The Use of Knowledge Correlation for Classification and Evaluation of a Distance Education Teaching Resource Database

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Abstract—Teaching information resource database is an important part of distance education in schools. Understanding the classification and characteristics of teaching resources in teaching information resource database can help teachers to search teaching resources more pertinently and make better use of these resources in actual teaching. Therefore, this article studies the classification and evaluation of distance education teaching resource database based on knowledge network. Combining the LSTM model and the conditional random field model, the resource entities that the target resource design knowledge points refer to are extracted from the resource text string of the teaching resource database. The resource entities that the extracted knowledge point refer to are matched and correlated with other resource entities related to the knowledge point in the teaching resource database, so as to realize the link of resource entities in the teaching resource database based on the concept of knowledge points. Starting with the feature extraction of resource text, this article innovates the resource classification algorithm of teaching resource database, and shows the new algorithm flow of feature extraction of resource text. Experimental results verify the effectiveness of the model.

Keywords—knowledge correlation, distance education, teaching resource database, resource classification

1 Introduction

Teaching information resource database, as an important part of distance education in schools, includes multimedia material database, teaching plan database, courseware database, test question database, subject database, etc. [1–6]. At the same time, the resource database should also provide teachers and students with full-text retrieval, attribute retrieval, increase, decrease and classification of resources, and also provide functions such as compression, packaging and downloading [7–14]. Resources refer to the general name of all materials, energy and information that can be developed and utilized by human beings. The text of teaching resources represents the key information of teaching resources, mainly including the names, attributes, uses and application fields of various digital materials, teaching software and supplementary materials [15–22]. Teaching resources have various forms and kinds. Understanding the classification and characteristics of teaching resources can help teachers to search teaching resources more pertinently and make better use of these resources in actual teaching.

With the development of computer and big data technology, it's possible now to classify teaching resources, which could not be realized before. However, due to the limitation of implementation, the traditional classification method can not meet the requirements of modern computing. The emergence of swarm intelligence algorithm makes it possible to classify teaching resources. The main purpose of Yang and Huang [23] is to apply swarm intelligence algorithm to the classification of English teaching resources, and provide reference for optimizing English teaching mode. The experimental results show that the proposed classification model of English teaching resources has good performance, which is beneficial to improve the utilization rate of teaching resources and is suitable for other disciplines. With the rapid development of network technology and the rapid growth of various online information resources, a large number of Chinese language and literature resources have emerged on the Internet. How to quickly and effectively obtain useful resource information and classify Chinese language and literature resources from a large number of information resources is the focus of Li [24]. Through the algorithm and experimental process, the idea and advantages of SVM are demonstrated for further improving the SVM algorithm. The proposed improved support vector machine greatly improves the classification efficiency, which is helpful to quickly search the information with high matching degree in various Chinese language and literature online resources. Current classification and retrieval methods are affected by the amount of data in the classification of multimedia learning resources, and there are some problems such as low classification accuracy, low retrieval rate and long retrieval time. In order to solve this problem, Zhong and Jiang [25] proposed a new multimedia learning method. Combining decision tree and hash algorithm, the resource classification and retrieval method is designed. The decision tree algorithm is used to collect and classify multimedia learning resources, hash algorithm is introduced to solve and preprocess the resources, and Lyapunov theorem is used to obtain features. Experimental results show that the improved method can effectively improve the retrieval accuracy and efficiency of multimedia learning resources, and has certain practicability.

In order to realize the classification of teaching resources in distance education, some scholars at home and abroad choose to weigh the text feature items of teaching resources in different degrees to extract the salient feature items. Some scholars also choose to expand the text feature items of teaching resources to optimize the text representation of teaching resources. Although the above methods are beneficial to the classification and evaluation of teaching resources, they do not consider the correlation between knowledge points of teaching resources, and cannot guarantee the fast and effective classification and evaluation. Therefore, this article studies the classification and evaluation of distance education teaching resource database based on knowledge network. In the second chapter, LSTM model and conditional random field model are combined to extract the resource entities that the knowledge points of target resource design refer to from the resource text string of teaching resource database.

In the third chapter, the resource entities that the extracted knowledge points refers to are matched and correlated with other resource entities related to the knowledge points in the teaching resource database, so as to realize the link of resource entities in the teaching resource database based on the concept of knowledge points. The fourth chapter starts with the feature extraction of resource text, innovates the resource classification algorithm of teaching resource database, and shows the new algorithm flow of feature extraction of resource text. Experimental results verify the effectiveness of the model.

2 Resource entity prediction of teaching resource database based on knowledge point correlation

The resource text of distance education teaching resource database is basically Chinese language, and is involved with some English texts. Based on the text data of teaching resource database and the description information of knowledge points, this article designs the corresponding entity link process of teaching resource, so as to better apply it to the task of classification and evaluation of resources in distance education teaching resource database and improve the classification and evaluation effect. Figure 1 shows the link process of resource entities in distance education teaching resource database.

It is assumed that the context semantic representation vector of the resource text string in the teaching resource database is represented by G, which has the semantic features of the resource text, the sequence vector representing the conceptual vocabulary boundary information of the knowledge points involved in the resource is represented by O_r, and the weight parameter matrix is represented by Q. In this article, G and O_r are concatenated firstly, and then the concatenated results are transformed linearly by Q, so that the feature vector fusion results can be obtained, which is represented by $U = \{U_{st}, U_1, U_2, \ldots\ldots, U_k, U_{en}\}$, namely:

$$U = Concate(G, O_R)Q \tag{1}$$

Compared with cyclic neural network, LSTM model has better prediction effect. In this article, LSTM model and conditional random field model are combined to extract resource entities that knowledge points of target resource design refer to from resource text strings of teaching resource database. It is assumed that the *sigmoid* function is represented by ε, the dot product multiplication operator is represented by $\cdot$, the p-th element in the fused vector U is represented by u_p, the implicit state vector is represented by f_p, that's, the corresponding output of u_p, and the output of vector U after passing through LSTM model is represented by $F = \{f_1, f_2, \ldots\ldots, f_P\}$. The following formula gives the calculation process of LSTM model for each time step p as follows:

$$c_p = \varepsilon\left(Q_i * \left[f_{p-1}, u_p\right]\right) \tag{2}$$

$$s_p = \varepsilon\left(Q_s * \left[f_{p-1}, u_p\right]\right) \tag{3}$$

$$\tilde{s}_p = \tanh\left(Q_d * \left[s_b \cdot f_{p-1}, u_p\right]\right) \tag{4}$$

$$f_p = (1 - c_p) \cdot D_{p-1} + c_p \cdot \tilde{f}_p \tag{5}$$

The conditional random field model consists of a fully connected layer and a CRF layer, which is used to predict and judge the implicit vector $F = \{f_1, f_2, \ldots\ldots, f_P\}$ output by *LSTM* model. $F = \{f_1, f_2, \ldots\ldots, f_P\}$ is transformed linearly through the fully connected layer of conditional random field model, and then the probability score of each character corresponding to each class tag of resource text string is obtained by processing the set with Softmax probability function. The following formula gives the expression of probability score set for each character prediction tag:

$$K_H = \left\{k_{H_{st}}, k_{H_1}, k_{H_2}, \ldots, k_{H_k}, k_{H_{en}}\right\} \tag{6}$$

The CRF layer of the conditional random field model uses K_H as the Emission state score matrix to model each class of tags and calculate the transition probability between tags to generate the corresponding score transition matrix to describe the correlation relationship between tags. It is assumed that the obtained resource text string sequence is represented by $H(F)$, the predicted tag sequence is represented by $\{\hat{b}_{st}, \hat{b}_1, \hat{b}_2, \ldots, \hat{b}_k, \hat{b}_{en}\}$, and the predicted tag sequence result of the string is represented by $\dot{B} = \{\hat{b}_1, \hat{b}_2, \ldots, \hat{b}_k\}$. Then $\{\hat{b}_{st}, \hat{b}_1, \hat{b}_2, \ldots, \hat{b}_k, \hat{b}_{en}\}$ can be obtained by decoding $H(F)$ through Viterbi algorithm, $\dot{B} = \{\hat{b}_1, \hat{b}_2, \ldots, \hat{b}_k\}$ can be obtained by eliminating the prediction tags corresponding to the start identifier *ST* and the end identifier *EN*, and $N = \{n_1, n_z, \ldots, n_l\}$ can be obtained by extracting the corresponding substrings on $\dot{B} = \{\hat{b}_1, \hat{b}_2, \ldots, \hat{b}_k\}$.

If the *j*-th character in the tagged training resource text string is represented by R_j and the corresponding tagged tag type is represented by b_j, the training text character data can be represented by $\{(r_j, b_j)\}_{j\in 1,M}$. Because the top layer of the model is a conditional random field model, $\{(r_j, b_j)\}_{j\in 1,M}$, the negative logarithmic likelihood function of path scores of all tag types under a specific character r is given as the loss function of the conditional random field model and the overall loss function of model training. The calculation formula is as follows:

$$LOSS = -\sum_j \log\left(t\left(b_j \mid r_j\right)\right) \tag{7}$$

The probability score of all possible types of paths for tags can be calculated by the following formula:

$$t(b \mid r) = \frac{\exp\left(\sum_i \left(EM_{i,b_i} + P_{b_{i-1},b_i}\right)\right)}{\sum_{\hat{b}} \exp\left(\sum_i \left(EM_{i,\hat{b}_i} + T_{\hat{b}_{i-1},\hat{b}_i}\right)\right)} \tag{8}$$

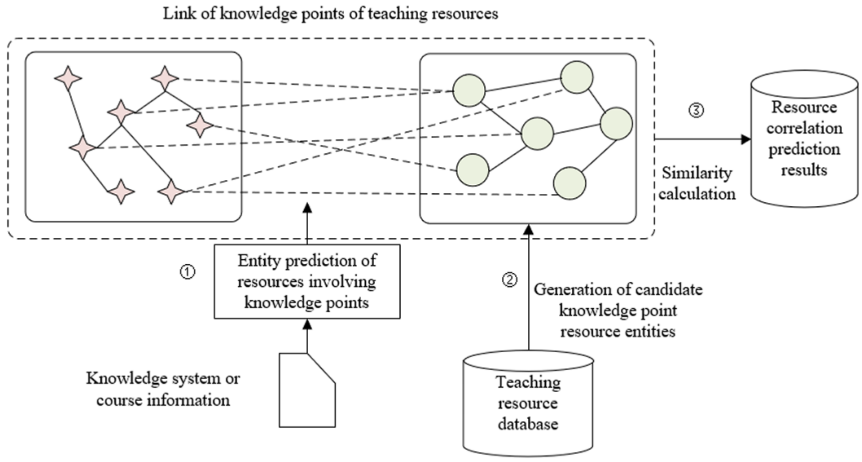

Fig. 1. Link flow of resource entities in distance education teaching resource database

After training, the model can predict the entities that knowledge points involved in the tagging sequence with the highest score, which lays a foundation for the next stage of resource link in the teaching resource database.

3 Link of resources entities of teaching resource database

In this article, the resource entities that the extracted knowledge point refer to are matched and correlated with other resource entities related to the knowledge point in the teaching resource database, so as to realize the link of resource entities in the teaching resource database based on the concept of knowledge points. Figure 2 shows the structure of the resource entity link model of the teaching resource database.

In order to avoid that the resource entities that knowledge points refer to cannot match or correlate with other resource entities related to knowledge points, this article chooses string fuzzy matching algorithm to generate candidate knowledge point resource entities that knowledge points refer to for improving the fault tolerance of the model. For the concept vocabulary n_i of knowledge points, the expression of candidate knowledge point resource entity set generated by fuzzy matching is given by the following formula:

$$RE_{n_i} = \left\{RE_1, RE_2, \ldots, RE_j\right\} \tag{9}$$

Then, the text description of each candidate knowledge point resource entity is encoded to obtain the vector representing the candidate knowledge point resource entity in the teaching resource database. It is assumed that the knowledge point description of the candidate knowledge point resource entity RE_i is represented by DS, the implicit vector corresponding to the identifier ST is represented by f_{st}, the encoded vector is represented by $F_{REi} = \{f_{st}, f_{d1}, f_{d2}, \ldots\ldots, f_{dk}, f_{en}\}$, the fully connected layer output vector is represented by u_{REi}, and the representation vector set of RE_{ni} is represented by $U_{ni} = \{u_{RE1}, u_{RE2}, \ldots, u_{REj}\}$. F_{REi} is obtained by using DS as the input of the encoding model, and u_{REi} is obtained by activating f_{st} through the fully connected layer with tank function, then u_{REi} satisfies $u_{REi} = tanh\ Dense\ (f_{st})$. Thus, U_{ni} is obtained.

For each representation of the resource entity that the concept vocabulary n_i refers to the knowledge point, this article encodes the knowledge system or course text $D = \{d_1, d_2, \ldots, d_k\}$ where the corresponding knowledge point resource entity is located, assuming that the representation vector of the acquired knowledge system or course text is represented by U_D, the encoding vector of each character in its text can be represented by $F_D = \{f_{st}, f_{d1}, f_{d2}, \ldots\ldots, f_{dk}, f_{en}\}$, and the position of plaintext substring represented by n_i in D can be represented by $LO_{ni} = \{SB, JS\}$, where SB and JS are the starting and ending positions of substring in D respectively. The encoding vector between SB and JS in LO_{ni} extracted from F_D is represented by $F_{ni} = \{f_{SB}, f_{SB+1}, \ldots, f_{JS}\}$. The text convolution network TextCNN is used to process F_{ni} to obtain the corresponding U_{ni}.

Concate the U_D and U_{ni}, and project them through the fully connected layer to obtain the output vector E_{ni}:

$$E_{n_i} = tanh\left(Dense\left(Concate\left(\left[U_{n_i}, U_D\right]\right)\right)\right) \tag{10}$$

By calculating the similarity of each vector in E_{ni} and U_{ni}, the correlation result with the resource entity that the knowledge point refers to can be obtained and represented by $s_{ni} = \{n_i, RE_i\}$.

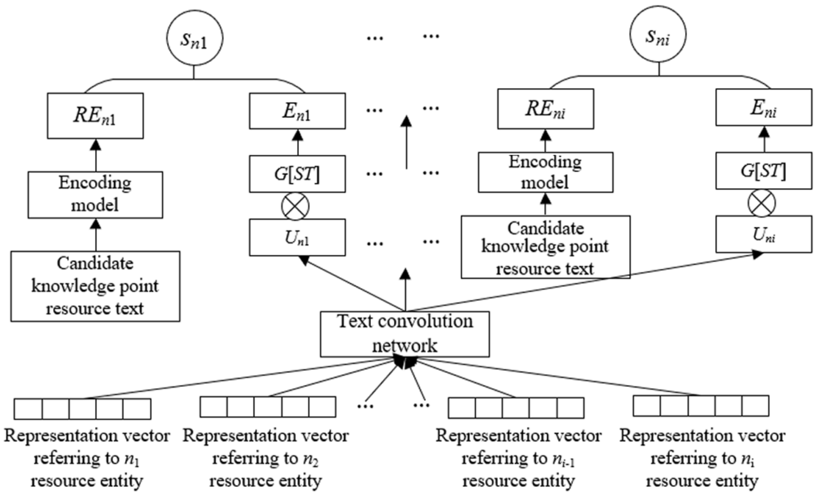

Fig. 2. Structure of resource entity link model of teaching resource database

4 Optimization of resource classification algorithm in teaching resource database

The resource classification process of teaching resource database includes word segmentation, resource text feature extraction, resource text representation and training of resource text classifier. Among them, feature extraction of resource text has the greatest influence on the reliability and accuracy of classification results. Next, this article will start with the feature extraction of resource text, and innovate the resource classification algorithm of teaching resource database. Figure 3 shows the flow of the new resource text feature extraction algorithm.

Compared with document frequency, chi-square statistics and other text feature extraction algorithms, mutual information algorithm has better text feature extraction effect. Assuming that the probability of resource texts containing both feature items p and belonging to class d_i is represented by $GL(p, d_i)$, the probability of resource texts containing the feature item p are represented by $GL(p)$, the probability of resource texts belonging to the class d_i are represented by $GL(d_i)$, and the probability of resource texts containing the feature item p in the class d_i are represented by $GL(p, d_i)$. The following formula gives the definition of the mutual information formula:

$$MUT\ (p,d_i) = \log \frac{GL\ (p,d_i)}{GL\,(p)\times GL\ (d_i)} = \log \frac{GL\,(p\,|\,d_i)}{GL\ (p)} \tag{11}$$

In the actual task of teaching resource database resource classification, the number of resource text features that need to be used is very large. This exposes that the traditional mutual information method is easy to ignore the negative correlation features which have an impact on classification and is easy to favor rare features. In view of the above two defects, this article makes some adjustments to the traditional mutual information method, so that the revised new algorithm not only fully considers the negative correlation features, but also emphasizes the selection proportion of concept vocabulary of high-frequency knowledge points.

In the traditional mutual information method, the balance of positive and negative correlation features is adjusted by introducing balance factor. Assuming that the number of documents containing feature items p under class d_i is represented by $g_i(p)$, and the average value obtained by comparing the sum of feature item p in all documents with the number of classes is represented by $g(p)^*$, the following formula gives the definition formula of balance factor:

$$BAFA = \frac{g_i(p) - g_i(p)^*}{g_i(p)^*} \tag{12}$$

It can be seen from the above formula that BAFA represents the difference between $g_i(p)$ and $g(p)^*$, and reflects the role of negative correlation features in the process of resource classification. The following formula gives the definition of mutual information with balance factor:

$$BFMUT(p) = BAFA \times GL(d_i)\sum_{i=1}^{n} MUT(p, d_i) \tag{13}$$

In order to solve the problem that traditional mutual information method favors rare features, this article introduces intra-class feature frequency to characterize the importance of feature items to resource texts. Assuming that the number of resource texts under class d_i is represented by m, the number of occurrences of feature item p in resource text $c_{il}(1 < l < m)$ is represented by $g_{il}(p)$, and the number of feature items contained in resource text $c_{il}(1 < l < m)$ in class d_i is represented by $g_{il}(q)$, the following formula gives the calculation formula of intra-class feature frequency of feature item p for class d_i:

$$CCF = \frac{\sum_{l=1}^{m} g_{il}(p)}{\sum_{l=1}^{m} g_{il}(q)} \tag{14}$$

The concentration degree in the resource classification of teaching resource database is introduced to characterize whether the feature item p has stronger distinguishing ability than other feature items. Assuming that the number of classes in the whole corpus set is represented by n, the following formula gives the calculation formula of intra-class concentration that belongs to class d_i when the feature item p appears:

$$CCC = \frac{\sum_{l=1}^{m} g_{il}(p)}{\sum_{i=1}^{n}\sum_{l=1}^{m} g_{il}(p)} \tag{15}$$

Fusion of BAFA, CCF and CCC indexes can calculate the new mutual information value, and further generate the optimal feature set and output.

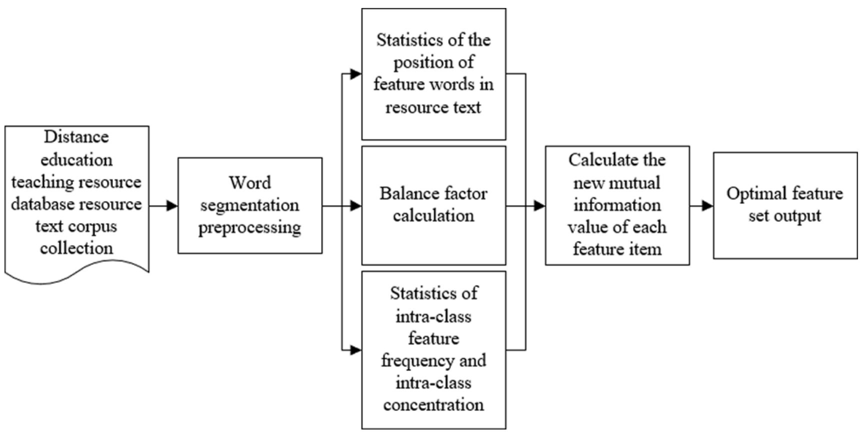

Fig. 3. Resource text feature extraction algorithm flow

5 Experimental results and analysis

Table 1 gives the comparison results of the prediction results of the resource entities in the teaching resource database. As can be seen from the table, the entity prediction model of teaching resource database proposed in this article is more excellent in the description text of MOOC distance education teaching resource database, because the model constructed in this article combines LSTM model with conditional random field model. Compared with RNN + conditional random field model, LSTM model and RNN model, the $F1$ score is improved by 3% ~ 10%. The main reason for the improvement is that the model proposed in this article uses LSTM model, which can better extract resource entities that knowledge points of target resource design refer to from resource text strings of teaching resource database. In addition, compared with the traditional LSTM and RNN models, the effect is improved, which mainly results from the modeling of various classes of tags and the calculation of the conversion probability between tag classes, realizes the description of the correlation relationship between tag classes, and solves the problem of the decline of prediction accuracy caused by the fuzzy boundary information of concept vocabulary of knowledge points involved in resources to a certain extent.

Table 2 gives the comparison of experimental results of resource entity link in teaching resource database. The table shows that in the case of the candidate knowledge point resource entity set generated by fuzzy matching, compared with EARL (Entity and Relation Linker) model, this model has been greatly improved in Precision, Recall and F13 indexes respectively. In the table, by comparing the experimental results of generating candidate knowledge point resource entities by using perfect matching and fuzzy matching methods, it can be found that fuzzy matching method can obviously improve the recall rate and $F1$ score of resource entity links in teaching resource database. This shows that the candidate knowledge point resource entity set generated by this model can avoid the problem that the resource entity that the knowledge point refers to cannot match or be correlated with other resource entities related to the knowledge point to a certain extent, and greatly improve the fault tolerance and robustness of the model in linking resource entities.

Table 3 gives the classification results of different resource text feature extraction algorithms under three classifiers. The classifiers participating in the comparison include logistic regression algorithm, support vector machine and fuzzy C-means clustering algorithm. See Figure 4 for the comparison of resource classification accuracy of different resource text feature extraction algorithms. It can be seen from Table 3 and Figure 4 that under the same experimental conditions, the algorithm in this article is higher than IG, PCA, QEMI, N-Gram and other algorithms in Precision, Recall and F1, which shows that it is effective to innovate the resource classification algorithm of teaching resource database from the extraction of resource text features, and the resource text features obtained by optimizing mutual information method are more suitable for the resource text classification of teaching resource database.

Table 1. Comparison of prediction results of resource entities in teaching resource database (%)

Model	*Precision*	*Recall*	*F*1
LSTM + CRF	84.51	86.95	84.72
RNN + CRF	82.63	83.62	86.59
LSTM	81.42	81.49	81.52
RNN	81.67	91.42	80.36

Table 2. Comparison of experimental results of resource entity link in teaching resource database (%)

Model	*Precision*	*Recall*	*F*1
EARL (Perfect matching)	71.42	76.29	72.61
EARL (Fuzzy matching)	85.96	82.45	81.96
The model (Perfect matching)	84.41	83.26	82.51
The model (Fuzzy matching)	86.62	81.62	85.74

Table 3. Results of classifiers under different resource text feature extraction algorithms (%)

Classification	Classifier 1			Classifier 2			Classifier 3		
	Precision	*Recall*	*F*1	*Precision*	*Recall*	*F*1	*Precision*	*Recall*	*F*1
IG	52.29	41.25	41.17	69.25	55.2	64.19	64.15	67.41	63.59
PCA	51.36	43.62	49.2	61.27	54.19	68.51	60.38	62.18	67.24
QEMI	58.19	47.15	48.52	65.38	61.28	67.35	67.24	69.03	63.8
N-Gram	62.48	52.52	54.36	68.15	63.41	69.12	69.11	67.24	60.17
The algorithm	63.52	56.01	50.28	61.72	68.26	67.35	65.27	61.18	63.42

Table 4. Results of classifiers under different index fusion methods (%)

Classification	Classifier 1			Classifier 2			Classifier 3		
	Precision	*Recall*	*F*1	*Precision*	*Recall*	*F*1	*Precision*	*Recall*	*F*1
BAFA	63.15	52.34	59.16	64.18	63.27	61.37	66.34	67.85	61.08
BAFA + CCC	69.02	58.02	55.27	72.36	51.49	65.24	74.19	51.27	67.35
BAFA + CCF	67.41	51.69	53.82	71.49	68.02	61.31	74.82	68.39	64.08
BAFA + CCF + CCC	68.25	57.31	61.5	78.42	63.84	74.59	76.15	61.24	74.52

Table 4 gives the resource classification results of three classifiers under different index fusion methods. The classifiers participating in the comparison also include logistic regression algorithm, support vector machine and fuzzy C-means clustering algorithm. See Figure 5 for the comparison of resource classification accuracy under different index fusion modes in Figure 4. As can be seen from Table 4 and Figure 5, under the same experimental conditions, BAFA, CCF and CCC are integrated in this article, which can obtain higher Precision, Recall and F1 index values than BAFA-CCC fusion, BAFA-CCC fusion and BAFA. This shows that the new algorithm, which can fully consider the negative correlation feature items and emphasize the selection proportion of concept vocabulary of high-frequency knowledge points, has better results in the text classification of teaching resources database resources, and is more suitable for application in the text classification and evaluation scene of teaching resources database resources.

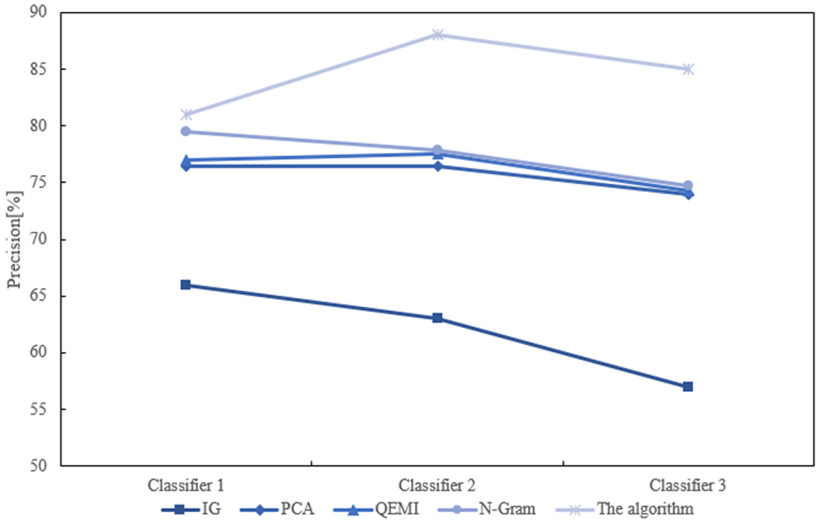

Fig. 4. Comparison of resource classification accuracy of different resource text feature extraction algorithms

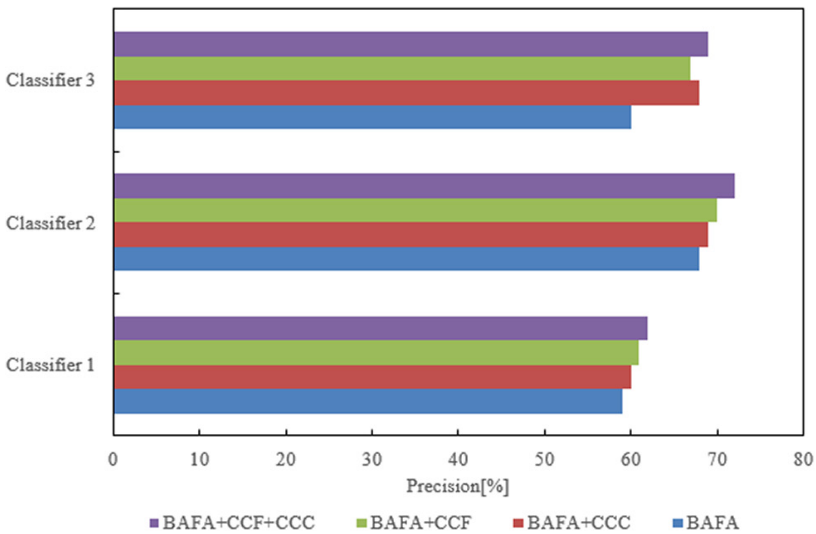

Fig. 5. Comparison of resource classification accuracy under different index fusion methods

6 Conclusion

This article studies the classification and evaluation of distance education teaching resource database based on knowledge network. Combining the LSTM model and the conditional random field model, the resource entities that the target resource design knowledge points refer to are extracted from the resource text string of the teaching resource database. The resource entities that the extracted knowledge point refer to are matched and correlated with other resource entities related to the knowledge point in the teaching resource database, so as to realize the link of resource entities in the teaching resource database based on the concept of knowledge points. Starting with the feature extraction of resource text, this article innovates the resource classification algorithm of teaching resource database, and shows the new algorithm flow of feature extraction of resource text. Contrast the prediction results of teaching resource database resource entities and the experimental results of teaching resource database resource entity link. The validity of extracting resource entities that the target resource design knowledge points refer to from resource text strings of teaching resource database is verified to show that the model has high fault tolerance and robustness in linking resource entities. It gives the resource classification results of different resource text feature extraction algorithms under three classifiers and the resource classification results of three classifiers under different index fusion methods. It is proved that the innovative idea of teaching resource database resource classification algorithm based on the feature extraction of resource text is effective, and the new algorithm has better effect in teaching resource database resource text classification.

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