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An Exercise Recommendation Method for K-12 Students Based on the Syllabus

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Abstract: For each subject, the syllabus specifies what knowledge points students should master and how well they should master them. Whether students can acquire the ability required by the syllabus is an important evaluation criterion for a student's learning achievements. However, most of the exercises for k-12 students at present contain knowledge points in the examination syllabus, but the difficulty of the examination of knowledge points is inconsistent with the teaching syllabus. Solving and studying such exercises does not help students acquire the skills required by the syllabus quickly. Therefore, students should choose exercises that fit well with the syllabus when practicing. However, at present, there is no way to recommend exercises that fit well with the syllabus for students, so as to improve learning efficiency. In order to solve the above problems, this paper proposes an exercise recommendation method for k-12 students based on the syllabus. It is proved by experiment that this method can recommend exercises that fit well with the syllabus for students, so as to improve their learning efficiency. The use of this method can help students achieve better learning outcomes and achieve higher scores in the final examination than ordinary students under the condition of learning and mastering the same number of exercises with the same difficulty.

Keywords: Exercise recommendation, Machine learning, Linear regression, EM algorithm

1. Introduction

At present, the problem of overloaded homework for k-12 students has become an important problem to be solved. In order to reduce the learning burden of students without reducing the learning effect of students, it is necessary to improve the fit between exercises and the teaching syllabus on the degree of mastery of various knowledge points, so as to help students avoid inefficient learning.

The syllabus for any course sets the requirements for each knowledge point. For different knowledge points, the syllabus has different requirements for students to master. If students can practice and learn by using exercises with the same difficulty in each knowledge point as in the syllabus, their learning efficiency will be improved and their learning burden will be reduced. However, the exercises in the current question bank often only show the knowledge points that the exercises examine, but do not show the depth of the exercises examine to the knowledge points. There are a lot of exercises that examine the knowledge points that are included in the syllabus but the depth of the examination of the knowledge points is different from the exercises that are required by the syllabus. For example, the syllabus requires that the assessment of knowledge point N1 is proficiency, and the assessment of knowledge point N2 is understanding. Now we have exercises Q1, Q2, Q3, Q4. Q1 requires proficiency in both knowledge points. Q2 requires understanding of both knowledge points. In question Q3, the assessment requirement for knowledge point N1 is understanding, and the assessment requirement for knowledge point N2 is proficiency. In question Q4, the assessment requirement for knowledge point N1 is proficiency, and the assessment requirement for knowledge point N2 is understanding. Of the 4 questions, only Q3 is consistent with the syllabus.

The existing exercises recommendation method cannot help teachers and students to screen out the exercises that fit the syllabus. In order to solve this problem, this paper proposes a method based on the syllabus to recommend exercises for k-12 students.

The contributions of this paper are as follows :(1) we propose RAE algorithm for cognitive diagnosis of students, which combines linear regression and EM algorithm to calculate the degree of each student's mastery of each knowledge point. (2) we put forward the KPLL algorithm, which can calculate the inspection degree of each exercise to each knowledge point. (3) this paper proposes a method to recommend exercises that fit well with the syllabus for students. It has been proved by experiments that using this method can help students achieve better learning results and get higher scores in the final examination when they learn and master the same number of exercises with the same difficulty.

2. Related Works

The current exercise recommendation methods are mainly based on two aspects: to recommend exercises for target students that contain weak knowledge points for target students, and to recommend exercises that are moderately difficult for target students. Y. Huo et al. proposed an exercise recommendation method based on collaborative filtering. This method can help students find weak knowledge points and recommend exercises containing weak knowledge points [1]. L. Fang proposed an exercise recommendation method that can recommend English exercises containing specified grammatical structures for students [2]. Changmeng J et al. proposed to recommend exercises of medium difficulty for target students according to the scope of knowledge points selected by students [3-6].

3. Method Design

The purpose of this method is to recommend the exercises that are consistent with the syllabus and contain the knowledge points designated by the target students to the target students. Since the k-12 final exam is formulated by the proposition expert strictly according to the syllabus, the requirements of the final exam on the mastery of various knowledge points can be approximately regarded as corresponding to the syllabus. For each question, the difficult questions on the final exam will be no more difficult than the syllabus requires, and the simple questions on the final exam will be less difficult than the syllabus requires. Therefore, for a specified knowledge point, we regard the requirement of the knowledge point on the final exam with the highest level of requirement as the requirement of the syllabus. First of all, we judge how well the syllabus requires students to master various knowledge points by their answers to the final examination questions. Then we choose the exercises that fit into the syllabus as candidate exercises. According to the range of knowledge points assigned by students, we recommend candidate exercises that meet the standards to target students. The specific steps of this method are as follows:

(1) We select a group of students who use the same syllabus, and extract the data of these students in solving daily exercises and solving final exams. Taking the data of these students' daily exercises as input, we use RAE method (the algorithm is described in detail in 3.1) to calculate the degree of each student's mastery of each knowledge point.

(2) We divide students' mastery of each knowledge point into five levels from low to high. Level 5 corresponds to the degree of mastery of the knowledge in the top 20% of the students, level 4 corresponds to the mastery of the knowledge degree ranking 20% ~ 40% of the students, level 3 corresponds to the mastery of the knowledge degree ranking 40% ~ 60% of the students, level 2 corresponds to the mastery of the knowledge degree ranking 60% ~ 80% of the students, level 1 corresponds to the mastery of the knowledge degree of 80% ~ 100% of the students.

(3) With each student's mastery of each knowledge point and the data of all students' answers to all the final examination questions as input, using the KPLL algorithm (which is described in detail in 3.2), we calculate the mastery level required by each final examination question for each knowledge point contained in it. For example, the level of knowledge required for knowledge point N in question Q is L, which means that only students with a level of knowledge point N no lower than L are likely to correctly solve question Q.

(4) For each knowledge point, we find out the final exam questions with the highest requirements for the mastery level of the knowledge point. We regard the mastery level required by this question for this knowledge point as the mastery level required by the syllabus for this knowledge point.

(5) With each student's mastery of each knowledge point and the data of all students' solutions to all exercises as input, we use KPLL algorithm to calculate the required mastery level of each exercise for each knowledge point contained in it.

(6) Choose the exercises that meet the following conditions as candidate exercises: this exercise requires the same level of mastery of all knowledge points as the syllabus requires for this knowledge point.

(7) According to the knowledge points selected by the students, we recommend the exercises containing the specified knowledge points from the candidate exercises.

3.1 RAE algorithm

The input of this algorithm is the historical answer data of all students, and each data includes student number, exercise number, the number of knowledge points contained in exercise, exercise score, and actual score. The output of this algorithm is each student's mastery of each knowledge point. First, define the concept of knowledge points mastery index. The concept of knowledge point mastery index is used to measure the degree of students' mastery of a certain knowledge point above or below the average level.

The formulas for calculating the knowledge points mastery index are defined respectively when the weight of knowledge point is unknown or known.

The formula for calculating knowledge point mastery Index G_{SK} of knowledge point without assigning the weight of knowledge point is as follows:

$$G_{SK} = \frac{\sum_{i=1}^{n}(s_i - m_i)}{\sum_{i=1}^{n} t_i} \quad (1)$$

Among them, s_i is the score of student S for exercise i, an exercise involving knowledge point K that he/she has done, m_i is the average score of exercise $\mathbf{i}$, and t_i is the total score of exercise $\mathbf{i}$.

The formulas for calculating knowledge point mastery Index G'_{SK} of knowledge point under the condition that the weight of knowledge point has been assigned are as follows:

$$G'_{SK} = \frac{\sum_{i=1}^{n}(s_i - m_i)k_i}{\sum_{i=1}^{n} t_i k_i} \quad (1)$$

Among them, s_i is the score of student S for exercise i, an exercise involving knowledge point K that he/she has done, m_i is the average score of exercise i, k_i is the weight of knowledge point K in exercise i, and t_i is the total score of exercise i.

Based on a pre-selected set of student answer data, the steps for cognitive diagnosis are as follows:

First, we choose questions with only a single knowledge point, use formula (1) to roughly calculate and store the knowledge point mastery Index of each student's all knowledge point.

We use the linear regression model to calculate the weight of each knowledge point in each question. We illustrate the use of the linear regression model with example question e and student s. We assume that there are n knowledge points in question e, student s's score prediction formula for question e is as follows:

$$h_i = \sum_{j=1}^{n} k_j x_j + b \quad (3)$$

h_i is the predicted score of the assigned question e for student s, x_j is the knowledge point mastery Index of the student s for the jth knowledge point of question e, and k_i is the weight of x_j. We use all the student history answer data to train the model, then we can get the weight of each knowledge point in each question.

We use formula (2) to calculate the more accurate knowledge point mastery Index of each student for each knowledge point when the weight of each knowledge point is known.

Using the EM algorithm, the previously calculated value of knowledge point mastery Index is taken as the current value of students' knowledge point mastery Index. Each time, the current value of knowledge point mastery Index is used to calculate the weight of knowledge point in a new round of exercises by linear regression. Then, the weight of knowledge point in the new round of exercises is used to calculate the knowledge point mastery Index of the new round of students through formula (2). After repeated iteration for 10 rounds, the final result of knowledge point mastery Index was obtained.

3.2 KPLL algorithm

The input of this algorithm is each student's mastery of each knowledge point and the historical answer data of all students. Each data includes student number, exercise number, the number of knowledge points included in the exercise, exercise score, and actual score. The output of this algorithm is the requirement of each question for each knowledge point.

This algorithm calculates the requirement of each question to each knowledge point. We illustrate this algorithm by using exercise Q and knowledge point K. First, we find out who has a level 5 command of all knowledge points except K contained in Q. (if there are no students meeting the above conditions, the requirement for the target students will be reduced to those who have mastered at least level 4 in all knowledge points except K included in the exercise Q) According to the mastery level of knowledge point Ki, all students are divided into 5 categories. Calculate the average score of each type of students for exercise Q. Considering the factors such as carelessness, we select categories which scored average of more than 80% of exercise Q’s total score. We mark the mastery level of knowledge point K required by the category with the lowest mastery level of knowledge point K among all selected categories as the mastery level required by exercise Q for knowledge point K.

4. Experiment

4.1 Experiment Environment

The data used in this experiment were provided by an online education company. Considering that China implemented a nationwide textbook update for primary and secondary schools in September 2017, the teaching syllabus also changed after the textbook update. If we use the answer data after September 2017, we will not be able to obtain enough final exams that fit into the syllabus. Therefore, the data we used is the online answer data of all the fifth-grade primary school students in a Chinese city from March 1 to April 1, 2017 for a certain chapter of mathematics. These data include the responses of 8,092 students to 1,149 questions, totaling 240,000 pieces of data. Each piece of data includes student id, exercise id, exercise type, id of knowledge points included in exercise, total score of exercise, actual score, starting time of exercise and ending time of exercise. The data for the experiment included two types of exercises, one for the final exam from 2012 to 2016 in each district of the city, and the other for general exercises. The data for this experiment includes 197 final exams and 952 general exercises.

4.2 Experiment Process

First of all, we divide all the answer data into two groups: the first group is the data of March 1, 2017 solstice, March 15, 2017, and the second group is the data of March 16, 2017 solstice, April 1, 2017. We use the method proposed in this paper, take the first group of data as input data, calculate the degree of each student's mastery of each knowledge point, and select the candidate exercises that fit the syllabus from the general exercises.

We selected students who correctly answered a certain number of candidate exercises in the first set of data and students who correctly answered the same number of general exercises and compared their performance on the final exam questions in the second set of data. By comparing the gap between the two, we can judge whether the candidate exercises selected by the method proposed in this paper have a higher fit with the syllabus. The specific steps are as follows:

(1) We randomly selected three knowledge points and recorded them as experimental knowledge points. In the first set of data, we found all the exercises that contained only one or several of the experimental knowledge points and recorded them as experimental exercises. We randomly selected five questions from the final exam from the second data set and recorded them as experimental examination questions. These five questions cover all the experimental knowledge points and are used to examine the recommendation effect.

(2) According to the classification criteria of whether the exercise is a candidate exercise, we divide all the exercise into two groups, which are respectively denoted as exercise group 1 and exercise group 2. The exercises in exercise group 1 are candidate exercises, while the exercises in exercise group 2 are not.

(3) We first select the students who have done all the experimental examination questions during March 16, 2017 solstice April 1, 2017. Among the selected students, we found out all the students who had done 3 exercises belonging to exercise group 1 and all of them answered correctly, all students who had done 4 exercises belonging to exercise group 1 and all had answered correctly, all students who had done 5 exercises belonging to exercise group 1 and all had answered correctly, and mark them as student group A1, student group A2 and student group A3 respectively.

(4) Among the selected students, we found out all the students who had done 3 exercises belonging to exercise group 2 and all of them answered correctly, all students who had done 4 exercises belonging to exercise group 2 and all had answered correctly, all students who had done 5 exercises belonging to exercise group 2 and all had answered correctly, and mark them as student group B1, student group B2 and student group B3 respectively.

(5) We found out the experimental exercises done by students in the above six groups, and calculated the average score rate of all other students for these exercises (average score/total score of exercises). We measure the difficulty of a problem by the average score rate of all the other students on the problem. If the average score rate of all other students for problem Q is s, the difficulty of problem Q is defined as 1-s. We randomly remove some students in student group B1, student group B2 and student group B3 who have done the experiment exercises with low difficulty. In this way, the average difficulty of experimental exercises done by students in student group B1, student group B2 and student group B3 is not lower than that of student group A1, student group A2 and student group A3, respectively.

(6) Calculate the average scores of 6 groups for all experimental examination questions.

4.3 Experiment Results

As shown in figure 1, we made statistics on the number of students in each group, the average difficulty of the experimental exercises done by all members in each group, and the average score of all members in each group on the experimental examination questions (converted into a full score of 100 points). We marked the average difficulty of all experimental exercises done by all members of the group as the average difficulty, and the average score of all members of the group for the experimental examination questions as the average score.

table 1

Statistical table of experimental data

Student group	Number of students	Average difficulty	average score
A1	17	0.21	89.3
B1	33	0.23	82.5
A2	11	0.19	92.7
B2	25	0.21	86.5
A3	9	0.22	94.1
B3	14	0.24	88.0

According to table 1, the average difficulty of the experimental exercises done by group A1, A2 and A3 is lower than that of group B1, B2 and B3, respectively. The average scores of group A1, A2 and A3 for the experimental examination questions were higher than those of group B1, B2 and B3, respectively. Therefore, students who do well on the same number of problem sets of the same difficulty are more likely to do well on the final exam than those who do well on the ordinary problem sets. As a result, students who did well on the same number of candidate exercises with same difficulty, which were recommended by this method, were more likely to do well on the final exam than those who did well on the regular exercises. It can be inferred that mastering the exercises recommended by this method is more likely to help students achieve good results in the final examination than mastering the common exercises with the same number and difficulty. Therefore, we can say that using this method can help students achieve better learning results than ordinary students and achieve higher scores in the final examination under the condition of learning and mastering the same number of exercises with the same difficulty. Since the requirement of mastering various knowledge points in the final examination can be approximately regarded as a fit with the examination syllabus, we can infer that this method can recommend exercises that fit with the teaching syllabus for students.

5. Conclusions

This paper proposes an exercise recommendation method for k-12 students based on the syllabus. It is proved by experiment that this method can recommend exercises that fit well with the syllabus for students, so as to improve their learning efficiency. The use of this method can help students achieve better learning outcomes and achieve higher scores in the final examination than ordinary students under the condition of learning and mastering the same number of exercises with the same difficulty.

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