valid. the convolution operation done by the convolution kernel means that the convolution kernel and the number of the coverage area are dot-product, and then the result is mapped to the convolution layer, so as to realize the extraction of features.

In this paper, the extraction is done according to equation (1):

$$G = f(V^{*}c) + b \tag{1}$$

where $G$ represents the extracted local features, $f$ uses the Relu activation function, $c$ is the character vector matrix, and $b$ represents the bias.

(2) Pooling layer: After the convolutional layer, a pooling layer is often added to further sample the features, which is mainly divided into two kinds, one takes the maximum value in the square region and maps it to the maximum pooling layer, and the other takes the average value in the square region and maps it to the average pooling layer.

(3) Fully connected layer: the obtained abstracted features are mapped to the sample marking space

for integration and normalization, which is essentially a matrix transformation, which is convenient for the CRF layer to do classification.

### 2.1.2. Bidirectional Long and Short-Term Memory Networks

Bidirectional Long Short-Term Memory Network (BiLSTM) [19] is a kind of recurrent neural network RNN, which combines forward LSTM and reverse LSTM, splicing to get the final hidden layer vector, and at the same time considers the forward and reverse information in the sentence, which can effectively capture contextual environments, learn historical information and future information, and effectively acquire contextual features at a distance.

BiLSTM layer mainly extracts features at the sentence level, and can get the probability distribution matrix of the label space corresponding to each element in the sequence to be labeled, then each sequence element can also have an optimal label, but at this time the label does not take into account the transfer and constraint relationship between the labels. If there is a long dependency between the output layers, the performance will be limited.

### 2.1.3. Conditional Random Fields

Conditional Random Field (CRF) [20] does not consider long term information like LSTM models, but considers weighted combinations of local features of the sentence, which are labeled according to the feature template and decoded by the Viterbi algorithm to obtain the optimal solution. By calculating the overall likelihood probability instead of the likelihood probability of a single point at a certain moment, it optimizes not the sequence at a certain moment, but the final target sequence, it can be trained to learn the transfer probability matrix, and therefore it can take into account the features of transfer constraint relationship between the labels, which makes it performs better in the sequence labeling work. The sequence labeling score formula is as follows:

$$Score(x, y) = \sum_{i=1}^{n} P_{i,y_i} + \sum_{i=1}^{n+1} A_{y_{i-1},y_i} \tag{2}$$

where $P_{i,y_i}$ is the state probability matrix and $A_{y_{i-1},y_i}$ is the transfer probability matrix.

The probability value of each label sequence $y$ is defined as follows:

$$P(y|\ X) = \frac{e^{s(X,y)}}{\sum_{\tilde{y}\in Y_X} S(X,\tilde{y})} \tag{3}$$

The goal of the training process is to maximize this probability value.

Using the log-likelihood, which maximizes the correct probability tag, the loss function is defined as:

$$\log\left(p\left(y|X\right)\right) = s(X,y) - \log\left(\sum_{\tilde{y}\in Y_X} e^{s(X,\tilde{y})}\right) \tag{4}$$

At the time of decoding, the Viterbi algorithm is chosen to obtain the sequence with the highest score using the following formula to solve for the optimal labeled sequence, thus improving the accuracy of entity recognition:

$$y^* = \arg\max_{\tilde{y}\in Y_X} S(X,\tilde{y}) \tag{5}$$

## *2.2. Course Knowledge Graph Construction Process*

The construction framework of multimodal course knowledge graph is shown in Figure 1, and the specific construction can be divided into the following steps:

(1) Data model definition

Based on the data schema of some existing course knowledge graphs, this paper divides the knowledge point entity types into three categories, which are algorithms, structures, and related terms, and there are five kinds of relationships between the knowledge point entities, which are containment relationship, antecedent relationship, the same relationship, brotherhood relationship, and correlation relationship. Meanwhile, speech is also added to the knowledge graph as a kind of entity node, and the relationship between speech nodes and other entities is defined as association relationship.

(2) Data Acquisition

By writing a crawler program separately, based on the course outline, the knowledge point words and posts related to the knowledge points were acquired from the website, and the knowledge point dictionary of the innovation and entrepreneurship education course for college students was constructed. At the same time, the PPT courseware as well as videos of teachers' lectures were obtained from the platform of fine Chinese catechism.

(3) Data Preprocessing

Firstly, the text data in the PPT courseware is extracted, and the audio is extracted from the video through the command line and saved respectively. Then the knowledge point phrases and post data are processed such as sentence and word division.

(4) Named Entity Recognition

The manually labeled text data is used as the training set and test set of the model, and in this paper, CNN+BiLSTM-CRF algorithm is used to recognize three kinds of entities, namely, algorithm, structure, and related terms.

(5) Relationship Recognition

First, the text data is divided into sentences and words, and the program is used to filter out the sentences that have two entities in one sentence. By labeling the relationship between two entities in a sentence in the courseware data, then the automatic labeling of the relationship in the data is completed. Finally, different models are used for training and classification, and the relationship classification effect of each model is analyzed and evaluated.

(6) Multimodal entity linking

Using speech recognition technology and text matching algorithm to match the speech with the entities to realize the multimodal entity linking, and define the correspondence between the two as the association relationship.

(7) Knowledge graph storage and platform construction

This paper adopts Neo4j graph database to complete the storage and visualization of multimodal knowledge graph. Knowledge point entities, speech entities and inter-entity relationships are imported into the graph database. And based on the knowledge graph, a multimodal search platform is built to provide semantic search and knowledge graph visualization services.

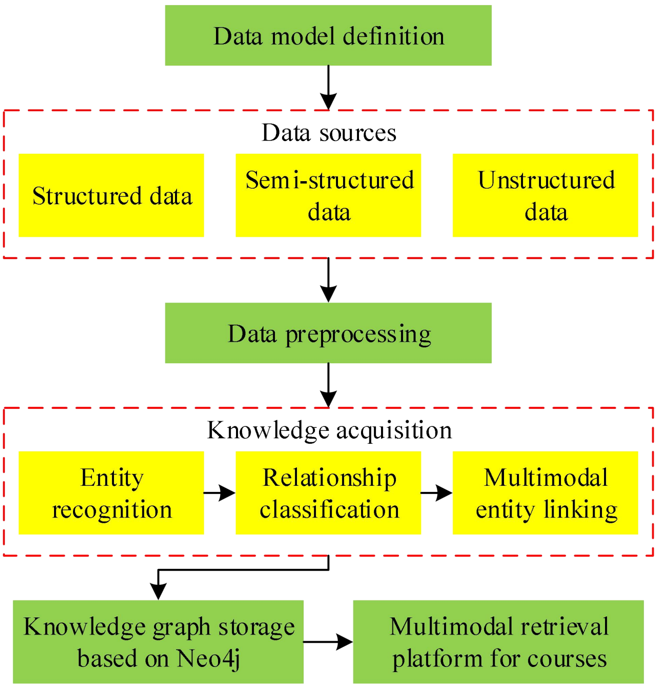


***Figure 1.*** Construction framework of multimodal curriculum knowledge graph.

## *2.3. Named Entity Recognition Based on CNN+BiLSTM-CRF*

In this paper, based on the BiLSTM-CRF model, combined with the constructed lexicon, a named entity recognition model based on CNN+BiLSTM-CRF is designed by fusing the global and local feature information.The algorithmic framework of CNN+BiLSTM-CRF is shown in Fig. 2, which mainly contains four parts, namely, Keras Embedding layer, CNN layer and CRF layer. layer, CNN layer, BiLSTM layer, and CRF layer.The Keras Embedding layer mainly represents the text data in word embedded form, maps the data into low-dimensional vectors, CNN extracts the local features of the text, and BiLSTM extracts the global features, and then splices the character vectors and the word vectors one by one and inputs them to the fully-connected layer and the CRF layer, and then decodes the spliced vectors to obtain the optimal labeled sequence. , the optimal labeling sequence is obtained.

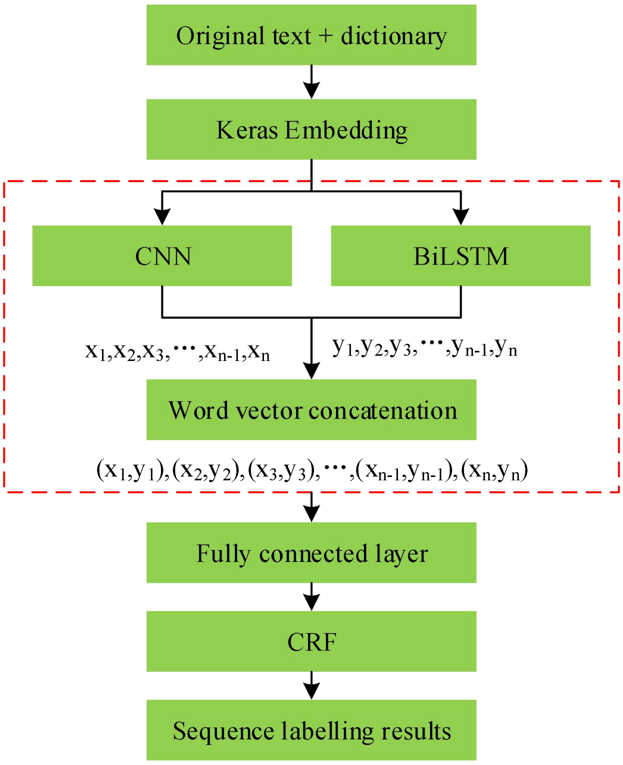


***Figure 2.*** CNN+BiLSTM-CRF algorithm framework.

Based on the designed algorithmic framework, the experimental flow of entity recognition is shown in Fig. 3. Among them, the work of data acquisition and dictionary construction has been introduced in the previous section. The main work presented in this section includes data annotation, word embedding model, model training and model prediction, and finally output the entity result set.

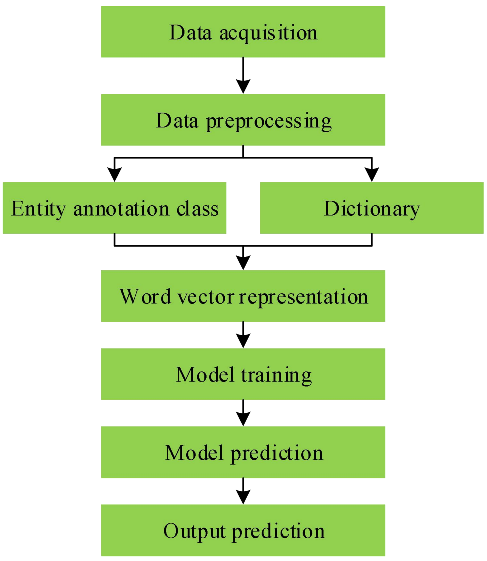

***Figure 3.*** Experimental Process of Entity Recognition.

(1) Data labeling

In this paper's acquired courseware pages total 1324 pages, the extracted text data of the courseware is used as a labeled dataset, and markers are specified to mark the entities. The texts of different chapters are combined as a dataset, and the labeled dataset is divided into training set, testing set and validation set in the ratio of 8:1:1.

(2) Word vector representation

For the input text data of the previous layer, this paper uses Keras Embedding model to do the transformation of word embedding matrix, which is input to the next training model.

(3) Model training and entity recognition

Training is performed using the built named entity recognition model.

(4) Output entity set

The entity sets are obtained through model training and entity prediction, and for the convenience of later storage, the duplicate entities are subjected to data cleaning to obtain the final entity sets. The entity sets are saved as CSV files respectively, and the entities in each file are numbered as the entity sets of the knowledge graph in this paper.

## *2.4. Integration of multimodal Curriculum Resources*

### 2.4.1. Hierarchical Filtering Based Knowledge Fusion Modeling

Hierarchical filtering idea is to set different levels to deal with related tasks, each level has its own unique filtering criteria and conditions filtering method, only to meet the conditions to enter the next level, this kind of approach can effectively filter to shorten the processing cycle of the data to improve the efficiency and accuracy.

Based on the idea of hierarchical filtering, this paper proposes a multimodal course resource fusion method for the knowledge graph of college students' innovation and entrepreneurship education courses as shown in Figure 4.

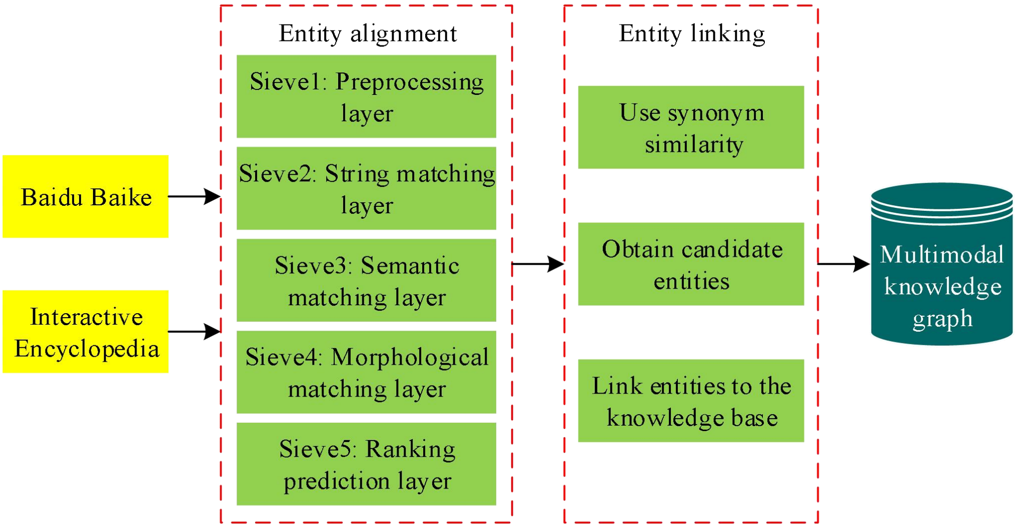


***Figure 4.*** Curriculum knowledge fusion model based on hierarchical filtering.

### 2.4.2. Entity Alignment

Entity alignment task is the task of determining whether the word resources in Baidu Encyclopedia and Interactive Encyclopedia knowledge communities correspond to the same entity. Entity alignment is performed through preprocessing layer, string matching layer, semantic matching layer, word shape matching layer, and ranking prediction layer.

(1) Preprocessing Layer

In order to establish the connection between the entities in the textbook and the multimodal resources in Baidu Encyclopedia and Interactive Encyclopedia, the attributes, text profiles, images and video resources in the encyclopedia are crawled based on the existing entities in the knowledge graph. The profile or attribute data usually contains some irrelevant special symbols such as "superscript citation", which will affect the effect of the subsequent model alignment, so they are deactivated, and the picture and video links are not processed. The processed word data is formally expressed as $E_{BB}=\left(id, entity_{BB}, prof_{BB}, prop_{BB}, image_{BB}, video_{BB}\right)$ and $E_{HB}=\left(id,\ entity_{HB}, prof_{HB}, prop_{HB}, image_{HB}, video_{HB}\right)$, where $entity$ represents the entity name and $prof$ represents the profile text, which is an unstructured text that summarizes the information of a concept or entity. $prop$ stands for attributes and refers to labeled descriptive content.

(2) String Matching Layer

For entity pairs whose entity names and profile information are identical, the two entities are considered to be perfectly matched, and only one entity's information is retained. If the entity name and profile information of the entity pair are not completely consistent, then enter the semantic matching layer to continue screening.

(3) Semantic Matching Layer

In this paper, the similarity calculation based on synonyms is used to do the screening of entity names, if the semantic similarity of entity names is greater than 0.5, then the two are judged to be semantically similar, and continue to enter the word-form matching layer to determine whether the entities are aligned or not, and vice versa, the judgment is not aligned.

(4) Word Matching Layer

After the semantic matching layer screens the entities, it obtains the semantically related set of the two entities, on this basis, it calculates the similarity probability of the profile text through the word shape matching layer, and judges whether the word resources are aligned or not.

(5) Ranking prediction layer

The similarity probability of each interactive encyclopedia text corresponding to the Baidu encyclopedia text is stored, and then it is ranked, and the highest ranked one is selected as the final aligned entity pair. At the same time, the negative sampling strategy is utilized to expand the dataset by using the lower ranked profile text pairs as negative samples to improve the performance of the classifier.

### 2.4.3. Fine-Tuning Entity Alignment for BERT Word Embeddings

In this paper, Baidu Encyclopedia Knowledge Base is used as the known knowledge base, and Interactive Encyclopedia is used as the knowledge base to be fused, for the synopsis text corresponding to each entry in Baidu Encyclopedia Knowledge Base, the classification model of fine-tuning BERT [21] is utilized to traverse the synopsis text of the entities in the Interactive Encyclopedia and filter the pairs of synopsis text with the highest probability of similarity, and at the same time, to address the imbalanced proportion of the samples in the dataset, the strategy of negative sampling is utilized to to fill in the negative samples to further improve the AUC value of the model.

The structure of the classification model with fine-tuned BERT word embeddings is shown in Fig. 5, whose inputs are two profile text sentences, which are first token-sliced and then spliced: a [CLS] symbol is set at the beginning of the sentence, and [SEP] is set at the end of the sentence. Transform all the sample data into an indexed array of tokens, with a fixed length of 128, and if the sample length is less than 128, make up zeros for the missing parts.

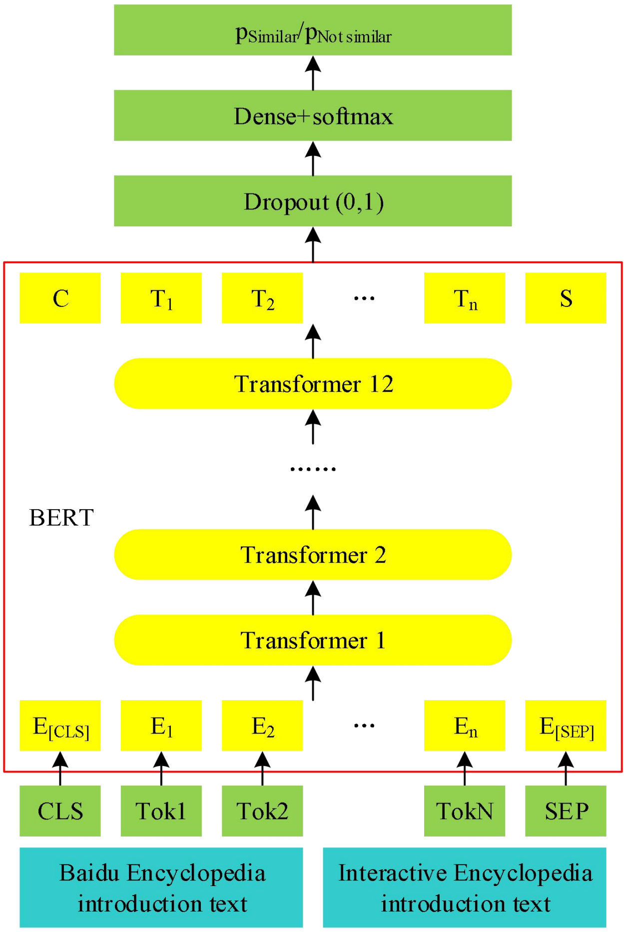


***Figure 5.*** Fine-tunes the classification model of BERT word embedding.

Considering that the deep learning model has a large number of hyperparameters and the model data samples used in this paper are small, the output of the BERT model is connected to a random deactivation layer (dropout) to solve the model's possible overfitting problem. The specific process is as follows:

Step1: Temporarily remove the hidden layer neurons from the network with a specific probability.

Step2: Propagate that input forward in that network, then propagate that input backwards on that network and update the corresponding weights $W$ and biases $b$ according to the stochastic gradient reduction algorithm after each batch_size is completed.

Step3: Re-generate the discarded neurons, where the parameters of the discarded neurons are not discarded, and update the parameters of the non-discarded neurons.

Step4: Iterate Step1-3.

Obtain $h_d$ after the above steps:

$$h_d = Dropout\left(h_b\right) \tag{6}$$

The output of BERT model is processed using Dense+softmax, Dense is the fully connected layer. The output vector of BERT model is connected to dropout layer to obtain $h_d$, linear mapping is performed in the fully connected layer, normalized using softmax function, and the probability of the corresponding category is output in order to predict the semantic relationship between two text pairs as shown in Eq. (7):

$$P = soft\max\left(W_p h_d + b_p\right) \tag{7}$$

where $W_p$ and $b_p$ represent the weights and bias vectors, respectively, and $h_d$ denotes the output of the dropout layer.

The cross-entropy loss function is applied to measure the difference between the predicted labels and the actual labels, and the gradient obtained from the cross-entropy loss function is used to optimize the internal structure parameters and softmax parameters of BERT, and the model is iteratively fine-tuned until the abstract semantic features are effectively extracted.

Aiming at the problem of difficulty in recognizing negative samples, a negative sampling strategy is proposed:

(1) For each Baidu wikipedia profile text, traverse the collection of interactive wikipedia profile texts filtered by semantic matching layer, and sort them according to probability, and store the sorting results.

(2) According to the number of negative samples to be filled, traverse the sorted list corresponding to each Baidu encyclopedia synopsis text, select the M synopsis text pairs with the lowest probability of similarity to be stored, and select a certain number of synopsis text pairs to be labeled and used as negative samples to expand the dataset from the stored results.

(3) Input the expanded dataset into the fine-tuned BERT+softmax model for further training, and continuously adjust the weights of neurons to continuously improve the prediction performance of the model.

### 2.4.4. Entity Links

Entity linking is the task of linking multimodal course resources into the knowledge graph. The specific process is as follows:

(1) Establish the set of entity names that Baidu encyclopedia entries and interactive encyclopedia entries jointly point to $\left\{BaikeEntity_1, BaikeEntity_2, \cdots\cdots BaikeEntity_n\right\}$ and the set of entity names in the knowledge graph $\left\{BaseEntity_1, BaseEntity_2, \cdots\cdots BaseEntity_n\right\}$.

(2) Use Word2vec to model the vector representation of entity words, and calculate the similarity using the synonyms-based method to obtain the set of candidate entities corresponding to each entity in the knowledge graph $E_i$.

(3) Store and sort each candidate entity and output the highest ranked entity.

(4) If the similarity score of an entity is less than a manually set threshold of 0.80, it is considered unlinkable, otherwise the entity is stored as the final matching set in the course knowledge graph.

## *2.5. Knowledge Graph Storage and Visualization*

### 2.5.1. Knowledge Graph Storage

After the realization of knowledge acquisition and knowledge fusion, the RDF text format file of the relational triad is obtained, which needs to be stored, given that the purpose of constructing KG is the optimization of college students' innovative entrepreneurship education curriculum system, there is a higher need for querying and visualization of the knowledge graph, while the graph structure of the database can be clearly portrayed through the attribute graph structure of nodes and edges to clearly portray the complex relational semantics, because of its own structure to facilitate the realization of efficient query and other complex operations. Because of its own structure, it is easy to realize complex operations such as efficient querying, this paper adopts Neo4j to store the knowledge graph.The data model of Neo4j is attribute graph structure, and the attribute graph structure is shown in Figure 6.

The dark cyan shaded text in Figure 6 represents the information stored in the Neo4j graph database, and the yellow shaded text represents the description of the information. It can be seen that the storage types of Neo4j data are nodes, edges, attributes and labels, nodes correspond to entities in the knowledge graph, nodes can have one or more labels, and the use of labels realizes the distinction of entity types. Attributes of nodes are entity attributes, which store information about nodes in the form of key-value pairs. Edges correspond to relationships with type and direction, edges can also have attributes and the number of relationships between nodes is not fixed.The ontology building tool used by KG outputs the results in the form of RDF files, and the programming implements the process of importing OWL format files into Neo4j software.

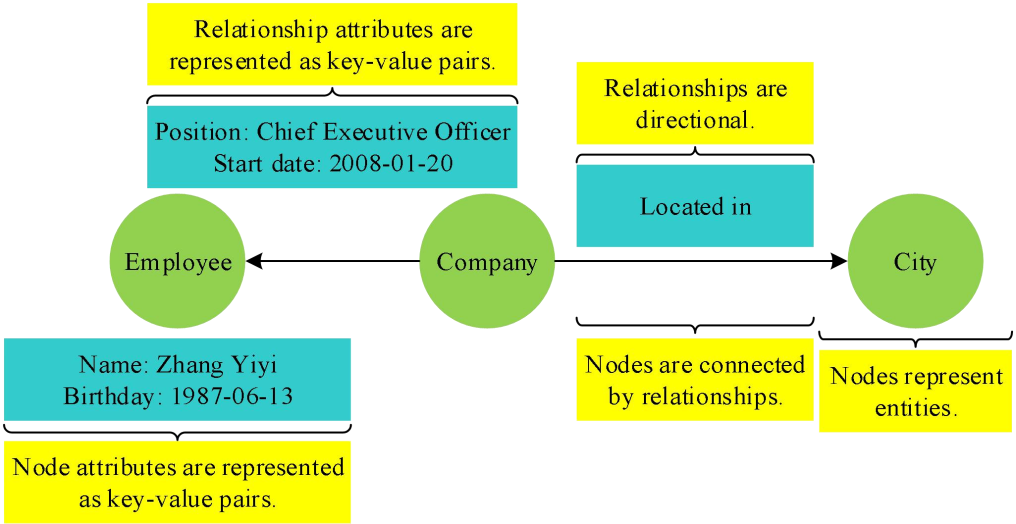


***Figure 6.*** Property Graph structure.

### 2.5.2. Knowledge Graph Storage Visualization

After importing the knowledge graph entities and relational data constructed in this paper into the graph database Neo4j, the knowledge graph is visualized using Cypher query statements.

The partial display of the knowledge graph of college students' innovation and entrepreneurship education course is shown in Figure 7, in which the blue nodes indicate the course knowledge entities, including the course knowledge system, knowledge tree, knowledge modules, and knowledge point entities, the red nodes indicate the innovation and entrepreneurship elements, and the brown color indicates the innovation and entrepreneurship materials, and the innovation and entrepreneurship elements are distributed between the course knowledge entities.

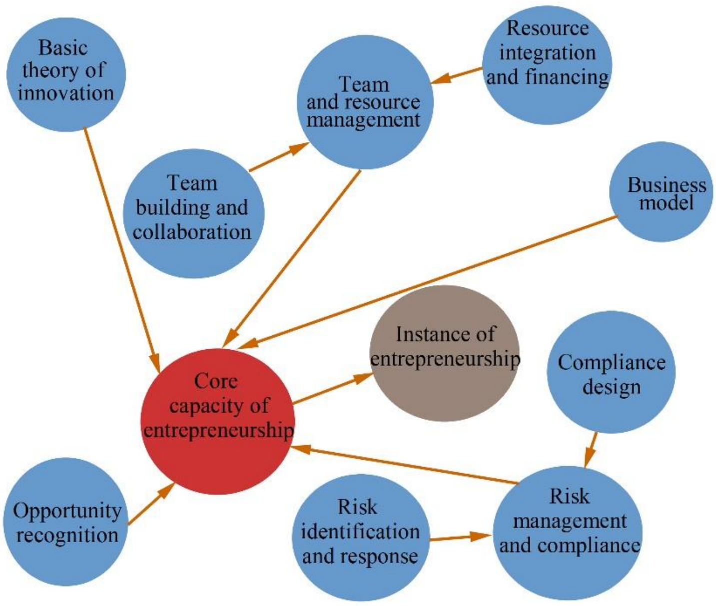


***Figure 7.*** A partial display of the course knowledge graph.

## 3. Entity Recognition and Alignment Experiments for Knowledge graphs

In this chapter, the entity recognition and alignment algorithm of the proposed knowledge graph is experimentally verified, so as to provide an effective algorithmic tool for the optimization of the innovative entrepreneurship education curriculum system for college students.

### *3.1. Entity Recognition Experiments*

### 3.1.1. Experimental Data Set

This experiment uses two sets of datasets, one of which is the self-constructed course NER dataset to validate the model. The other set is the Resume public dataset, which is used to validate the generalization of the model. The datasets used in the experiments are divided into training, validation and test sets in the ratio of 8:1:1. The specific information of the two experimental datasets is shown in Table 1.

***Table 1.*** Statistical Information of the dataset.

| Data set | Type | Training set | Verification set | Test set |
|---|---|---|---|---|
| Resume | Sentence | 5.4K | 0.7K | 0.7K |
| | Character | 143.2K | 15.7K | 17.2K |
| The foundation of college students' entrepreneurship | Sentence | 3.2K | 0.4K | 0.4K |
| | Character | 84.3K | 10.8K | 11.2K |

### 3.1.2. Evaluation Indicators

The values of precision $P$, recall $R$ and $F1$ are used as evaluation metrics for the model. $P$ denotes the ratio of the number of correctly recognized entities to the number of all recognized entities, $R$ denotes the ratio of the number of correctly recognized entities to the number of all entities in the text, and $F1$ denotes the reconciled mean of $P$ and $R$. The calculation formula is as follows:

$$P = \frac{T_p}{T_p + F_p} \times 100\% \tag{8}$$

$$R = \frac{T_p}{T_p + F_N} \times 100\% \tag{9}$$

$$F1 = 2 \times \frac{P \times R}{P + R} \times 100\% \tag{10}$$

where $T_p$ denotes the number of correctly recognized entities, $F_p$ denotes the number of entities recognized that are not related to the correct entity, and $F_N$ denotes the number of incorrectly recognized entities.

### 3.1.3. Experimental Setup

The model in this paper is experimented in Python 3.13.1, Pytorch 2.6.0. The optimizer uses Adam's algorithm and the experimental hyperparameters are set as shown in Table 2.

***Table 2.*** Experimental hyperparameter setting.

| Parameters | Meaning | Value |
|---|---|---|
| max_len | Maximum sequence length | 128 |
| dropout | Loss rate | 0.6 |
| bacth_size | Data batch size | 64 |
| lr | Learning rate | 0.0001 |
| wordvec dom | Word vector dimension | 200 |
| epoch | Number of iterations | 200 |

### 3.1.4. Experimental Results and Analysis

In order to verify the effectiveness of the model in this paper on the self-constructed course NER dataset, BiLSTM-CRF is chosen as the Baseline for comparison test in this experiment.

In order to verify the effectiveness of adding modules, only Convolutional Neural Network and Course Knowledge Point Dictionary are chosen to be added on Baseline for comparison test respectively.

In order to verify the effectiveness of the course knowledge point dictionary, the BERT-BiLSTM-CRF model and the Lattice-LSTM model, which also introduces lexical information, are chosen for comparison tests. The comparison of the experimental results of different models on the course NER dataset is shown in Table 3.

As seen from the experimental results, the F1 values of the BiLSTM-CRF model and the Lattice-LSTM model incorporating lexical information are 70.30% and 71.92%, respectively, which are significantly lower than those of the other four models, which demonstrates that the convolutional neural network improves the recognition effect quite significantly.

The model with course knowledge point dictionary added separately on top of Baseline has some improvement in P, R, and F1 values on the course NER dataset, which indicates that the addition of course knowledge point dictionary can effectively improve the NER recognition effect. The F1 value of the model with the addition of the convolutional neural network alone, 74.69%, is higher than the F1 value of the model with the addition of the course knowledge point dictionary alone, 74.64%, but the recall, R, is 74.35%, which is lower than that of the model with the addition of the course knowledge point dictionary alone, 74.51%, which demonstrates that the two modules of the convolutional neural network and the course knowledge point dictionary are both effective for the improvement of the recognition effect, but the convolutional neural network is more effective for NER enhancement, while the addition of the course knowledge point dictionary gives the model a higher recall rate R, representing that the course knowledge point dictionary makes the model more inclined to check all rather than checking accurately. In addition, compared with the commonly used BERT-BiLSTM-CRF model, the P, R, and F1 values of this paper's model are higher, indicating the effectiveness of this paper's model in knowledge graph ontology recognition.

***Table 3.*** Comparison of experimental results of different models on the course NER dataset.

| Model | Course NER dataset | | |
|---|---|---|---|
| | P /% | R /% | F1 /% |
| BiLSTM-CRF(Baseline) | 70.44 | 70.17 | 70.30 |
| Lattice-LSTM | 72.49 | 71.36 | 71.92 |
| BERT-BiLSTM-CRF | 74.37 | 73.48 | 73.92 |
| Baseline+CNN | 75.04 | 74.35 | 74.69 |
| Baseline+Dictionary | 74.78 | 74.51 | 74.64 |
| CNN+BiLSTM-CRF (Ours) | 75.23 | 74.86 | 75.04 |

To verify that the performance improvement of the models in this paper is not specific to the self-built course NER dataset, the experiments use the Resume public dataset to verify the generalization of the models. A comparison of the experimental results of different models on the Resume dataset is shown in Table 4. It can be seen that the P, R, and F1 values of this paper's model are higher than those of all other models, reaching 96.90%, 96.49%, and 96.69%, respectively, which fully demonstrates that the proposed model in this paper has considerable generalization ability.

***Table 4.*** Experimental results comparison of different models on the course Resume dataset.

| Model | Resume dataset | | |
|---|---|---|---|
| | P /% | R /% | F1 /% |
| BiLSTM-CRF(Baseline) | 94.71 | 94.22 | 94.46 |
| Lattice-LSTM | 95.62 | 95.07 | 95.34 |
| BERT-BiLSTM-CRF | 96.24 | 96.16 | 96.20 |
| Baseline+CNN | 96.78 | 96.37 | 96.57 |
| Baseline+Dictionary | 96.31 | 96.72 | 96.51 |
| CNN+BiLSTM-CRF (Ours) | 96.90 | 96.49 | 96.69 |

Combining the experimental results in Table 3 and Table 4, it can be seen that the P, R, and F1 values of all the models in the Resume dataset are much higher than the experimental results in the course NER dataset, which is due to the fact that the annotation quality of the self-built dataset is not as good as that of the public dataset of Resume, which makes it difficult to recognize the named entities, and improving the quality of the self-built dataset will be one of the directions of the next step of work. The F1 value of this paper's model, which incorporates convolutional neural network and course knowledge point dictionary, is 96.69% and 75.04% in two datasets, Resume and course NER dataset, respectively, both of which have achieved the best results, which verifies the validity and generalization of the model.

## *3.2. Physical Alignment Experiment*

In order to better explore the effectiveness of the entity alignment algorithm proposed in this paper for entity alignment of knowledge points in the knowledge graph of college students' innovation and entrepreneurship education courses, this section compares the algorithm with some existing common entity alignment algorithms.

### 3.2.1. Introduction to the Data Set

In order to better validate the performance of the entity alignment method proposed in this paper, experiments are conducted on the public dataset MED-BBK-9K and the dataset of college students' innovative entrepreneurship education courses, the details of the datasets are as follows:

(1) MED-BBK-9K is a real-scenario medical dataset with entity alignment data labeling done manually by experts in the medical field. The data comes from two knowledge graphs, MED and BBK, MED is the medical knowledge graph built by the laboratory itself, and BBK is the medical knowledge graph constructed based on lexical entries.The specifics of the MED-BBK-9K dataset are shown in Table 5.

***Table 5.*** The MED-BBK-9K dataset.

| Knowledge graph | Entity number | Relationship category | Attribute category | Align entity pairs |
|---|---|---|---|---|
| MED | 9274 | 34 | 21 | 9274 |
| BBK | 9274 | 22 | 24 | |

(2) The dataset of college students' innovation and entrepreneurship education courses used in this experiment comes from the knowledge graph data acquired in this paper. With two sets of data, entity alignment across course resources and entity alignment across course categories between PPTs and textbooks are performed, respectively. A PPT resource mapping and a textbook resource mapping are constituted by PPTs and textbooks, respectively. The PPTs of innovation foundation courses constitute the innovation foundation resource mapping, and the PPTs of entrepreneurship core courses and practice tools constitute the entrepreneurship and practice resource mapping. The specifics of the college students' innovation and entrepreneurship education course dataset are shown in Table 6. The annotation by experts in the field of college students' innovation and entrepreneurship education is adopted to screen out the entity pairs with consistent information of knowledge points in real life among all the entity pairs of knowledge points, and the equivalent entity pairs obtained provide data support for the training and testing of the model afterwards.

***Table 6.*** Data set of college students' innovation and entrepreneurship education courses.

| Experimental group | Knowledge graph | Number of knowledge point entities | Total number of entities | Relationship category | Attribute category | Align entity pairs |
|---|---|---|---|---|---|---|
| Experiment 1 | Textbook resource map | 9046 | 10157 | 2 | 2 | 1524 |
| | PPT resource map | 3138 | 3249 | 2 | 2 | |
| Experiment 2 | Innovation basic resource map | 5794 | 6012 | 2 | 2 | 1137 |
| | Entrepreneurship and practice resource map | 3457 | 3594 | 2 | 2 | |

### 3.2.2. Evaluation Indicators

There are three mainstream ways to evaluate the performance of entity alignment algorithms as follows, Hit@m series, MR and MRR.

(1) Hits@m, refers to the size of the proportion of correctly aligned entities appearing in the first $m$ positions of the result ranking, if the larger the value of Hits@m, it means that the entity alignment method is more effective. The specific calculation is as follows:

$$Hits@m = \frac{1}{|E|}\sum_{i=1}^{|E|} g\left(rank_{e_i} \le m\right) \tag{10}$$

where $\left|E\right|$ is a non-zero integer representing the total number of entities in the data set $E$ . $e_i$ is the $i$ th entity in the entity dataset $E$ . The $rank_{e_i}$ denotes the rank of entities correctly aligned with $e_i$ appearing in the result sequence. The function $g\left(\cdot\right)$ is a judgment function, the value of the function is 1 when the input $rank_{e_i}$ satisfies the condition, and the value of the function is 0 when the condition is not satisfied.

(2) MR, reflecting the average value of the median of the correctly aligned entities in the result ranking, if the MR value is smaller, it means that the entity alignment method is more effective. The specific calculation is as follows:

$$MR = \frac{1}{\left|E\right|}\sum_{i=1}^{\left|E\right|} rank_{e_i} \tag{12}$$

(3) MRR, reflecting the average of the median inverse of the result ranking for correctly aligned entities, if the MRR value is larger, it means that the entity alignment method is more effective. The specific calculation is as follows:

$$MRR = \frac{1}{\left|E\right|}\sum_{i=1}^{\left|E\right|} \frac{1}{rank_{e_i}} \tag{13}$$

In this paper, three metrics, Hits@3, Hits@10 and MRR, are chosen for the evaluation of entity alignment algorithms.

### 3.2.3. Experimental Environment and Setup

In the experiments, 30% of the aligned entity pairs of each dataset are input as seed entity pairs, and the remaining 70% of the dataset is used as the test set for the experiments.

The BERT model CLS embedding vectors used in the experiments have a dimension of 768 dimensions, which are adjusted to 400 dimensional vectors after a fully connected layer. Using a learning rate of 0.0001, 200 rounds of training were performed. Six negative samples are collected per round for each entity.

The environment used in the experiments of this paper is shown in Table 7.

***Table 7.*** Experimental environment.

| Experimental environment | Configuration |
|---|---|
| Operating system version | Ubuntu 24.04 |
| GPU version | RTX 4090 (24GB) |
| CPU version | 16 vCPU Intel(R) Xeon(R) Platinum 850c CPU @2.60GHz |
| Memory capacity | 256GB |
| Deep learning framework | PyTorch-GPU 2.6.0 (Cuda12.1) |
| Develop languages. | Python 3.13.1 |
| Development tools | VScode, PyCharm |

### 3.2.4. Comparison Experiments

In this section, the entity alignment algorithm BERT+softmax in this paper is compared with some existing entity alignment algorithms based on knowledge representation learning. Based on the type of knowledge representation and the information utilized for entity alignment, the comparison models can be classified into the following three types: entity alignment models MTransE and BootEA that utilize only structural information, entity alignment models JAPE and AttrGNN that utilize structural and attribute information, and entity alignment models HGCN, RNM and OntoEA that utilize structural and entity name information.

The performance results of this paper's BERT+softmax model and the above entity alignment models on the MED-BBK-9K dataset and the college students' innovation and entrepreneurship education course dataset are shown in Table 8 and Table 9, respectively.

Combining the experimental results in Table 8 and Table 9, it can be seen that the entity alignment model BERT+softmax proposed in this paper performs better than other models on each dataset. It shows that the design of this model is reasonable and can better serve the entity alignment task.

***Table 8.*** Experimental results of the MED-BBK-9K dataset.

| Model | Hits@3 /% | Hits@10 /% | MRR |
|---|---|---|---|
| MTransE | 0.6 | 2.7 | 0.018 |
| BootEA | 12.8 | 31.14 | 0.192 |
| JAPE | 0.9 | 3.9 | 0.026 |
| AttrGNN | 19.5 | 44.6 | 0.274 |
| HGCN | 31.4 | 43.8 | 0.375 |
| RNM | 37.5 | 40.7 | 0.393 |
| OntoEA | 52.8 | **80.9** | 0.664 |
| BERT+softmax (Ours) | **62.9** | 69.6 | **0.671** |

***Table 9.*** Experimental results of the courses dataset.

| | Experiment 1 | | | Experiment 2 | | |
|---|---|---|---|---|---|---|
| Model | Hits@3 /% | Hits@10 /% | MRR | Hits@3 /% | Hits@10 /% | MRR |
| MTransE | 31.4 | 55.2 | 0.371 | 28.5 | 51.2 | 0.357 |
| BootEA | 32.8 | 54.3 | 0.364 | 44.2 | 52.8 | 0.382 |
| JAPE | 41.6 | 62.5 | 0.503 | 37.4 | 66.4 | 0.561 |
| AttrGNN | 66.7 | 73.8 | 0.647 | 63.1 | 72.2 | 0.643 |
| HGCN | 71.3 | 80.4 | - | 73.4 | 79.5 | - |
| RNM | 74.5 | 83.6 | 0.815 | 73.7 | 84.1 | 0.839 |
| OntoEA | 74.9 | 77.2 | 0.767 | 75.5 | 76.6 | 0.784 |
| BERT+softmax (Ours) | **84.7** | **93.7** | **0.889** | **82.4** | **95.2** | **0.865** |

### 3.2.5. Ablation Experiments

In order to better explore the influence of different modules in the BERT softmax model on the entity alignment task, ablation experiments are carried out on the string matching module, semantic matching module, lexicon matching module and negative sampling module respectively. The results of ablation experiments on the MED-BBK-9K dataset and the college students' innovation and entrepreneurship education course dataset are shown in Tables 10 and 11, respectively. Among them, BERT softmax is the complete model used in this paper, "-wo SM1" is the model with the string matching module removed, "-wo SM2" is the model with the semantic matching module removed, "-wo WM" is the model with the lexical matching module removed, and "-wo NSM" is the model with the negative sampling module removed.

Combining the experimental results in Table 10 and Table 11, it can be seen that the performance of the BERT+softmax model will be significantly degraded after removing any of the four modules. Comparing the models with the modules removed, the BERT+softmax model performs more superiorly in both the real public dataset MED-BBK-9K and the college students' innovation and entrepreneurship education course dataset, which indicates that string matching, semantic matching, and word-form matching can efficiently enrich the semantic and structural information of the entities in the Knowledge Graph, whereas the negative-sampling strategy can provide richer latent information for the entity alignment task . In particular, comparing the performance of BERT+softmax (-wo SM1) on the two types of datasets, the influence of the string matching module is more obvious in MED-BBK9K, which also reflects that when the variety of relationships between entities is more diverse, string matching can better capture the role of tail entities of different relationships on head entities, and characterize the entities in the Knowledge Graph more comprehensively in terms of their Structural Characterization of Entities in the Knowledge Graph.

***Table 10.*** Ablation experiment results of the MED-BBK-9K dataset.

| Model | Hits@3 /% | Hits@10 /% | MRR |
|---|---|---|---|
| BERT+softmax | 62.7 | 68.9 | 0.668 |
| -wo SM1 | 46.4 | 48.5 | 0.472 |
| -wo SM2 | 41.3 | 46.2 | 0.446 |
| -wo WM | 45.7 | 54.3 | 0.501 |
| -wo NSM | 47.8 | 55.7 | 0.514 |

***Table 11.*** Ablation experimental results of the courses dataset.

| | Experiment 1 | | | Experiment 2 | | |
|---|---|---|---|---|---|---|
| Model | Hits@3 /% | Hits@10 /% | MRR | Hits@3 /% | Hits@10 /% | MRR |
| BERT+softmax | 84.7 | 93.5 | 0.884 | 82.4 | 95.5 | 0.863 |
| -wo SM1 | 76.3 | 81.8 | 0.752 | 74.2 | 82.6 | 0.776 |
| -wo SM2 | 55.2 | 64.7 | 0.568 | 53.4 | 68.5 | 0.628 |
| -wo WM | 61.7 | 83.6 | 0.704 | 59.6 | 79.7 | 0.694 |
| -wo NSM | 64.9 | 81.5 | 0.741 | 62.8 | 83.2 | 0.741 |

# 4. Visual Empirical Analysis of Innovation and Entrepreneurship Education for University Students

This chapter provides a visual empirical analysis of college students' innovation and entrepreneurship education research, including keyword co-occurrence analysis, keyword clustering analysis, and keyword burst detection.

## *4.1. Keyword Co-Word Analysis*

Keywords are highly refined, summarized and core characterization of the theme and content of the paper, keyword frequency is a concentrated reflection of the research hotspot of a discipline, and the distribution pattern of keyword frequency represents the migration route of the research theme in this field. Co-word analysis is one of the most commonly used statistical methods in bibliometrics, when two or more keywords appear in the same document at the same time, it is called keyword co-occurrence. The frequency of keyword co-occurrence is positively correlated with the degree of connection between keywords, and keyword co-occurrence analysis can reveal the knowledge structure, research hotspots and evolution trajectory of research in this field. Co-occurrence clustering is based on co-occurrence analysis and utilizes the statistical method of clustering to simplify co-occurrence network relationships into a relatively small number of categories.

### 4.1.1. High-Frequency Keyword Analysis

Firstly, high-frequency keyword analysis is conducted, and the top ten keyword frequency rankings are shown in Table 12. The centrality represents the media ability and bridge function of the keywords, and the greater the centrality, the greater the influence of the keywords. Generally speaking, a centrality value greater than 0.1 indicates that the keyword has greater influence. According to this criterion, among the keywords ranked in the top ten in terms of frequency, there are seven keywords with greater influence, namely, innovation education, quality education, innovation ability cultivation, talent cultivation, innovation ability, innovative talents and education reform, with centrality values of 0.58, 0.54, 0.31, 0.52, 0.37, 0.19 and 0.18 respectively.

***Table 12.*** Keyword frequency ranking.

| Rank | Key words | Occurrence frequency | Centrality |
|---|---|---|---|
| 1 | Innovative education | 592 | 0.58 |
| 2 | Quality-oriented education | 95 | 0.54 |
| 3 | Cultivation of innovation ability | 61 | 0.31 |
| 4 | Talent cultivation | 58 | 0.52 |
| 5 | Higher education | 49 | 0.09 |
| 6 | Innovation ability | 49 | 0.37 |
| 7 | Innovative talent | 49 | 0.19 |
| 8 | Educational reform | 42 | 0.18 |
| 9 | Knowledge economy | 34 | 0.06 |

| | | | |
|---|---|---|---|
| 10 | Teaching reform | 30 | 0.07 |

### 4.1.2. Co-Word Matrix Analysis

After having a preliminary understanding of the high-frequency keywords through keyword analysis, the extracted high-frequency keywords were made into a covariance matrix using Bicomb software, and the covariance matrix was analyzed.

The co-word matrix of some keywords is shown in Table 13. It can be seen that the matrix is symmetrically distributed on the diagonal axis, and the two keywords, college students and entrepreneurship education, co-occur 72 times in the literature.

***Table 13.*** Key word co-word matrix (Part).

| Key words | Code | A1 | A2 | A3 | A4 | A5 | A6 |
|---|---|---|---|---|---|---|---|
| College students | A1 | 0 | 72 | 61 | 45 | 90 | 25 |
| Entrepreneurship education | A2 | 72 | 0 | 21 | 20 | 14 | 17 |
| Innovation and entrepreneurship education | A3 | 61 | 22 | 0 | 21 | 19 | 15 |
| Innovation and entrepreneurship | A4 | 45 | 20 | 21 | 0 | 10 | 17 |
| Start a business | A5 | 90 | 14 | 19 | 10 | 0 | 10 |
| College students' entrepreneurship | A6 | 25 | 17 | 15 | 17 | 10 | 0 |

## *4.2. Burst Detection of Keywords*

Keyword prominence detection is a dynamic presentation of literature research, which demonstrates the sudden decrease or increase in the citation frequency of literature through keyword mapping, and then reflects the direction of research hotspots in a certain research field and realizes the tracking of research hotspots. The distribution of keyword sudden increase is shown in Figure 8, in which the keywords K1~K6 indicate talent cultivation, education concept, college students, innovation ability cultivation, entrepreneurship education, and innovation education, respectively.

Six keywords suddenly increased in this study, which are talent cultivation, education concept, college students, innovation ability cultivation, entrepreneurship education, and innovation education.

Based on the pattern of sudden increase of keywords, it can be seen that at the beginning of innovation education research, i.e., from 2004 to 2006, people paid attention to the role of education innovation in talent cultivation and the change of education concept. From 2008, innovation education about college students became a research hotspot, and this research hotspot lasted for five years until 2012. In the decade from 2013, entrepreneurship education was put on the agenda, and together with the cultivation of innovation ability, it became the focus of research in this period. In the four years between 2017 and 2020, the term “innovation education” comes to the fore, but with a focus on entrepreneurship education.

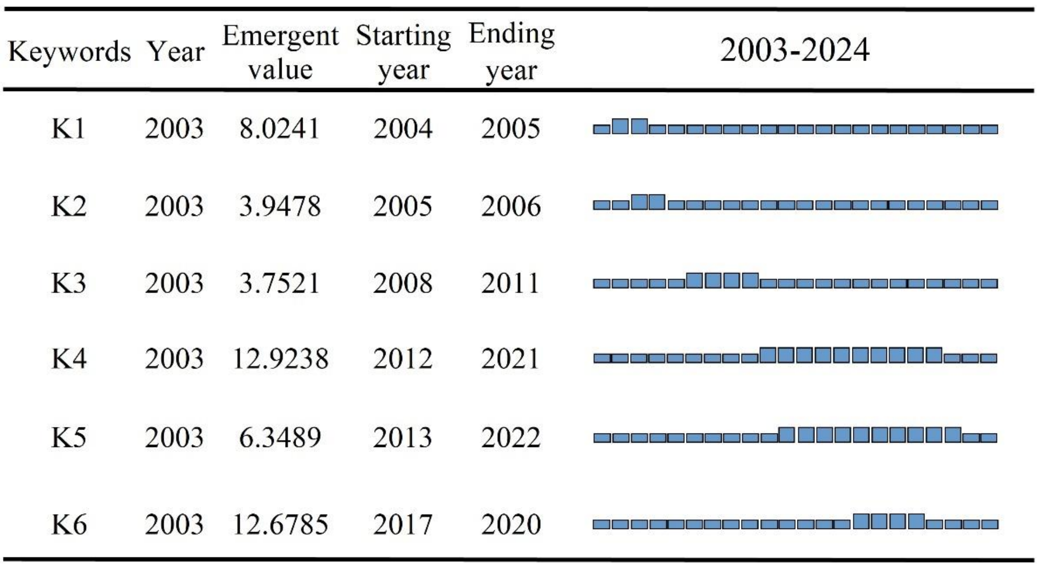


***Figure 8.*** Distribution of keyword highlighting.

### 4.3. Keyword Clustering Analysis

On the basis of keyword co-occurrence analysis and burst detection, this paper summarizes the hotspots of college students' entrepreneurship research by using the cluster analysis method, and some of the keyword clustering maps are shown in Figure 9. The main research hotspots summarized are as follows:

(1) The motivating effect of entrepreneurship education on entrepreneurial consciousness. This includes 12 keywords such as innovation and entrepreneurship education, ideological and political education, and curriculum system. College students, as the newborn main force in the trend of "mass entrepreneurship and innovation", the relevant literature mainly focuses on the discussion of innovation and entrepreneurship education issues and development paths, as well as entrepreneurship education and ideological and political education in promoting entrepreneurship to play a positive role. We can enrich the talent cultivation program and stimulate the entrepreneurial enthusiasm of students by strengthening ideological and political education, carrying out innovation and entrepreneurship education, and improving the innovative curriculum system.

(2) Research on the accumulation of entrepreneurial practice experience and experience. This includes 16 keywords such as practical teaching and entrepreneurial practice. The research content of related literature is mainly the exploration of innovation and entrepreneurship practice mode, and the research on the path of combining entrepreneurship education and practice. Many college students who fail in entrepreneurship are due to the lack of practical experience, while practical teaching enables college students to directly experience the process of entrepreneurship, and the cultivation of entrepreneurial intention and the enhancement of innovation and entrepreneurship ability also require focusing on practical education. Schools can organize innovation and entrepreneurship competitions, social practice activities and other forms to build entrepreneurial practice mode, providing a platform for students to accumulate entrepreneurial experience.

(3) Research on improving entrepreneurial quality and ability by combining new Internet technologies. This includes 10 keywords such as network entrepreneurship, e-commerce, entrepreneurial ability and so on. The research direction of related literature is mainly the exploration of college students' entrepreneurial mode under the background of the prevalent Internet economy. As potential self-employed entrepreneurs, college students, utilizing new Internet technologies such as e-commerce to open up the road of network entrepreneurship, have put forward new requirements on the entrepreneurial quality and ability of college students.

(4) Research on teaching reform, employment guidance, and improvement of innovation and entrepreneurship mechanism. This includes seven keywords such as employment guidance and teaching reform. The research direction of related literature is how to promote innovation and entrepreneurship of college students in private colleges and universities. The teaching curriculum and entrepreneurial practice can be combined to give full play to the guiding role of private colleges and universities and employment instructors, thus expanding the potential entrepreneurial population base of college students.

***Figure 9.*** Clustering diagram (Part).

## 5. Conclusion

In this paper, we construct the knowledge graph of college students' innovation and entrepreneurship education courses, and propose a named entity recognition model based on CNN+BiLSTM-CRF and an entity alignment model with fine-tuned BERT word embedding, which realizes data fusion and big data analysis in the optimization of the course system.

The model with course knowledge point dictionary added separately on top of BiLSTM-CRF shows some improvement in P, R, and F1 values on the course NER dataset, indicating that the addition of course knowledge point dictionary can effectively improve the NER recognition effect. In addition, compared with the commonly used BERT-BiLSTM-CRF model, the P, R, and F1 values of this paper's model are higher, indicating the effectiveness of this paper's model in knowledge graph ontology recognition.

In different datasets, the entity alignment model BERT+softmax proposed in this paper performs better than the other models, indicating the rationality of the design of this model for entity alignment tasks. In addition, the performance of the BERT+softmax model is significantly degraded after removing any of the modules, further validating the effectiveness of the model in this paper.

Through the visualization and analysis of big data, this paper concludes that the research hotspots of innovation and entrepreneurship education courses for college students are as follows:

(1) The motivating effect of entrepreneurship education on entrepreneurial consciousness.

(2) Research on the accumulation of entrepreneurial practical experience and experience.

(3) Research on improving entrepreneurial quality and ability by combining new Internet technology.

(4) Research on teaching reform, employment guidance, and improvement of innovation and entrepreneurship mechanism.

When optimizing the curriculum system of innovation and entrepreneurship education for college students, we can focus on these aspects.

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