# A personalized exercise recommendation method for teaching objectives

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## ABSTRACT

It can improve the learning effect and reduce the learning burden to recommend exercises which are in accordance with the teaching objectives to students. How to accurately judge the needs of students and recommend exercises that are consistent with the teaching objectives is an urgent problem to be solved in the field of personalized education. This paper proposes a personalized exercise recommendation method for teaching objectives. This method can recommend exercises that are highly compatible with the syllabus for students according to their selected knowledge points and expected score range. According to the experimental test, the average prediction success rate of this method is 72.5%, 57.2% higher than the exercise recommendation method based on collaborative filtering and KNN, and 10.6% higher than the exercise recommendation method based on cognitive diagnosis and probability matrix decomposition.

**Keywords:** Personalized education, exercise recommendation method, primary and secondary school students, teaching objectives

## 1. INTRODUCTION

As we all know, the current primary and secondary school students have a heavy workload, which has become a social problem that needs to be solved. In order to reduce students' workload without affecting the learning effect, for the same knowledge point, it is necessary to improve the fit between the mastery degree's requirement of exercises and syllabus, so as to improve the quality of students' exercises, which is exactly the problem to be studied in this paper.

Each course has its own assessment requirements for each knowledge point in the syllabus, such as mastery level 4, mastery level 3, mastery level 2 and mastery level 1. Obviously, students need to master different levels of knowledge for different knowledge points. If students can learn different knowledge points to different degrees according to the requirements of the syllabus, instead of learning all knowledge points according to the highest standards, the learning burden of students can be reduced. At present, there are a large number of exercises in various question Banks. Each question usually indicates only the knowledge points investigated by the topic, but does not indicate the depth of the investigation of the knowledge points. At present, a lot of knowledge points investigated by exercises are indeed included in the syllabus, but the depth of knowledge points investigated by these exercises is different from that of the syllabus. For example, the syllabus requires that the assessment of knowledge points of A should be at level 4, while the assessment of knowledge points of B should be at level 1. Now there are three questions: a, b and c. Question a has a great depth of investigation on the two knowledge points. Only the students who have mastered the two knowledge points at the level of 4 can do it. Question b examines the knowledge point A to A relatively shallow degree, and examines the knowledge point B to A relatively deep degree. In order to solve question b, students must have mastered the knowledge point B at the level of 4, while they only need to have mastered the knowledge point A at the level of 1. Question c examines the knowledge point B at B relatively shallow level, and examines the knowledge point A at A relatively deep level. In order to solve question c, students must master the knowledge point A at A level of 4, while they only need to master the knowledge point B at A level of 1. Of the three questions, only c fits the syllabus.

However, a large number of questions like a and b, which seem to be consistent with the syllabus but do not fit, are filled in the current question Banks. How to screen out exercises that fit the outline is of great significance to reduce students' burden and improve their performance. At present, there is no relevant method to help teachers and students screen out exercises that fit the outline. The method we propose can measure and mark the knowledge mastery of each student

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through the method of cognitive diagnosis, and then judge the investigation depth of each knowledge point according to the answers of different students to the question, and then label the question. For example, this exercise requires mastery level 1 for knowledge point a and level 4 for knowledge point b. Teachers and students can then use labels to screen out questions that fit well with the teaching objectives. In this way, students only need to do the test with a high degree of fit with the teaching objectives, instead of doing some of the knowledge points more or less than the requirements of the syllabus, so as to reduce the burden of students to do the test, and improve the effect of students to do the test. In addition, this method can also control the range of students' expected scores. Students can use this method to recommend questions that not only fit into the syllabus, but also meet their own requirements for difficulty.

The contributions of this paper are:

(1) This method recommends exercises whose requirements for the mastery degree of knowledge points is fit to the syllabus to students. With this method, students can only do exercises that fit well with the teaching objectives and do not need to do the exercises which require a higher mastery degree level of knowledge point than the syllabus. This method reduces the burden of students and improves the effect of doing exercises.

(2) This method USES feed-forward neural network to predict the students' performance, which can control the expected score range of the target students for the recommended exercises, and has a high accuracy rate. Students can choose the difficulty of the exercise according to their own needs.

## 2. RELATED WORKS

In recent years, with the increasing demand for personalized teaching in primary and secondary education, various exercise recommendation algorithms emerge. At present, the existing exercise recommendation algorithms mainly include exercise recommendation algorithm based on personalized difficulty[1-6], exercise recommendation algorithm oriented to students' weak links[7-8], and exercise recommendation algorithm aiming at improving students' learning effect[9-10].

## 3. DETAILED DESIGN OF THE SYSTEM

This method calculates the degree of each student's mastery of each knowledge point and marks the level of each student's mastery of each knowledge point. According to different students' score for the same exercise, who have different mastery degree of the knowledge points included in that exercise, judge the degree of knowledge point required by the exercise and label the exercise. According to the requirements of the syllabus, select all exercises that fit the syllabus. For students who need to recommend exercises, first of all, the exercises are selected according to the knowledge points selected by the students. Then, according to the value of each knowledge point, the feedforward neural network is used to calculate the expected score of each exercise. In all the exercises that have been selected in accordance with the syllabus, select the exercises with the expected score in the constituency of the target student and recommend these exercises to the student.

### 3.1. Calculation of students' mastery of knowledge points

Define the average score rate, denoted by $\mathrm{P_a}$, to represent the percentage of the total score of all the exercises that student a has done as a percentage of the total score of all the questions that student a has done.

Define the knowledge point proficiency level index and write it as $G_{ab}$.The knowledge point proficiency level index represents the level of students' mastery of knowledge point B, which can be intuitively understood as the degree to which students' score on a certain knowledge point is higher or lower than the average level. The formula is as follows:

$$G_{ab}=\frac{\sum_{i=1}^{m}(p_i-a_i)}{\sum_{i=1}^{n}t_i} \tag{1}$$

In the above equation, $p_i$ is student a's score of the problem which only contains knowledge point *b*, $a_i$ is the average score of all students for this problem, and $t_i$ is the total value of this problem.

The method to calculate student S's knowledge point proficiency level index of knowledge point *k* in a period of time is as follows: For student S, all the answer records of student S in the specified time period are obtained first. Then find out all the exercises that student S has done that only include knowledge *k*. Then equation (1) is used to calculate the student's mastery index of knowledge point *k*.

### 3.2. Students' knowledge level setting

For each point set up five kind of mastery level, Students whose knowledge points mastery Indexes rank is in top 10% in all students is defined as a mastery level 4, ranking 10%-30% of the students is defined as a mastery level 3, ranking 30%-50% of the students is defined as a mastery level 2, ranking 50%-70% of the students is defined as a level 1, mastery level 0 is defined as the other students. Label each knowledge point for each student.

### 3.3. Exercises selection

For each exercise with n knowledge points, set 4n+1 conditions respectively, and find out 4n+1 group of students meeting these 4n+1 conditions. The specific method is that, for each knowledge point, the mastery level of other knowledge points should be set as level 4 at first, and the mastery level of this knowledge point should be set as 0, 1, 2 and 3 successively, so as to select four groups of students. Finally, find out the students who have mastered all the knowledge points at level 4 as a group.

For each exercise, calculate the average score rate of each group of students for the exercise. We believe that if the average score rate of a group of students for a certain exercise is more than 0.9, it means that this kind of students can successfully work out the exercise.

For each exercise, calculate the requirements of the exercise on the mastery degree of each knowledge point it contains. Specific calculation method is as follows (calculate the requirements of the exercise on the mastery degree of knowledge point a as an example) For this exercise, the average score rate of each group of the students with the mastery level of other knowledge points of 4 and the mastery level of knowledge points a of 0, 1, 2, 3 and 4 is calculated. Students with an average score rate of more than 0.9 were selected. Find the group of students with the lowest level of knowledge point a in all the selected groups. The mastery level of this group of students on knowledge point a is taken as the requirement of this exercise.

This exercise requires level 2 for knowledge point a and level 4 for knowledge point b. This is because when students master knowledge point b at level 4, they must master knowledge point a at least at level 2 to ensure that the average scoring rate is higher than 0.9. When the level of knowledge point a is 4, the level of knowledge point b should be at least 4, so as to ensure that the average score is above 0.9. Therefore, if the level of mastery required by the syllabus for knowledge points a and b is level 2 and level 4 respectively, the exercise is consistent with the syllabus.

The exercises which are completely consistent with the requirements of the syllabus are selected as the recommended exercises.

## 4. EXPERIMENT

### 4.1. Experiment environment

The purpose of this experiment is to test whether the recommendation algorithm proposed in this paper can recommend students to predict scores in the specified range of exercises.

The data used in this experiment were provided by an online education company. The data include all the online answer data of all the primary school students in grade six from March 15, 2021 to April 15, 2021 for a chapter of mathematics. These data include the responses of 8,312 students to 1,231 exercises, totalling 243,681 pieces of data. Each data includes student number, exercise number, score of this exercise, actual score, time to start doing exercises and time to end doing the exercise.

### 4.2. Experiment process

In order to verify the accuracy of this method in recommending test questions to students based on expected scores, this experiment compared the accuracy of this method with the accuracy of the following methods:

(1) Exercises based on collaborative filtering and KNN method recommended: to specify students and exercises, by answering question situation of the students have to do exercises, looking for the students with high similarity with the students, according to several students of similar to the student the most scores of the exercises on to predict the scores of the students in the exercises, and then to the scores of students recommended interval exercises in the specified range.

(2) Problem recommendation method based on cognitive diagnosis and probability matrix decomposition: for the assigned students and the assigned exercises, first of all, the cognitive diagnosis is carried out on the students according

to the students' existing answers, so as to obtain the students' knowledge level. Then, combining with the students' knowledge level, the probability matrix decomposition is used to predict the students' answers, and then the exercises within the specified score range are recommended for the students.

The specific steps of this experiment are as follows:

(1) The time node is set as March 20, 2021. This time node is used to divide the role of data for students to work on. The data before March 20, 2021 is selected to calculate the excellence of each student's knowledge points mastery Indexes, and then the examination degree of each exercise on the related knowledge points is calculated, so as to screen out the exercises that are consistent with the syllabus. The data after March 20, 2021 are selected to calculate the success rate of exercise recommendation.

(2) For each student, the test questions containing only a single knowledge point are used, with formula (1) being used to calculate each student's knowledge points mastery Indexes of each knowledge point.

(3) Each student's mastery level of each knowledge point is marked.

(4) The examination degree of each exercise on the related knowledge points is calculated.

(5) Combining with the examination degree of each exercise on the related knowledge points and the requirement of the teaching syllabus on the mastery degree of each knowledge point, the appropriate exercise is selected.

(6) 100 students were randomly selected, and 0-10, 10-20, 20-30, 30-40, 40-50, 50-60, 60-70, 70-80, 80-90, and 90-100 were used as the predicted scoring interval, and exercises were recommended for these 100 students. For each predicted scoring interval, perform one round of steps (7), (8), and (9).

(7) For each student who needs to recommend exercises, feedforward neural network is used to calculate the expected score of each problem for the student, and the exercises with the expected score within the specified range are recommended to the student. The data of students' exercises after March 20, 2021 were used to simulate the effect of students' exercises recommended for students. For each student who needs to recommend exercises, the public parts of the exercises that the student has done and the exercises that have been recommended to the student by this method in the data of the exercises that the student has done after March 20, 2021 shall be regarded as the exercises recommended to the student by this method in this experiment. For each student who needs to recommend exercises, calculate the average score of the exercises recommended by this method in this experiment, and then calculate the success rate of this method.

(8) Using the exercise recommendation method based on collaborative filtering and KNN to recommend exercises to every student who needs to recommend exercises. For each student who needs to recommend exercises, the common parts of the exercises that the student has done and the exercises recommended to the student by this method in the data of the exercises done by students after March 20, 2021 are taken as the exercises recommended to the student by this method in this experiment. For each student who needs to recommend exercises, calculate the average score of the exercises recommended by this method in this experiment, and then calculate the success rate of this method.

(9) The exercise recommendation method based on cognitive diagnosis and probability matrix decomposition is used to recommend exercises to every student who needs to recommend exercises. For each student who needs to recommend exercises, the public parts of the exercises that the student has done and the exercises that have been recommended to the student by this method in the data of the exercises that the student has done after March 20, 2021 shall be regarded as the exercises recommended to the student by this method in this experiment. For each student who needs to recommend exercises, calculate the average score of the exercises recommended by this method in this experiment, and then calculate the success rate of this method.

### 4.3. Experiment results

As shown in table 1, when the expected score range of this method is 0.8-0.9, the highest success rate is 90%, which is higher than 76% of the highest accuracy based on cognitive diagnosis and probability matrix decomposition and 77% of the highest accuracy based on collaborative filtering and KNN exercise recommendation method. When the expected score range is 0-0.1, the success rate is the lowest (62%), which is higher than the highest accuracy (53%) based on cognitive diagnosis and probability matrix decomposition and the highest accuracy (35%) based on collaborative filtering and KNN.

Table 1. Recommendation effect table.

| Expected scoring range/ method | This method | Collaborative filtering & KNN | Cognitive diagnosis & probability decomposition |
|---|---|---|---|
| 0.9-1 | 85% | 77% | 71% |
| 0.8-0.9 | 90% | 66% | 73% |
| 0.7-0.8 | 84% | 53% | 76% |
| 0.6-0.7 | 77% | 47% | 73% |
| 0.5-0.6 | 79% | 44% | 70% |
| 0.4-0.5 | 76% | 42% | 74% |
| 0.3-0.4 | 77% | 45% | 70% |
| 0.2-0.3 | 74% | 43% | 75% |
| 0.1-0.2 | 70% | 41% | 66% |
| 0-0.1 | 62% | 35% | 53% |
| Average prediction success rate | 77.5% | 49.3% | 70.1% |

When the expected score interval is set as a low interval, the success rate of various methods is relatively low. This is because some students have strong ability, and there are few exercises that can let these students get low scores. Therefore, the success rate of exercises with low expected score rate is relatively low when they are recommended to these students.

Except in the expected score range of 0.4-0.5 and 0.2-0.3, the prediction success rate of this method is slightly lower than that of the exercise recommendation method based on cognitive diagnosis and probability matrix decomposition. In other cases, the prediction success rate of this algorithm is higher than that of the recommendation method based on collaborative filtering and the motion recommendation method based on cognitive diagnosis and probability matrix decomposition.

The average prediction success rate of this method is 77.5%, 57.2% higher than that of the recommended method based on collaborative filtering and KNN, and 10.6% higher than that of the recommended method based on cognitive diagnosis and probability matrix decomposition.

It can be seen that this method can not only recommend exercises with high fit with teaching objectives for students, but also has a high success rate of score prediction.

## 5. CONCLUSION

This paper proposes a personalized exercise recommendation method based on teaching objectives. This method can recommend exercises that are highly compatible with the syllabus for students according to their selected knowledge points and expected score range. With this method, students can only do exercises that fit well with the teaching objectives and do not need to do the exercises which require a higher mastery degree level of knowledge point than the syllabus. In this way, the burden of students reduced, the effect of doing exercises improved. The experimental results show that the prediction success rate of this method is higher than that of the exercise recommendation method based on collaborative filtering and KNN and the exercise recommendation method based on cognitive diagnosis and probability matrix decomposition.

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