Accurate Exercise Recommendation Based on Multidimension-al Feature Analysis

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Abstract. With the rapid development of the Internet, online learning has developed rapidly, and learners are increasingly demanding the personalization and practicality of exercise. Facing the massive exercises in the online learning platform and the online examination system, how to choose the exercises that can be targeted and can make up for the knowledge loopholes has become a hot topic in the field of personalized recommendation of current teaching resources. In view of the fact that learners have a variety of learning features, and there are a large number of online exercises, various types and varying degrees of difficulty, this paper proposes a precise recommendation method based on Multidimensional features analysis for exercises. It quantifies the potential relationship between the learner and the exercise from three aspects: the heat of the exercise itself, the relevance of the knowledge among the exercises, and the similarity of the learner's style, using the linear combination and the Learning to Rank method to build the recommendation model to match learner and exercises exactly. Experiments show that the mean average precision of the ReMFA method reaches 36.8% when recommending five candidate exercises, which can provide learners with personalized exercise recommendation services, thereby improving the learner's learning efficiency.

1. Introduction
With the rapid development of the mobile Internet and the widespread popularization of smart mobile terminals, the informationization of college education has been greatly improved. Whether it is traditional education or online education, the quality of teaching resources plays a decisive role in teaching effectiveness. Facing the huge amount of exercise data in the online learning platform and online examination system, how to choose targeted exercises and make up for gaps in knowledge has become a hot topic in the field of personalized recommendation research of teaching resources.

In recent years, scholars have tried to apply various recommendation algorithms to the problem of problem recommendation in online education platform. In the traditional recommendation system, the recommendation algorithm based on Collaborative Filtering is one of the most widely used and successful technologies. This paper proposes a method for accurate recommendation of exercises based on multi-dimensional feature analysis. This method quantifies the potential relationship between learners and exercises from three aspects: Exercise heat, knowledge relevance, and style similarity. Complete the precise matching of exercises and learners.

2. Accurate recommendation method for exercises
This section first introduces the framework of the ReMFA method, then introduces the three-dimensional features and quantitative measurement rules between the learner and the exercise, and
finally introduces the precise recommendation algorithm for the exercise based on multidimensional feature analysis.

2.1. Framework of accurate recommendation method

The main idea of the ReMFA method is to use the learning data of learners in the learning platform to construct a measure model of the correlation between the learners and the exercises from the three dimensions, finally achieve personalized recommendations. The overall framework is shown in Figure 1.

Figure 1. The framework of precise exercises recommendation method based on multidimensional feature analysis

The method of accurate exercise recommendation based on multi-dimensional feature analysis mainly includes the following stages:

- Get learners' historical learning data
- Building an association network
- Training recommendation models
- Test recommendation results

2.2. Extracting multi-dimensional features and quantitative measures

This paper measures the relationship between learners and exercises from three different dimensions: exercise heat, exercise correlation, and style similarity among learners. It fully reflects the relationship between learners and recommended exercises.

2.2.1. Exercise heat

This paper measures the heat of an exercise based on the number of times it was collected and the number of times it was recorded. Based on the above two indicators, this paper designs the following formula to calculate the heat of an exercise:

\[ ep(j) = \text{nor(collect}(j)) + \text{nor(record}(j)) \] (1)

Among them, \( ep(j) \) represents the popularity of exercise \( j \), and \( \text{collect}(j) \) and \( \text{record}(j) \) represent the number of collected and recorded records of exercise \( j \), respectively.

2.2.2. Knowledge relevance

In this paper, a knowledge-related network of exercises is constructed based on the knowledge correlation between exercises. In this network, with the learner as the center, a node represents a problem, and the edge between nodes represents a correlation between two exercises, and the weight of the edge indicates the degree of correlation. As shown in Figure 2.

Based on this sub-network, this paper defines the knowledge relevance as the sum of the knowledge relevance between the learner's answers and favorites and the candidate exercise. The formula is:

\[ kr(L, j) = \sum_s kr(s, j) \] (2)
kr \((L, j)\) represents the correlation between a given learner \(L\) and exercise \(j\), kr \((s, j)\) represents the knowledge correlation between exercise \(s\) and exercise \(j\), and \(s\) represents all the exercises that the learner answered and collected.

\[
\text{Cor}(L, j) = a \times \text{nor}(\text{ep}(j)) + b \times \text{nor}(\text{kr}(L, j)) + c \times \text{nor}(\text{ss}(L, j))
\]

Among them, \(\text{nor}(x) = x / \max(x)\), which means that the dimension is normalized so that each feature operates at the same order of magnitude.

2.3. Recommendation Method Based on Ranking Learning

Sorting learning technology attempts to solve the sorting problem with machine learning methods, which has been deeply studied and widely used in different fields\(^4\). Learning to Rank uses machine learning algorithms to solve the ranking problem by training models. In the field of software engineering, there have been related researches to analyze and rank software data based on the LTR method\(^5\)\(^6\).

Ranking is the target value of the LTR method learning, which reflects the importance of the data record. The higher the record, the more important it is. In the learner’s answer data, the learner’s operation on a problem The greater the number of times, it indicates that it attaches more importance to the exercise, so this paper chooses the number of times the learner has performed the exercise (including free exercises, random exercises, repeated exercises, collections, etc.) as the target value, and also as the
mark value of the data record, used for LTR model training and testing. During model training, the exercises are sorted by the number of operations to get a list of exercises to be recommended.

3. Experimental results and analysis
This section first introduces the experimental data and evaluation indicators, and then compares, describes, and analyzes the experimental results obtained by the two methods.

3.1. Experimental data
The data set used in this paper is the data set generated by students in a freshman education platform of a school. The platform has registered a total of 4021 users, of which 3,916 freshman users, contains 4866601 free practice records, 175825 random practice records, 69826 Repeated exercise records, 45447 exercise collection records. The complete data set is divided into two parts, 70% of the data is used as a training set to train the recommendation model, and the remaining 30% of the data is used to test and evaluate the recommendation effect of the method proposed in this paper.

3.2. Evaluation index
In evaluating the experimental results, this paper mainly uses the accuracy rate, the average accuracy rate, and the average percentage ordering as the evaluation indicators. The accuracy rate here refers to the number of exercises that are actually answered or saved by a learner \(i\). Therefore, the formula for calculating accuracy is as follows:

\[
\text{precision}(k) = \frac{r_i}{k}
\]

\(k\) is the total number of exercises recommended for learner \(i\), and \(r_i\) is the number of exercises that learner \(i\) actually answered or saved.

Mean average precision (MAP) is a commonly used evaluation index in the field of information retrieval. It is used to evaluate the overall prediction accuracy of the algorithm\(^7\). First, we need to calculate the average precision (AP). Given a learner \(i\) and a sorted list \((j_1, j_2, ..., j_M)\) of length \(M\) recommended for it, suppose user \(i\) chooses \(N\) of them, you can calculate the average correct rate:

\[
\text{AP}(i) = \frac{\sum_{k=1}^{M} \text{precision}(k) \times \text{ref}(k)}{N}
\]

\(\text{precision}(k)\) is the accuracy of Top-\(k\). If \(j_k\) hits, \(\text{ref}(k) = 1\); otherwise, \(\text{ref}(k) = 0\). And MAP is the average of the average correct rate of all test users. The calculation formula of MAP is as follows:

\[
\text{MAP} = \frac{1}{|\text{Users}|} \sum_{i \in \text{Users}} \text{AP}(i)
\]

\(|\text{Users}|\) is the total number of users in the test set, The higher the MAP, the higher the recommendation accuracy of the algorithm.

Mean percentage ranking (MPR) is often used to measure the user’s satisfaction with the recommendation list. It is an evaluation index oriented to the recall rate\(^7\). We record the ranking position of product \(j\) in the ranked recommendation list provided for user \(i\) as rank\(_i,j\), we can get:

\[
\text{MPR} = \frac{1}{|\text{Users}|} \sum_{i \in \text{Users}} \frac{\text{ind}(i,j) \times \text{rank}^i_{i,j}}{\sum_{\beta} \text{ind}(i,\beta) \times \text{rank}^i_{i,\beta}}
\]

\(\text{ind}(i,j)\) is an indication function, if user \(i\) selects product \(j\), \(\text{ind}(i,j) = 1\), otherwise it is 0. The lower the MPR, the better the algorithm performs in predicting the recall rate. The MPR value of a completely randomly arranged recommendation list should be close to 50%.

3.3. Experimental results and analysis
This section introduces the recommendation results based on the linear combination model and the recommendation results based on the LTR model.

3.3.1. Recommendation based on linear combination model
We compare and analyze the model recommendation effects using single-dimensional, two-dimensional, and multi-dimensional features.
From figure 4, figure 5, figure 6, we find that the effect of the three-dimensional feature combination is better than the results of the two-dimensional feature combinations, and the MAP reaches 0.327 when recommending Top-10. It is 2.4 times the effect of the single-dimensional feature. The comparative experimental results show that the recommendation model established by the combination of multi-dimensional features has a better effect on the learner's exercise recommendation, and it is better to control the length of the recommendation list to 15 or less.

3.3.2. Recommendation based on LTR model
This section compares the recommendation results based on the LTR model with the recommendation results based on the linear combination model. The comparison result of MAP is shown in figure 7.

From the figure, we can see that the MAP of the LTR model is higher than the linear combination model, reaching the highest 0.368 when recommending Top-5, with the length of the recommendation list The increase of MAP also showed a downward trend, but the lowest value at Top-20 also reached 0.329. Below we add the comparison results of MPR indicators, as shown in table 1.
Table 1. Comparison of recommendation performance for linear-combination model and LTR model

| Evaluation index | Top-5 | Top-10 | Top-15 | Top-20 |
|------------------|-------|--------|--------|--------|
| MAP | | | | |
| multidimensional | 0.302 | 0.327 | 0.312 | 0.294 |
| LTR | 0.368 | 0.363 | 0.339 | 0.328 |
| Promotion rate | 21.9% | 11.0% | 8.7% | 11.6% |
| MPR | | | | |
| single-dimensional | 33.5% | 32.9% | 35.7% | 35.5% |
| two-dimensional | 30.3% | 30.4% | 34.5% | 34.4% |
| multidimensional | 20.4% | 19.5% | 20.0% | 19.3% |
| LTR | 17.6% | 16.3% | 15.3% | 15.0% |

From table 1, we can see that: under the MAP index, the effect of the LTR model is 21.9% higher than the effect of the linear combination model at Top-5, with the largest increase, and the improvement is smaller at Top-15. The MTR of the LTR model is lower than the MPR of the three-dimensional linear combination model, reaching a minimum of 15.0% at the Top-20. Whether it is the MAP index or the MPR index, the recommended number is from Top-5 to Top-20, and the effect of the LTR model both are better than the linear combination model, indicating that the LTR model can rank the results that are more likely to be selected by the user in the front of the recommendation list.

4. Conclusion

This paper proposes a method for accurate recommendation of exercises based on multi-dimensional feature analysis. This method quantifies the potential association between learners and exercises from three aspects: the degree of popularity of the exercises, the knowledge correlation between the exercises, and the style similarity between the learners, completes the precise matching of exercises and learners, and provides learners with personalized exercise recommendation services, and thus improves the learning efficiency of learners.

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