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PAPER

A New Collaborative Filtering Recommendation Algorithm for Course Resources Based on Language-Scoring Data

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ABSTRACT

As digital tools and online resources are widely used in education these days, providing students with personalized learning resource recommendations is now an important task for educators- however, the currently available recommendation algorithms created based on language-scoring data are deficient in aspects of sentence similarity calculation and students' acceptance of new knowledge, so this study proposed an automatic language-scoring method based on the improved sentence similarity calculation; then, combining with the language-scoring data of students, a new collaborative filtering recommendation algorithm of course resources was proposed for changes in the effect of students' acceptance of new knowledge. The proposed new algorithm can more accurately evaluate students' language ability, with students' interests and capacity taken into consideration, and it can give more suitable and personalized recommendations of learning resources for students. In terms of algorithm design, both efficiency and accuracy have been taken into account and balanced, so the algorithm is applicable to large-scale data processing and real-time recommendation. This study not only helps in improving students' learning effect, but also provides useful references for educational institutions to optimize course design and teaching methods. Research findings of this study can be used in other disciplines and fields as well.

KEYWORDS

language-scoring data, sentence similarity, automatic language scoring, collaborative filtering, course resource recommendation, personalized learning, educational techniques

1 INTRODUCTION

Thanks to the development of information technology, digital tools and online resources are now widely used to improve the teaching effect in the field of education. Taking the English major as an example, students can contact a wealth of learning resources during their learning process, such as online courses, e-books, audio

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materials, and exercise database [1–5]. However, they often feel confused when facing such a sea of learning resources, and some of them are not able to find the learning materials most suitable for themselves. Particularly for English as a language discipline, students' learning effect is usually measured by their language expression ability, and the improvement of this ability needs the support of learning resources that are suitable for the learning level and needs of individual students [6–9].

The data of students' language scores are important for recommending suitable learning resources for them. By analyzing these data, teachers can understand students' strengths and weakness in language learning, thereby formulating customized learning resource recommendation and improving their learning effect [10–14]. For instance, for students with poor English writing ability, resources about writing skills and writing exercises can be recommended, and such a recommendation system can help students utilize learning resources more efficiently and increase learning enthusiasm, meanwhile providing references for educational institutions to optimize course content and teaching methods [5, 6].

Currently available recommendation algorithms created based on language-scoring data generally have some shortcomings. First, when calculating sentence similarity, many algorithms adopt only simple methods, such as the bag-of-words model, making it difficult to accurately reflect the semantic information of sentences [15–18]. Second, existing algorithms often ignore the changes in the effect of students' acceptance of new knowledge, which can lead to inconsistency between the recommended resources and students' real learning needs [19, 20]. Third, many available algorithms only have a low efficiency in processing large-scale data and cannot meet the requirement of real-time recommendations in practical applications.

In view of the shortcomings summarized above, this study proposed an automatic language-scoring method based on improved sentence similarity calculation and put forward a collaborative filtering recommendation algorithm of course resources for changes in the effect of students' acceptance of new knowledge. At first, an advanced sentence representation method was adopted to improve the accuracy of language scoring. Then, according to the data of students' language scores, the changes in students' acceptance of new knowledge were analyzed so that more personalized course resources could be recommended for them. By introducing the collaborative filtering mechanism, the proposed algorithm can comprehensively consider students' interests and capacity, making the recommended resources better fit students' real learning needs. Furthermore, both efficiency and accuracy have been taken into account in algorithm design, enabling the algorithm to meet the requirement of large-scale data processing and real-time recommendation.

The significance of this study lies in that the improved language-scoring method and the collaborative filtering recommendation algorithm can more accurately evaluate students' language ability, so that more suitable learning resources can be recommended to them and help improve the learning effect. For students, these newly proposed methods could increase learning effectiveness, enhance language skills, and improve learning performance; for educational institutions, these new methods provide useful evidences to optimize curriculum design and teaching methods; moreover, the proposed algorithm can even be used in other disciplines and fields to support systems of individualized education and intelligent recommendation.

2 AUTOMATIC LANGUAGE-SCORING METHOD

When processing natural languages, common methods tend to consider only the semantic features of words; the structural information of sentences is often ignored, causing loss of semantics. Similarly, for sentences with complex structure, the calculated similarity results may be unreliable if sentence structure is not considered. Regarding these matters, this study proposed a method for creating dependence relation triplets, the advantage of which lies in that it takes into account the similarity of sentences not only at the word level, but also at the sentence-dependent grammar level. This means that this method can capture the semantic information of sentences more comprehensively. With the help of the introduced sentence-dependent grammar, it can better interpret the relationship between words; for instance, by analyzing the dependence structure of sentences, we can figure out which words are predominant, which words are modifiers, and how they are related to each other. This knowledge is helpful to accurately identify the meaning of *policeman's* in specific sentences, and for automatic language scoring, this method has a particularly positive role. In addition, through accurate analysis and comparison of the semantics of sentences, students' language expression ability and understanding ability can be evaluated more accurately, and such deep-level semantic analysis can also help capture the changes in the effect of students' acceptance of new knowledge.

The improved sentence similarity calculation method proposed in this study was mainly implemented through creating dependence relation triplets, then sorting based on the created dependence relation triplets, and then calculating the similarity between the dependence relation triplets.

At first, the sentences to be compared were subject to sentence-dependent grammar analysis to reveal the grammatical relationships between words in sentences. For each sentence, a dependence triplet was created, containing a head, a dependent word, and the dependence relation between them. Assuming: o represents the dependent word, w represents the independent word, e represents the dependence relation between the two, $Y\,(o,w,e)$ represents the dependence triplet and it satisfies $(o,w \in C) \cap (o \neq w) \cap \langle o,w \rangle \in R,\ e \in E$.

Assuming: two sentences S and N of students' course resource evaluation, respectively, contain l and b dependence triplets; $Y_{Su}(o_{Su},w_{Su},e_{Su})(1 \le k \le l)$ represents the u-th dependence triplet of S, wherein the three elements o_{Su}, w_{Su}, e_{Su}, respectively, present the dependent word, the independent word, and the dependence relation; $Y_{Nk}\ (o_{Nk}, w_{Nk}, e_{Nk})(1 \le k \le b)$ represents the k-th dependence triplet of N, wherein the three elements o_{Nk}, w_{Nk}, e_{Nk}, respectively, present the dependent word, the independent word, and the dependence relation.

To ensure stable and consistent comparison of sentences, the dependence triplets of each sentence need to be sorted out based on multiple criteria, such as sort out first according to the sequence of head words and then according to the type of dependence relations. This step helps to standardize the structure of triplets to facilitate comparisons in subsequent steps. This study introduced a dependence similarity indicator $E\_SI\ (e_{Su},e_{Nk})$ whose value range is given by the following formula:

$$E\_SI(e_{Su},e_{Nk}) = \begin{cases} 1, e_{Su} = e_{Nk} \\ 0, e_{Su} \neq e_{Nk} \end{cases} (1 \le u \le l, 1 \le k \le b) \tag{1}$$

Next, the similarity between dependence triplets was calculated. In this step, the dependence triplets of two sentences were compared and their similarity was calculated. The similarity calculation considered several factors, including the head words, the semantic similarity of dependent words, and the type of dependence relation. Let $1 \le k \le l$ and $1 \le k \le b$, $SI\ (o_{Su}, o_{Nk})$ represents the word similarity of o_{Su} and o_{Nk}, $SI\ (w_{Su}, w_{Nk})$ represents the word similarity of w_{Su} and w_{Nk}, $E\_SI\ (e_{Su}, e_{Nk})$ represents the indicator of dependence relation similarity; if the information of dependence relation between words in the evaluation sentences is considered, then the following formula can be used to calculate the similarity between dependence triplets:

$$SI\left(Y_{Su},Y_{Nk}\right)=SI\left(o_{Su},o_{Nk}\right)\times SI\left(w_{Su},w_{Nk}\right)\times E\_SI\left(e_{Su},e_{Nk}\right) \tag{2}$$

In order to avoid the problem that the importance of dependence relation cannot be represented by smaller similarity degree values, the above formula was corrected as follows:

$$SI\left(Y_{Su},Y_{Nk}\right)=\sqrt{SI\left(o_{Sk},o_{Nk}\right)\times SI\left(w_{Sk},w_{Nk}\right)}\times E\_SI\left(e_{Sk},e_{Nk}\right) \tag{3}$$

By sorting out the similarity calculation results of all dependence triplets of *S* and *N*, a similarity matrix shown as the formula below can be created:

$$\begin{bmatrix} SI(Y_{S1},Y_{N1}) & \cdots & SI(Y_{S1},Y_{N1}) \\ \cdots & SI(Y_{Su},Y_{Nk}) & \cdots \\ SI(Y_{Sl},Y_{N1}) & \cdots & SI(Y_{Sl},Y_{Nb}) \end{bmatrix} \tag{4}$$

The values of each element $SI\ (Y_{Su},\ Y_{Nk})$ in the matrix can be calculated by formula 3. By fusing the dependence relation factors of evaluation sentences given by students on the course resources, the formula for calculating the similarity of sentences can be attained as below:

$$SI(S,N)=\frac{\left(\dfrac{\sum_{u=1}^{l}Q(e)*y_{Su}}{\sum_{u=1}^{l}Q(e)}+\dfrac{\sum_{k=1}^{b}Q(e)*y_{Nk}}{\sum_{k=1}^{b}Q(e)}\right)}{2} \tag{5}$$

$y_{Su}=\underset{k=1\ldots b}{MAX}\{SI(Y_{Su},Y_{Nk})\}$, $y_{Nk}=\underset{u=1\ldots l}{MAX}\{SI(Y_{Su},Y_{Nk})\}$, wherein Figure 1 shows the flow of similarity calculation.

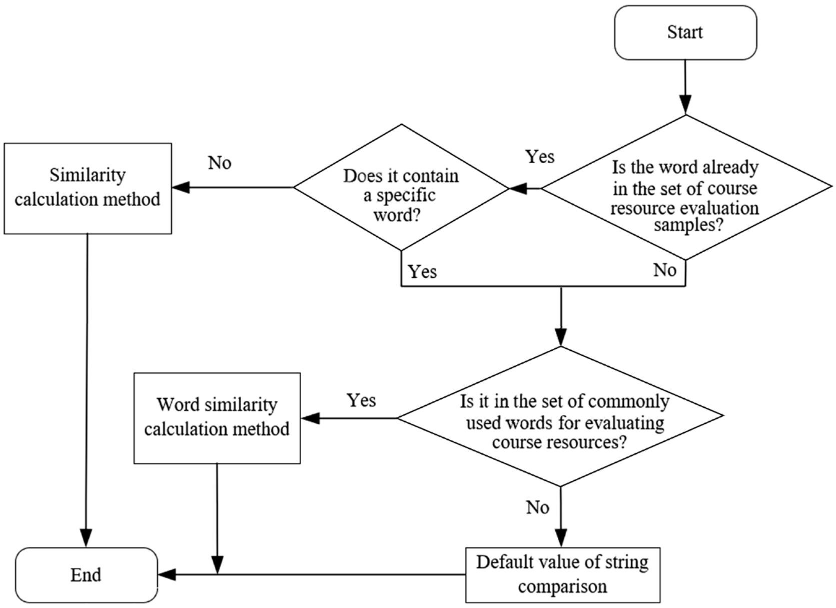

Fig. 1. Flow of similarity calculation

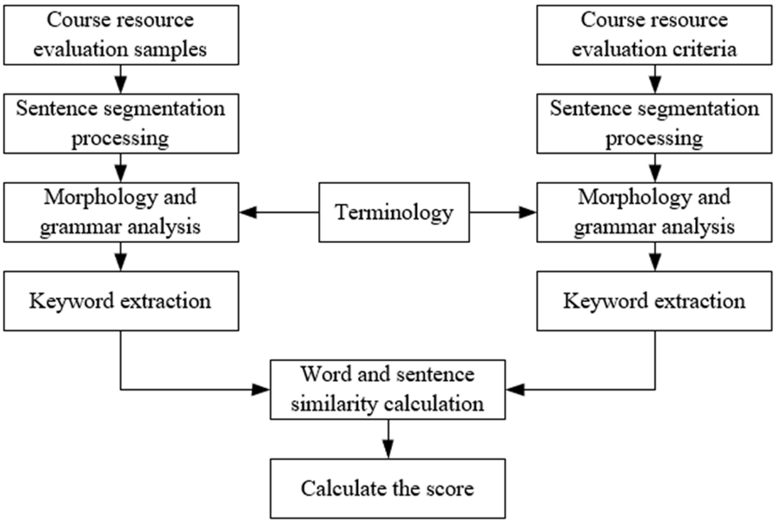

Fig. 2. Automatic language-scoring process

This study proposed an automatic language-scoring method, aiming at improving the accuracy of automatic scoring by introducing an adjustment parameter. Specifically speaking, this method is based on two key points of manual review; namely, keyword scoring and sentence expression scoring, through which the core elements in students' answers and their expression ability can be comprehensively considered and the quality of students' answers can be better captured than simply adding the scores of each part. The introduction of an adjustment parameter makes the scoring more flexible and better adapt to different topics and the differences in students' answers. This has simulated the manual scoring process to some extent and can help improve the accuracy of automatic scoring. Figure 2 shows the automatic language-scoring process.

In order to get automatic language-scoring results that can reflect the changes in students' acceptance of new knowledge, the proposed method gave accurate evaluations on students' performance in keyword use and sentence expressions, through which teachers can better understand the progress made by students in these aspects, which is helpful to monitor the situation of students' acceptance of new knowledge.

$$\text{Error value} = |\text{Manual scoring} - \text{Auto scoring}| \tag{6}$$

Assuming: there are a total of *b* sentences in student course resource evaluation, *Y* represents the total evaluation score, *DF* represents the student course resource evaluation score, *J_SI* represents the similarity degree of keywords, *J_q* represents the proportion of keyword scores, *A_SI* represents the similarity degree of the *n*-th sentence in student course resource evaluation, *A_qu* represents the proportion of the *n*-th sentence, *D* represents the adjustment parameter, then the formula of automatic language scoring can be expressed as:

$$DF = \left(J\_q + \sum_{u=1}^{b} A\_SI_u * A\_q_u\right) * Y + D \tag{7}$$

The introduction of an adjustment parameter uses the average of multiple error values to adjust the automatic scoring, thereby improving the accuracy of automatic scoring. This method uses the error between manual scoring and automatic scoring to adjust the adjustment parameter and to make the automatic scoring approach to the level of manual scoring. Such adjustment helps to improve the accuracy of scoring, thereby more accurately reflecting students' knowledge mastery level and the progress they made. It has a positive effect on attaining the automatic language-scoring results that can reflect the changes in the effect of students' acceptance of new knowledge.

3 THE COURSE RESOURCE RECOMMENDATION ALGORITHM CONSIDERING THE DECAY OF ACCEPTANCE EFFECT OF NEW KNOWLEDGE

It is a common phenomenon that the effect of students' acceptance of new knowledge gradually diminishes with the passage of time, and many reasons can cause this situation. For instance, students may forget the newly learned knowledge if they do not have the opportunity to actually use it, as practice and application can deepen their understanding and memory of the new knowledge; or the students may face huge amounts of information and tasks during the learning process that might exceed their ability of cognition and processing, which can result in inefficient absorption and retention of the new knowledge; or if the students are not interested in what they learned or think it is not important to their life or career goals, they may not invest enough time or energy to sustain their mastery of this new knowledge.

The vocabulary students use in their written or oral expressions can reflect their mastery of new knowledge. If a student can use the technical terms and concepts of the subject he/she is learning, then it means that the student has already accepted and understood this new knowledge. In the meantime, sentences with good grammatical structure and coherent expressions are important indicators to evaluate whether the student can convey his/her thoughts clearly and logically. If a student is able to use complex sentence structures while maintaining consistency, this may indicate that the student already has a deep-level understanding of the new knowledge. By analyzing students' written or oral expressions and the language-scoring data, the effect of students' acceptance of new knowledge can be figured out, thereby assisting the evaluation of their comprehension and applicability of the new knowledge.

Assuming: o_0 represents the initial effect of new knowledge acceptance, y represents the time elapsed after the new knowledge was taught, j represents the decay rate parameter, $o(y,j)$ represents the current effect of new knowledge acceptance, then the decay rate function of acceptance effect can be expressed as:

$$o(y,j) = o_0^{-jy} \tag{8}$$

To make the above function adapt to the changes in students' ability to accept new knowledge in both long and short terms, this study constructed a memory curve model of students' long- and short-term acceptance ability. Assuming t_{CQ} and t_{DQ}, respectively, represent the decay curves of long- and short-term acceptance ability, β represents the decay factor, then there are:

$$t_{CQ} = 0.5 + 0.5e^{-\beta Y} \tag{9}$$

$$t_{DQ} = \frac{2}{1+e^{\beta Y}} \tag{10}$$

Assuming: y_{iu} represents the scoring time of student i for learning resource u, y_{iMIN} represents the earliest scoring time of student i, y_{iMAX} represents the latest scoring time of student i, then the calculation formula of time Y is:

$$Y = 1 - \frac{y_{iu} - y_{iMIN}}{y_{iMAX} - y_{iMIN}} \tag{11}$$

By calculating the proportion of a target student's total weight of attributes of a certain learning resource in the total weight of attributes of student feature set, whether this learning resource is within the long- and short-term acceptance ability interval of the student can be judged, and this method has an important and positive effect on the course resource recommendation results with the decay effect taken into consideration, as it can provide students with more personalized learning resource recommendations based on their specific features and capabilities, and this is more effective than recommendations made based on a single criterion, as it has taken into account the students' different needs and preferences. In the meantime, by distinguishing between long-term and short-term acceptance ability of students, more suitable resources could be provided to them in a more targeted and accurate manner. For instance, for students with a better long-term acceptance ability, materials with deeper-level and more complex content could be recommended; while for students with a better short-term acceptance ability, more condensed and easily digested content could be recommended to them.

Assuming: $RA(i,u)$ represents the weight of acceptance ability of student i for learning resource u, $\sum_{j=1}^{b} O_{i,j}$ represents the sum of acceptance ability of student i for all attribute features of learning resource u, $\sum_{j=1}^{y} O_{i,j}$ represents the sum of acceptance ability of student i for all attribute features of learning resources, then the formula below calculates the weight of proportion of the attribute features of a certain learning resource in the new knowledge acceptance effect model of the student:

$$RA(i,u) = \frac{\sum_{j=1}^{b} O_{i,j}}{\sum_{j=1}^{y} O_{i,j}} \tag{12}$$

Combining with the long- and short-term acceptance effect decay model proposed in this study, the students' long- and short-term acceptance ability was distinguished by setting threshold values. If the proportion of the attribute features of a learning resource in the new knowledge acceptance effect model of the student is greater than the threshold, then it is the long-term acceptance ability; otherwise, it is the short-term acceptance ability. Assuming: $D(i,u)$ represents the acceptance ability of student i for learning resource u, $RA(i,u)$ represents the weight of attribute features of learning resource u in the new knowledge acceptance effect profile of student i, and the final acceptance ability of student i for the learning resource u which the student had scored before can be calculated as follows:

$$D(i,y) = \begin{cases} (0.5 + 0.5r^{-sy}) \times RA(i,y) & RA(i,y) >= \alpha \\ \dfrac{2}{1 + r^{sy}} \times RA(i,y) & RA(i,y) < \alpha \end{cases} \tag{13}$$

If the attribute weight of learning resource i is greater than α, then it is the long-term acceptance ability, and the decay rate of acceptance effect is slower than that of the short-term acceptance ability; if the attribute weight is smaller than α, then the decay rate of acceptance effect is faster.

When making recommendations for a target student, the student's scoring history, the learning resources rated by the student, and the decay rate of the student's acceptance effect should be fully considered. Compared with conventional recommendation algorithms, the proposed method can better reflect the changes in students' acceptance ability and improve the recommendation accuracy. Assuming: RE_{iu} represents the recommendation degree of target student i for learning resource u which is to be recommended, k represents learning resources contained in the history learning resource set of student i, then the attained final recommendation degree of learning resources can be calculated by the following formula:

$$RE_{iu} = \sum_{k=1}^{b} SI_{NS}(u,k) \times D(i,k) \tag{14}$$

This study proposed a collaborative filtering recommendation algorithm considering the changes in students' acceptance effect of knowledge, and the flow of the algorithm is detailed below:

Step 1: Extract the learning resource scoring data set and learning resource feature data set of a student, and create the learning resource scoring matrix and the learning resource feature matrix of the student;

Step 2: Calculate the similarity between learning resources, create a list of similarities between each learning resource and other learning resources, and find out the K nearest neighbors of each learning resource;

Step 3: Create a list of attribute features of learning resources according to the learning resource feature matrix;

Step 4: Combine the student's scoring history record of learning resources with the list of attribute features of learning resources, model the student's acceptance effect of new knowledge, and divide the short- and long-term acceptance ability of the student according to the set threshold values;

Step 5: Combine the student's scoring history record of learning resources with the set of learning resources to be recommended created based on the K nearest neighbors of learning resources in Step 2;

Step 6: Combine the similarity calculation algorithm in Section 3 and the long- and short-term acceptance ability model in Step 4 to predict the score of the learning resource list to be recommended;

Step 7: Recommend learning resources to the student based on the predicted score of learning resources.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Performance comparison of five similarity calculation methods

Method	Precision/%	Recall/%	*F* value/%
Cosine Similarity	69.4	56.3	62.4
Jaccard Similarity	77.3	74.5	73.6
Word Embedding + Euclidean distance	82.6	74.2	81.1
BERT model	84.2	82.6	82.1
The proposed method	88.3	82.1	84.5

Table 1 lists the performance of five sentence similarity calculation methods in terms of precision, recall rate, and F value. *Cosine Similarity* gave a precision rate of 69.4%, a recall rate of 56.3%, and an F value of 62.4%, which were the worst among the five methods, and it has been further proved that the *Cosine Similarity* method is too simple in terms of word frequency, as it does not dig deep into the semantic information of sentences. *Jaccard Similarity* gave a precision rate of 77.3%, a recall rate of 74.5%, and an F value of 73.6%, which were better than *Cosine Similarity*, but not as good as the deep learning method, and this indicates that solely considering the co-occurrence of words is not enough to capture the complex semantics of sentences. As for the *Word Embedding + Euclidean distance* method, it gave a precision rate of 82.6%, a recall rate of 74.2%, and an F value of 81.1%, which were obviously better than the first two methods, indicating that word embedding can capture well the semantics of words, and Euclidean distance can measure the spatial similarity of these embedding. The *BERT* model gave a precision of 84.2%, a recall rate of 82.6%, and an F value of 82.1%, which were better than the *Word Embedding + Euclidean distance* method in terms of all three indicators. As a pre-trained model established based on deep learning, the *BERT* model can capture the deeper level semantic information of sentences. As for our proposed method, its precision was 88.3%, recall rate was 82.1%, and F value was 84.5%; its performance was the best in terms of all three indicators, which further verified that the proposed method can more comprehensively capture the semantics of sentences via combining with word similarity and sentence dependence.

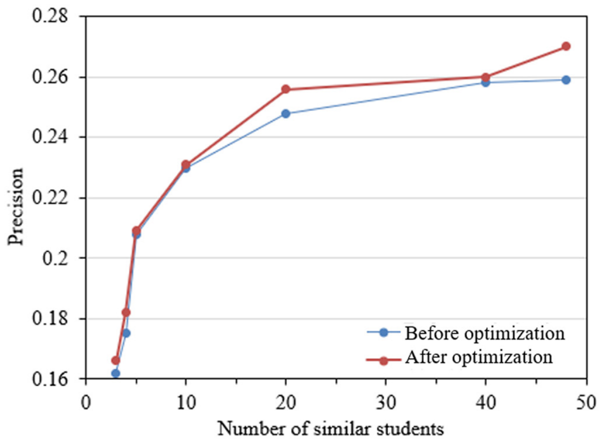

Fig. 3. Comparison of precision of the collaborative filtering recommendation algorithm before and after optimization

Figure 3 plots the precision of the collaborative filtering recommendation algorithm before and after optimization in case of different numbers of similar students. When the number of similar students was 3, the precision before algorithm optimization was 0.162, and the value increased to 0.166 after optimization. When the number was smaller, the precision increased slightly after optimization; when the number was 4, the precision before optimization was 0.175 and optimized precision was 0.182. It can be seen that that the optimized algorithm continued to give a higher precision at this level. When the number was increased (to 5, 10, 20, 40, 48) gradually, the optimized algorithm gave higher precision under all conditions. Although the increment was not much, the smallest improvement still counts in the recommendation system. Changes in these data clearly show that the precision of the improved collaborative filtering recommendation algorithm was higher than that before algorithm optimization at all levels of the number of similar students, indicating that the improved algorithm can better utilize the data of similar students to give more accurate recommendations.

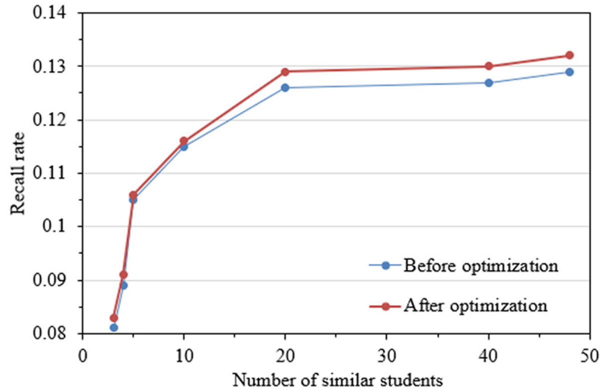

Fig. 4. Comparison of recall rate of the collaborative filtering recommendation algorithm before and after optimization

Figure 4 plots the recall rate of the collaborative filtering recommendation algorithm before and after algorithm optimization in the case of different numbers of similar students. When the number was 3, the recall rate was 0.081 before optimization and 0.083 after optimization, suggesting that in the case of a smaller number of similar students, the improved algorithm could find more truly valuable items. When the number was 4, the recall rate was 0.089 before optimization and 0.091 after optimization, suggesting that after optimization, the algorithm gave a slight improvement. When the number was increased further (to 5, 10, 20, 40, 48), it can be observed that the recall rate of the improved algorithm was slightly higher than that before algorithm optimization under all conditions, indicating that in the case of a greater number of similar students, the improved algorithm can more effectively find out items that are valuable for users. Data in the figure show that, at all levels of similar student number, the recall rate of the improved collaborative filtering recommendation algorithm was slightly higher than that before algorithm optimization. Although the improvement was not that obvious, it still indicates that the improved algorithm can more effectively give recommendations that are valuable for users. In the recommendation system, increasing the recall rate means increasing the coverage of items that users are interested in, and this has a positive effect on improving user experience and satisfaction. Therefore, the improved algorithm exhibited some advantages and practical utility.

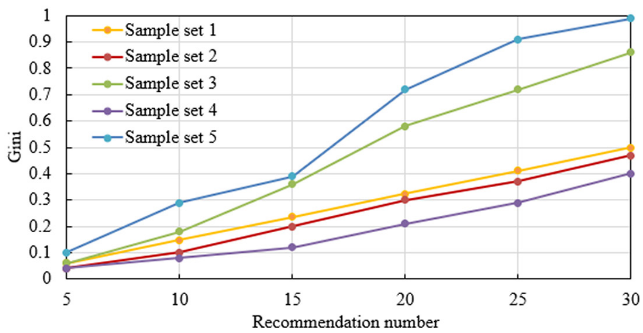

Fig. 5. Variations of *Gini* coefficient with recommendation number in different sample sets

Figure 5 plots the variations of the *Gini* coefficient with the recommendation number in different sample sets. In the high-level-subject–style sample set (Sample set 1), the *Gini* coefficient increased as the recommendation number grew, indicating that in this type of sample, recommending more items can increase the diversity of recommendations. A similar trend can be observed in multimedia-style samples (Sample set 2); that is, the *Gini* coefficient grew together with the number of recommendations. The increase of *Gini* coefficient was the most significant in basic knowledge–style samples (Sample set 3), and this indicates that in the field of basic knowledge, recommending more items can bring a higher diversity. In terms of personalized and special interest–style samples (Sample set 4), the growth of the *Gini* coefficient was slower, indicating that in this type of sample, the growth of recommendation diversity was not as significant as other types. The *Gini* coefficient of practice and application-style samples (Sample set 5) grew the fastest, indicating that in this type of samples, increasing the recommendation number can significantly increase the diversity of recommendations.

Table 2. Comparison of recommendation results of 7 models on the basic knowledge–style sample set

Evaluation Indicator	*PDLR*	*DMF++*	*MB-CF*	*MFB-CF*	*II-CF*	*UU-CF*	The Proposed Method
MAE	0.71	0.68	0.63	0.74	0.73	0.75	0.73
RMSE	0.89	0.84	0.85	0.83	0.95	0.94	0.82
Gini	0.37	0.39	0.37	0.36	0.42	0.47	0.55

Based on the basic knowledge–style sample set, the recommendation results of seven models (*PDLR*, *DMF++*, *MB-CF*, *MFB-CF*, *II-CF*, *UU-CF*, and the proposed method) were evaluated using three performance indicators (also *MAE*, *RMSE*, and *Gini* coefficient) (Table 2). The *MAE* of the proposed method was 0.73, which was at an average level among the other reference models. In terms of this indicator, the performance of the *MB-CF* model was the best, as its *MAE* reached 0.63, while the performance of the *UU-CF* model was the worst, as its *MAE* was 0.75. In terms of *RMSE*, the performance of the proposed method was the best, with a value of 0.82, showing its better performance in accuracy. In contrast, the *RMSE* of the *PDLR* model was the highest, reaching 0.89. In terms of the *Gini* coefficient, the proposed method significantly outperformed other models, reaching 0.55, indicating its excellent performance in terms of recommendation diversity and fairness. In contrast, the *Gini* coefficient of the *MFB-CF* model was the lowest, only 0.36. Comprehensively considering all indicators, the performance of the proposed method was the best on the basic knowledge–style sample set, and its recommendation accuracy and diversity were both higher.

Table 3. Comparison of recommendation results of 7 models on the high-level-subject–style sample set

Evaluation Indicator	*PDLR*	*DMF++*	*MB-CF*	*MFB-CF*	*II-CF*	*UU-CF*	The Proposed Method
MAE	0.61	0.64	0.67	0.75	0.75	0.77	0.75
RMSE	0.87	0.86	0.88	0.87	0.85	0.84	0.72
Gini	0.38	0.34	0.47	0.32	0.47	0.49	0.85

Based on the high-level-subject–style sample set, the recommendation results of the above seven models were also evaluated using three performance indicators (also *MAE*, *RMSE*, and *Gini* coefficient) (Table 3). In terms of *RMSE,* the performance of the proposed method was the best; the value was 0.72, suggesting a good performance in terms of precision. In contrast, the *RMSE* of the *MB-CF* model was higher, and the value was 0.88. In terms of the *Gini* coefficient, the performance of the proposed method was significantly better than other models, reaching 0.85, and this indicates that the proposed method was superior in recommendation diversity and fairness. In contrast, the *Gini* coefficient of the *MFB*-CF model was the lowest, reaching a value of 0.32. Thus, in terms of *RMSE* and the *Gini* coefficient, the proposed method performed excellently, indicating its good performance not only in precision, but also in recommendation diversity and fairness. In terms of *MAE*, the performance of the proposed method was at an average level, but the value was relatively high.

5 CONCLUSION

This study discussed a number of subjects related to course resource recommendation, sentence similarity calculation method, and the corresponding evaluation indicators. Combining with theoretical and experimental research results, the following conclusions were drawn:

1. About course resource recommendation:
   The effect of course resource recommendation is the kernel content of this study. Considering that the effect of students' acceptance of new knowledge would decay with the passing of time, through the adjustment parameter, this study took into account the students' long- and short-term acceptance ability, and the contribution of various attribute features of course resources to the effect of students' acceptance of new knowledge.
2. About sentence similarity calculation:
   This study also discussed the method of sentence similarity calculation, which was very important for understanding students' evaluations of course resources. Experimental results suggested that the *BERT* model and the *Word Embedding*–based method performed better in terms of some evaluation indicators, while the proposed method gave a comprehensive good performance in terms of multiple indicators.
3. About collaborative filtering recommendation algorithm:
   The collaborative filtering recommendation algorithm was improved in this study, and its performance was evaluated based on precision and recall rate. Data suggested that the improved algorithm gave better precision and recall rate results.
4. Analysis of evaluation indicators and results:
   In the experiment, the proposed method exhibited good performance, especially in terms of recommendation diversity and precision, which provides online education platforms an effective means to more accurately recommend course resources that can better fit students' learning needs and interests.

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