Personalized Exercise Recommendation driven by Learning Objective within E-Learning Systems

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Abstract

To enhance the personalization of an e-learning system, an automatic approach of exercise recommendation that is driven by learning objective is proposed. Firstly, the formal models about knowledge points, exercises and their relations are presented based on a course knowledge tree. Then, a computing method is proposed to constantly and automatically update learning objectives in the learning process. According to the learner’s learning state, an approach is proposed to accurately describe the learner’s learning needs. In order to realize the personalization within the e-learning system, three kinds of influencing factors, including learning objective, the grasp state of knowledge point and learner’s answer preferences, are taken into account for the exercises recommendation. A running example is analyzed to demonstrate the feasibility and validity of the proposed approach for recommending exercise to a complete learning objective in a rapid manner.

Keywords: learning objective; e-learning; course knowledge tree; content recommendation

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1. Introduction

With the emergence of e-learning platforms, such as MOOC and SPOC, a large-scale of learners began learning online since 2012 [1]. Similar to homework and practice links in traditional teaching, the online practice is an integral part of the e-learning system. However, the existing systems show the same learning resources for all learners without taking into account the individual characteristics of learners. Therefore, they cannot meet the needs of personalized learning [2]. Furthermore, most of the learning content navigation in existing systems are presented in the form of text, and it cannot completely show the relation among the knowledge points (i.e., the knowledge structure), which may affect learning efficiency [3-4].

The learning objectives in this paper include two meanings. First, it refers to the target knowledge points that reflect a learner’s learning needs. The second is that the learner must meet the mastery of knowledge points that are set by the teacher by doing exercises. The research purpose is to automatically recommend exercises for a learner based on his or her real learning needs, knowledge level and preferences. To this end, the research focuses on the following aspects:

1) The knowledge points, exercises and the relationship between them are modeled so as to realize the automatic recommendation of personalized exercises.

2) The learner’s real learning needs are obtained through the learning behavioral data of the learner, which include target knowledge points, grasp state of knowledge point, and answer preference data. Therefore, the accurate recommendation of personalized exercises can be ensured [5].

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3) In the learning process, the learner’s knowledge state and the knowledge context can be visualized so as to improve the learning efficiency.

To this end, the study firstly uses the course knowledge tree to model the knowledge points, exercises and their relationships. Learner’s learning needs are quantified based on his or her learning behavior and state data. The exercise difficulty and answering preferences are also considered in the calculation process. In this way, the learner’s knowledge state and learning needs are accurately described, and the exercises are accurately recommended for the learner to ensure the interpretability and rationality of the recommended results. The knowledge trees are used to visualize the complete knowledge structure in the learning process and the learner can clearly see his or her progress and knowledge deficiency. Thus, the cognitive load and Trek phenomenon brought about by text message are reduced.

The remainder of the paper is organized as follows. In Section 2, the related work relevant to this study is reviewed. Section 3 presents the method of personalized exercises recommendation driven by learning objective within e-learning systems. A case is analyzed to verify and evaluate the proposed approach in Section 4. Section 5 concludes the whole paper and presents our future work.

2. Related Work

In the past few decades, a variety of personalized techniques have been proposed and applied to e-learning systems, which show good results in practice. Many researchers are also committed to providing personalized education resources and real-time learning services for learners to study and promote different recommendation systems [2, 6-7]. [8] emphasized that one of the most important applications of recommendation systems in an e-learning environment is personalization and recommendation of learning resources. Recommender systems in e-learning domain play an important role in assisting learners to find useful and relevant learning materials that meet their learning needs. At present, the main recommendation techniques in e-learning include collaborative filtering, content-based, knowledge-based and hybrid recommendation.

The recommendation systems based on collaborative filtering are as follows. [9] built models based on learner’s information and learning behavior, and the collaborative filtering algorithm was used to recommend the learning content. The most important characteristic was to estimate the behavior preference of the new similar learners according to the behavior data of the existing learners and recommend the personalized learning resources for them. [10] proposed an ontology-based collaborative filtering recommendation algorithm that could help a user find the nearest neighbors and calculate the similarity of user’s rating knowledge points. In the content-based recommendation, the system recommends items that are similar in terms of content features to the ones that the user liked in the past. [11] proposed a content-based recommendation algorithm based on convolutional neural network (CNN). The recommendation algorithm could be used to predict the latent factors from the text information. The latent factors were utilized to predict the rating scores between learners and learning resources. [12] presented a content-based recommendation strategy that used techniques such as spreading activation and semantic associations as well as ontology for discovering additional knowledge about the learner’s preferences. The recommendation systems based on knowledge recommended items to a user based on domain knowledge and how items met user’s preferences [13]. Knowledge-based recommender systems needed to employ three types of knowledge: knowledge about the users, knowledge about the items and knowledge about the matching between the item and user’s need. [14] proposed a knowledge-based personalized recommender system for e-learning materials. Their system used ontology for knowledge representation. Hybrid recommendation technique is very useful because it can overcome most of the limitations experienced by the individual conventional recommendation approaches. For example, [15] presented a personalized learning objects recommendation model (LORM) that used ontology and a hybrid method of preference-based algorithm and correlation-based algorithm. [16-17] proposed a hybrid recommendation algorithm based on generating rules, and collaborative filtering was used to recommend the learning resources. A hybrid algorithm based on concept map and immune algorithm was proposed to realize personalized learning resource recommendation [18].

The goal of e-learning recommender systems is to assist the learners to find relevant and useful learning materials that meet their learning needs. So, unlike in other domains, e-learning recommender systems require additional information on learner personalization characteristics, such as learning history, knowledge level and learning style during the recommendation process. To demonstrate this, [19] proposed a personalized e-learning system that could automatically adapt to the interests, habits and knowledge levels of learners. Personalized learning resources were recommended for learners based on the learners’ learning interest, preferences and other factors [20]. According to the learner’s multidimensional characteristics and behavioral tendencies, such as learning style, interest, ability level and so on, [21-23] presented a personalized learning path, and learning resources were recommended according to the dynamic needs of learners in the learning process. In the research of the exercises or questions recommendation, [24-25] calculated the similarity of programming problem or learners based on the online evaluation system data, and the programming topics
were recommended by collaborative filtering recommended technology. In a case study of C language teaching, firstly the label thinking is combined with modeling the relationship among learners, labels and exercises based on the learners’ historical record. Then, exercises are recommended according to the learner’s knowledge weaknesses [26]. The exercise recommendation system could recommend the interesting exercises for the learners according to the historical information records of their exercises [27]. [28] proposed a method for personalized recommendation of assignments (tasks or exercises) in an adaptive educational system, which has enhanced existing adaptive navigation approaches by considering the limited time for learning, learners’ knowledge level and the difficulty of the exercises. [29] proposed a recommendation method that was based on the learners’ learning state to recommend the appropriate difficulty exercises. Because when learners freely choose learning objects without recommendation, they will choose learning objects that are currently too easy and too difficult for them. Moreover, a number of researchers have used ontology for knowledge representation in e-learning resource recommendation and their results have shown improvement in the quality of recommendations. For instance, [30] showed that use of ontology for knowledge representation in e-learning recommender systems could improve the quality of recommendations.

Through the above analyses, scientific and rational knowledge representation can improve the quality of recommendation. The exercise or question recommendation methods in the above study did not comprehensively consider the difficulty of the exercises, the answer correct rate, the grasp state of the knowledge points and other factors. So, it was difficult to guarantee the explanations and rationality of the recommendation results in the personalized exercises recommendation [31]. Furthermore, the navigation and feedback information in the learning process did not exploit the learning objective and the knowledge state diagram, which affected the learning efficiency a lot.

To this end, the formal models about knowledge points, exercises and their relations are presented based on a course knowledge tree in this study. Then, a computing method is proposed to constantly and automatically update learning objective. According to the learner’s learning state data, an approach is proposed to accurately describe the learner’s learning needs. In order to realize the personalization of e-learning, three kinds of influencing factors, including learning objective, the grasp state of knowledge point and learner’s answer preferences, are taken into account for the exercises recommendation.

3. A Framework of Personalized Exercises Recommendation Driven by Learning Objective

3.1. Recommendation Framework

The framework of personalized exercises recommendation driven by learning objective within e-learning systems is presented firstly. It is shown in Figure 1. The framework is able to recommend the related exercises to complete learning objectives in a rapid manner and realize personalized learning. The main components contained in the framework include the following:

![Figure 1. Framework of personalized exercises recommendation driven by learning objective](image)

1) **Course Knowledge Tree (CKT):** The CKT, which is the representation of the course knowledge, is predefined by the instructor with suitable granularity and scale. It presents the structure of the course content and organizes the knowledge points of different granularity in a course into a tree structure. Furthermore, it is the basis for establishing the links between
the knowledge points and the exercises in the question bank and setting the learning objective. Based on the learning objective in the CKT position, the learning objectives are updated by reasoning, and the atom knowledge points are calculated.

2) Learner’ s learning behaviors: According to the learner’s learning objectives and the difficulty, the numbers of right or wrong answers of his or her corresponding exercises and other learning behavior data can be calculated and used to determine whether the learning objectives are completed. Answer preferences are calculated based on the learner’s history answer behaviors.

3) Recommendation model: The instructor selects the recommendation strategies and creates the recommendation rules. The recommendation module focuses on the learner’s learning objective to recommend personalized exercises by his or her grasp state and answer preferences.

3.2. Main Function Module Analysis

3.2.1. Construction of Course Knowledge Tree

The course knowledge tree is the knowledge organization and representation by decomposing the course knowledge into knowledge points of different granularity and using a tree structure to organize them. The link among knowledge points and all kinds of resources can be established based on the course knowledge tree as the center, and knowledge points as the index within the e-learning system [32].

Firstly, the concept of knowledge points is proposed.

**Definition 1 (Knowledge Point)** A knowledge point is a three-tuple \(KP=(ID, Name, Type)\), where

1) \(ID\) is the unique number of a knowledge point.

2) \(Name\) is the name of a knowledge point.

3) \(Type\) is the type of knowledge point, which is divided into atom knowledge points and compound knowledge points.

A knowledge point is the basic element of teaching content and can be used to describe a course. The knowledge point that cannot be subdivided is called an atom knowledge point. A composite knowledge point is a knowledge point that can be divided into other knowledge points, such as a course chapter, a section, and so on.

**Definition 2 (Knowledge Point Relationship)** In general, the knowledge point relationship can be divided into three categories:

1) Prerequisite Relation (Precedence-of). It notes for the \(Pre(KP_i, KP_j)\) and means that \(KP_i\) is a Prerequisite of \(KP_j\).

2) Inclusion Relation (Subtopic-of). It notes for the \(Sub(KP_i, KP_j)\) and means that \(KP_i\) is a part of \(KP_j\).

3) Parallel Relation (Parallel-of). It notes for the \(Para(KP_i, KP_j)\) and means that there is a logically parallel relationship between \(KP_i\) and \(KP_j\).

Prerequisite relation can ensure that the prerequisite knowledge is learned before learning a knowledge point. A compound knowledge point can often be broken down into smaller composite knowledge points or several atom knowledge points. The relationship between them is called inclusion relation. There is a logically parallel relation between the two atom knowledge points for loop and while loop in the compound knowledge point loop.

**Definition 3 (Course Knowledge Tree)** A course knowledge tree (CRT) is defined as a four-tuple \(CKT=(KPSet, KPR_{pre}, KPR_{sub}, KPR_{para})\), where

1) \(KPSet\) means the set of knowledge points.

2) \(KPR_{pre}, KPR_{sub}, KPR_{para}\) means the prerequisite relation set, inclusion relation set and parallel relation set among knowledge points, respectively.
The whole knowledge architecture of a course is described as a multi-layered tree structure that is composed of courses, chapters, sections and knowledge points, that is a CKT (as shown in the top part of Figure 2). The three relations among knowledge points constitute the network structure of knowledge, so each level forms a directed knowledge structure graph.

The CKT is graphically represented in Figure 2. The elements in the KPSet are represented by circles, each representing a node for the knowledge point. The elements in the KPSpers, KPRsub, and KPRpar are respectively represented by different types of lines, and each line represents the corresponding relation. We can get the graphical representation of the CKT as shown in the top part of Figure 2.

Definition 4 (Exercise) An Exercise is a three-tuple $\text{Excs}=(\text{ExcsID},\text{KP}_\text{Excs},\text{ExcsDif})$, where

1) $\text{ExcsID}$ is the unique number of an Exercise.

2) $\text{KP}_\text{Excs}$ is the set of knowledge to which the exercise attaches. It notes for $\text{KP}_\text{Excs}=[\text{KP}_1,\text{KP}_2,\ldots,\text{KP}_n]$. The affiliation relation between an exercise and the knowledge points (Association-of) notes for $\text{Asso}(\text{Excs}_i,\text{KP}_j)$. It means that $\text{Excs}_i$ is attached to $\text{KP}_j$.

3) $\text{ExcsDif}$ is the difficulty coefficient of an exercise. According to its size, the exercises are divided into three different difficulty levels: Diff, Midd and Easy.

According to the relation between an exercise and the knowledge points in Definition 4, the association between the exercises and the knowledge points can be established. The bottom part of Figure 2, where the rhombus leaf node represents the exercise resources, shows the exercise bank.

3.2.2. Learning Objective Representation and its Updating Process

Learning objective reflect learner’s learning needs. Here, the completion of the learning objective is based on the changing knowledge state of a learner.

Definition 5 (Learning Objective) The learning objective is formalized as a set of knowledge points in the CKT, so $\text{LO}=$KPSet=$\{\text{KP}_1,\text{KP}_2,\ldots,\text{KP}_m,\text{KP}_{11},\ldots,\text{KP}_{21},\ldots,\text{KP}_{nn}\}$.

According to the knowledge point type and the relation among knowledge points in the CKT, the learning objective can be divided into atom knowledge point learning objectives and compound ones.

After logging into the online practice system, a learner chooses or determines a learning objective by the instructor. The system first reverses reasoning based on the CKT. Then, it finds its predecessor knowledge point set in the course knowledge base and finally checks their states. This kind of reasoning algorithm, which is driven by learning objective based on CKT, can realize the personalized learning by learner’s learning state data.
Learner’s learning behavior and state data are the key factors to realize personalized learning, and learner’s learning needs can be acquired by them [33-35]. Here, learner’s learning behavior data mainly refer to the information of answering exercises that can be used to calculate the grasp state of the knowledge points and learner’s answer preferences.

Definition 6 (Answer Exercises Statistics) Learner’s answer exercises statistics of a knowledge point include the number of different difficulty exercises, \( AE = \langle N_{d}, N_{m}, N_{e} \rangle \), and the number of answering right exercises, \( AE^r = \langle N^r_{d}, N^r_{m}, N^r_{e} \rangle \), where

1) \( N_{d}, N_{m}, \) and \( N_{e} \) represent the number of exercises for difficulty levels of Diff, Midd and Easy.

2) \( N^r_{d}, N^r_{m}, \) and \( N^r_{e} \) represent the number of correct exercises for difficult levels of Diff, Midd and Easy.

Definition 7 (Grasp State of Knowledge Point) After a learner answers the exercises of a knowledge point, the grasp state of a knowledge point is determined by the score of the knowledge point. The calculation process is as follows:

1) \( W_{d}, W_{m}, \) and \( W_{e} \) represent the weight of the three kinds of exercises: Diff, Midd and Easy.

2) The score of the knowledge point is calculated by the number of answering right exercises and their weights. The calculating formula is \( SC = W_{d} \times N^r_{d} + W_{m} \times N^r_{m} + W_{e} \times N^r_{e} \).

3) \( GS \) is the state of the knowledge point, and \( GS \in \{C, B, F\}. C, B \) and \( F \) respectively mean three levels of the knowledge state, which are Complete Grasp, Basic Grasp and Fail Grasp. Its value depends on the \( SC \) value of the knowledge point.

3.2.3. The Algorithm of Updating Learning Objective

The reasoning algorithm for updating learning objective is described in Algorithm 1.

**Algorithm 1** The algorithm of updating learning objective.

**Input:** \( KP \) is a learning objective; \( CKT \) is the course knowledge Tree.

**Output:** \( RecommendedKSet \) is the recommended set of target knowledge points.

1. \( KP \)\{ 
2. If (\( KP.GS == B \) or \( KP.GS == F \)) // KP.GS is the grasp state of KP. B and F respectively represent Basic Grasp and Fail Grasp.
3. isReady=True;
4. For Each (preK\( \in \)PreKnow) // The prerequisite of KP is represented by preK.
5. if (\( preK.GS == B \) or \( preK.GS == F \)) // The grasp state of preK is represented by preK.GS.
6. isReady=False;
7. break;
8. if (isReady=True)
9. \( RecommendedKSet=RecommendedKSet\cup\{KP\}; \)
10. \}
11. The knowledge points in the \( RecommendedKSet \) are output.
12. \}

During the learning process, the target knowledge points are automatically updated by the learning state data until the initial learning objective is completed. Their completion is mapped to the \( CKT \) one by one, and the corresponding node is colored based on the grasp state of the knowledge. Complete Grasp and Basic Grasp are respectively black and gray, and Fail Grasp is not colored. The personalized knowledge state diagram can be determined during the learner’s learning process. The following example illustrates the process of learning objective updated.

Figure 3(a) shows a learner’s knowledge state diagram at a certain time in learning process, where \( A_1, B_1, \) and \( B_2 \) nodes are compound knowledge points. \( C_1-C_6 \) nodes are atom knowledge points. \( C_1 \) and \( C_2 \) are black and gray. From the above coloring rules, we can find that the grasp state of \( C_1 \) and \( C_2 \) are respectively Complete grasp and Basic grasp.

Without generality, assume that the learner chooses the learning objective \( B_2 \). According to Algorithm 1, the learning objective updating process is as follows:
1) Firstly, direct prerequisite knowledge point $B_1$ of $B_2$ are found.

2) By checking the state of $B_1$, we can see that the grasp state of $B_1$ is Fail Grasp. According to the inclusion relation $Sub(B_1, C_1), Sub(B_1, C_2), Sub(B_1, C_3)$ and the direct prerequisite dependencies $Pre(C_1, C_2), Pre(C_2, C_3)$, the state of $C_1, C_2, C_3$ are checked.

3) We can see that the state of $C_1$ is Complete grasp, which meets the learning requirements. Then, $C_2$ and $C_3$ need to be learned.

4) Next, the learning objectives are updated to $C_2, C_3$.

5) After $C_2$ and $C_3$ are learned, it is determined whether their learning results have reached the threshold.

6) If their learning results have reached the threshold, then $C_2$ and $C_3$ are painted black, as shown in Figure 3(b).

7) Next, the learning objective is updated to $B_2$, as shown in Figure 3(c). According to the inclusion relation $Sub(B_2, C_4), Sub(B_2, C_5), Sub(B_2, C_6)$ and the direct prerequisite dependencies $Pre(C_4, C_5), Pre(C_5, C_6)$, the next learning objective are updated to $C_4, C_5, C_6$ in turn.

![Knowledge state diagram at a certain time](image)

![Completed part of the learning objective](image)

![Updated learning objectives](image)

**Figure 3. An example of updating learning objective**

3.2.4. Recommendation Method

In order to reflect a learner’s behaviour preferences in the learning process, we introduce the concept of Answer Preference.

**Definition 8 (Answer Preference)** The answer preference is calculated based on the ratio of the different difficulty problems accumulated by learner’s historical answer behaviours and the answer correct rate. The preference formula of the difficult, middle and easy exercises is respectively as follows: $Pre_d = \alpha Ra_d + \beta Ri_d; Pre_m = \alpha Ra_m + \beta Ri_m; Pre_e = \alpha Ra_e + \beta Ri_e,$ where

1) $\alpha$ and $\beta$ are the weights, and their values can be set as required, where $\alpha \in [0,1], \beta \in [0,1]$, and $\alpha + \beta = 1$.

2) $Ra_d, Ra_m$ and $Ra_e$ respectively represents the ratio of answering the difficult, middle and easy exercises. The calculating formula is respectively $Ra_d = N_d/(N_d + N_m + N_e), Ra_m = N_m/(N_d + N_m + N_e), Ra_e = N_e/(N_d + N_m + N_e)$.

3) $Ri_d, Ri_m$ and $Ri_e$ respectively represents the answer correct rate of difficult, middle and easy exercises. The calculating formula is respectively $Ri_d = N_d^*/N_d, Ri_m = N_m^*/N_m, Ri_e = N_e^*/N_e$.

On the basis of the answer preferences, we give the specific algorithm of exercises recommendation driven by the learning objective (Algorithm 2). The process is shown in Figure 4, and the specific implementation is as follows:

1) Any recommended exercise group includes $N$ exercises and covers the different difficulty grades (there are Diff, Midd and Easy) of exercises.

2) When the exercise group is recommended, if there is no learner’s history answer records, the difficulty ratio distribution of the exercises is randomly set; otherwise, it depends on the learner’s answer preferences.

3) After the learner has done a group of exercises, the system will automatically calculate the $SC$ of the knowledge point and then judge the $GS$ of the knowledge point. If the $GS\equiv C$, the learning objective is finished. If the $GS\equiv F$, then a
group of exercises that includes \( N \) exercises are recommended for this learning objective. If the \( GS=B \), it is necessary to continually recommend exercises for the knowledge point. But, to make learners complete the learning objectives as soon as possible, a group of exercises containing \( N \) exercises is no longer recommended. The number of recommended exercises depends on the difference between the current \( SC \) of the knowledge point and the upper limit of \textit{Complete Grasp}, and the difficulty distribution ratio depends on the answer preferences.

**Algorithm 2** The algorithm of exercises recommendation driven by learning objective.

**Input:** \( KP \) is a learning objective. \( LB \) is the learner's historical learning behaviour.

**Output:** Learning objective is finished.

1. \textbf{If} (Exist \( LB \)) { 
2. \hspace{1em} Compute \( Pr_e, Pre_m, \) and \( Pre_c \); \hspace{1em} // \( Pr_e, Pre_m, \) and \( Pre_c \) are the answer preferences.
3. \hspace{1em} Based on the answer preferences, an exercise group (\( N \) exercises) is recommended;
4. \}
5. \textbf{else} 
6. \hspace{1em} Randomly recommend an exercise group (\( N \) exercises);
7. \}
8. \hspace{1em} Exercises recommended will be answered by learner;
9. \hspace{1em} Compute \( KP.SC \); \hspace{1em} // \( KP.SC \) is the score of \( KP \).
10. \hspace{1em} \textbf{While} (\( KP.GS==B \) or \( KP.GS==F \)) \hspace{1em} // \( KP.GS \) is the grasp state of \( KP \). \( B \) and \( F \) mean Basic Grasp and Fail Grasp respectively.
11. \hspace{1em} \hspace{1em} \textbf{if} (\( KP.GS==F \)) { 
12. \hspace{1em} \hspace{1em}\hspace{1em} Compute \( Pr_e, Pre_m, \) and \( Pre_c \);
13. \hspace{1em} \hspace{1em}\hspace{1em} Based on the answer preferences, an exercise group (\( N \) exercises) is recommended;
14. \hspace{1em} \hspace{1em} }
15. \hspace{1em} \hspace{1em} Exercises recommended will be answered by learner;
16. \hspace{1em} \hspace{1em} Compute \( KP.SC \);
17. \hspace{1em} \hspace{1em} \textbf{else if} (\( KP.GS==B \)) 
18. \hspace{1em} \hspace{1em} \hspace{1em} Calculate the number and difficulty distribution ratio of the exercises recommended;
19. \hspace{1em} \hspace{1em} \hspace{1em} Recommend exercises;
20. \hspace{1em} \hspace{1em} \hspace{1em} Exercises recommended will be answered by learner;
21. \hspace{1em} \hspace{1em} \hspace{1em} Compute \( KP.SC \);
22. \hspace{1em} \hspace{1em} }
23. \hspace{1em} Learning objective is finished.

The proposed algorithm can be applied to the completion of a single atom knowledge point learning objective. If the learning objective is a compound knowledge point, the set of the atom knowledge point should be firstly calculated using
Algorithm 1. Then, the compound knowledge point learning objective can be obtained by composing these atom knowledge points.

4. Case Analysis

The course C Language Programming Design is used as an example to evaluate the proposed approach in the paper. The feasibility and effectiveness of the method are verified in this section. Figure 5 is the knowledge tree of the Program Structure part of the course. Specifically, KP is Program Structure, KP1 and KP2 are Select Structure and loop Structure, KP11 and KP12 are If Statement and Switch Statement, KP21, KP22 and KP23 are While Statement, Do While Statement and For Statement. According to Definition 5, LO=[KP, KP1, KP2, KP11, KP12, KP21, KP22, KP23]. Among them, the nodes KP, KP1, and KP2 are the compound knowledge point learning objectives. The nodes KP11, KP12, KP21, KP22, and KP23 are the atom knowledge point learning objectives.

Assume that a learner U chooses the learning objective KP1, and we know that it is the compound knowledge point in Figure 5. According to Algorithm 1, KP11 and KP12 need to be completed in order. If there is no learner’s learning behaviour data in the system, an exercise group is randomly recommended according to Algorithm 2, and the proportion of the exercise categories is randomly distributed. The number of exercises in an exercise group is set to N=10 and the number of recommendation is fixed each time. Set the knowledge point SC∈[0, 1]. After the learner U has completed the first recommended exercise, the system will automatically calculate the value of KP11.SC. The recommended rules are as follows:

1) If 0.85≤KP11.SC≤1, then KP11.GS=Complete Grasp, and the KP11 is finished.

2) If 0≤KP11.SC<0.6, then KP11.GS=Fail Grasp, and a group of exercises that includes N exercises is recommended for KP11.

3) If 0.6≤KP11.SC<0.85, then KP11.GS=Basic Grasp. It is necessary to continually recommend exercises for KP11. The number of recommended exercises depends on the difference between the current SC and its upper limit 1 and the number of exercises N in an exercise group, and the difficulty distribution ratio depends on the current answer preferences.

In the following, the learning behaviours and state data calculation of the learner U and follow-up exercises recommendation process are described in detail. The specific steps are as follows:

(1) When the learner U has finished the first exercises recommended of KP11, he or she will get a problem record as shown in Table 1. Where, the “1” indicates the correct answer, and “0” indicates the wrong answer.

<table>
<thead>
<tr>
<th>Type</th>
<th>ID</th>
<th>Answer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Easy exercises</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Middle exercises</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>0</td>
</tr>
<tr>
<td>Difficult exercises</td>
<td>8</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>1</td>
</tr>
</tbody>
</table>

(2) The exercises statistics are calculated according to Definition 6: KP11.AE=＜N_d, N_m, N_w＞=＜3, 4＞, KP11.AE* =＜N_d*, N_m*, N_w*＞=＜2, 2, 3＞.

(3) Calculate the grasp state of KP11 according to Definition 7:
• Set the weight of three kinds of exercises: $W_d=0.15$, $W_m=0.1$, $W_e=0.05$
• Calculate the grasp state of $KP_{11}$:

$$KP_{11}.SC = KP_{11}.SC_i = W_d \times KP_{11}.N_d^i + W_m \times KP_{11}.N_m^i + W_e \times KP_{11}.N_e^i = 0.15 \times 3 + 0.1 \times 2 + 0.05 \times 2 = 0.75$$

We can see $KP_{11}.GS=B$, then $KP_{11}$ has not yet reached the learning requirement, and we need to continually recommend exercises. According to the colouring rules, the corresponding nodes are greyed in the CKT, and knowledge state of the learner is shown in Figure 6(a).

(4) Calculate the answer preferences of the learner $U$ according to Definition 8:

• Calculate the answer ratio of three kinds of exercises: $Ra_d=3/10=0.3$, $Ra_m=3/10=0.3$, $Ra_e=4/10=0.4$.
• Calculate the answer correct rate of three kinds of exercises: $Ri_d=2/3$, $Ri_m=2/3$, $Ri_e=3/4=0.75$.
• Set $\alpha=\beta=0.5$, calculate the answer preferences of three kinds of exercises:

$$Pre_d = \alpha Ra_d + \beta Ri_d = 0.5 \times 0.3 + 0.5 \times 2/3 \approx 0.48$$
$$Pre_m = \alpha Ra_m + \beta Ri_m = 0.5 \times 0.3 + 0.5 \times 2/3 \approx 0.48$$
$$Pre_e = \alpha Ra_e + \beta Ri_e = 0.5 \times 0.4 + 0.5 \times 0.75 = 0.575$$

• Normalized the value of the answer preferences:

$$Pre_d' = Pre_m' = 0.48/(0.48 + 0.48 + 0.575) \approx 0.31$$
$$Pre_e' = 0.575/(0.48 + 0.48 + 0.575) \approx 0.38$$

(5) Calculate the total number of exercises for the second recommendation of $KP_{11}$ according to the recommendation method: $KP_{11}.Num_i=N \times (1 - KP_{11}.SC_i) = 10 \times (1 - 0.75) = 2.5 \approx 3$, and then calculate the number of three kinds of exercises according to the answer preferences:

$$KP_{11}.Num_d = KP_{11}.Num_i \times Pre_d' = 3 \times 0.31 \approx 1$$
$$KP_{11}.Num_m = KP_{11}.Num_i \times Pre_m' = 3 \times 0.31 \approx 1$$
$$KP_{11}.Num_e = KP_{11}.Num_i \times Pre_e' = 3 \times 0.38 \approx 1$$

That is, the number of exercises recommended for $KP_{11}$ is 3 this time, where the number of difficult, middle and easy exercises are 1, 1 and 1.

(6) Calculate the total number of exercises for the second recommendation of $KP_{12}$ according to the recommendation method this time, and we can see that $KP_{12}.Num_i= N \times KP_{11}.Num_i=10 \times 3=7$. Then, calculate the number of three kinds of exercises in 7 exercises according to the answer preferences: $KP_{12}.Num_d=7 \times 0.31 \approx 2$; $KP_{12}.Num_m=7 \times 0.31 \approx 2$; $KP_{12}.Num_e=7 \times 0.38 \approx 3$. That is, the number of exercises recommended for $KP_{12}$ is 7 this time, where the number of difficult, middle and easy exercises are 2, 2 and 3.

(7) Suppose the learner $U$ rightly answers all the exercises recommended for the second time, and calculate $KP_{11}.SC$ and $KP_{12}.SC$ at this time:
Then, at this time $KP_{11}, GS=C$, the learning objective $KP_{11}$ is completed. But $KP_{12}, GS=B$, so we need to continually recommend exercises for $KP_{12}$. According to the colouring rules, the corresponding nodes are painted in the CKT, and a learner’s knowledge state is shown in Figure 6(b), where $KP_{11}$ is painted black and $KP_{12}$ is painted grey. The colour of $KP_{1}$ depends on the state of the child nodes $KP_{11}$ and $KP_{12}$. As long as the compound knowledge points included in the atom knowledge points are at least one of the mastery of the state $B$, then the compound knowledge point is painted grey. We can see that $KP_{1}$ is painted grey.

(8) Update the value of the answer preferences again, and the calculation process is as follows:

- From (5), (6) we can see that the number of difficult, middle and easy exercises of the second recommendation is 3, 3 and 4. Combined with the answer situation from the first exercises that were recommended, the number of total exercises recommended of difficult, middle and easy exercises are 6, 6 and 8. Among them, the number of exercises done correctly for difficult, middle and easy problems are 5, 5, and 7.
- Calculate the answer ratio of three kinds of exercises: $Ra_{d}=6/20=0.3; Ra_{m}=6/20=0.3; Ra_{e}=8/20=0.4$.
- Calculate the answer correct rate of three kinds of exercises: $Ri_{d}=5/6; Ri_{m}=5/6; Ri_{e}=7/8$.
- Set $\alpha = \beta=0.5$, calculate the answer preferences of three kinds of exercises:

$$
Pre_{d} = \alpha Ra_{d} + \beta Ri_{d} = 0.5 \times 0.3 + 0.5 \times 0.5 \times 5/6 \approx 0.57
$$
$$
Pre_{m} = \alpha Ra_{m} + \beta Ri_{m} = 0.5 \times 0.3 + 0.5 \times 0.5 \times 5/6 \approx 0.57
$$
$$
Pre_{e} = \alpha Ra_{e} + \beta Ri_{e} = 0.5 \times 0.4 + 0.5 \times 0.7 \times 5/8 \approx 0.64
$$

- Normalize the value of the answer preferences:

$$
Pre'_{d} = Pre'_{m} = 0.57/(0.57 + 0.57 + 0.64) \approx 0.32
$$
$$
Pre'_{e} = 0.64/(0.57 + 0.57 + 0.64) \approx 0.36
$$

(9) Calculate the number of exercises recommended again for $KP_{12}$ at this time: $KP_{12}.Num_{d}=10 \times (1-0.65) \approx 4$. Then, calculate the number of three kinds of exercises in 4 exercises according to the answer preferences:

$$
KP_{12}.Num_{d} = KP_{12}.Num_{m} = 4 \times 0.32 = 1
$$
$$
KP_{12}.Num_{e} = 4 \times 0.38 = 2
$$

That is, the number of exercises recommended for $KP_{12}$ is 4 this time, where the number of difficult, middle and easy exercises are 1, 1 and 2.

(10) Assuming that the answers of difficult exercises are all wrong, and the answers of other exercises are all right this time, calculate $KP_{12}.SC$: $KP_{12}.SC= KP_{12}.SC_{1}+KP_{12}.SC_{2}=0.65+0.1 \times 1+0.05 \times 2=0.85$.

We can see $KP_{12}.GS=C$, and the learning requirement is met and the learning objective $KP_{1}$ is completed. Knowledge state of the learner is shown in Figure 6(c) at this time.

5. Conclusion

To enhance the personalization of an e-learning system, a personalized exercise recommendation approach that is driven by learning objective has been proposed. Firstly, the scientific and rational representation of the course knowledge and knowledge points is given, and exercises as well as their relations are modeled by using CKT. Then, a computing method is proposed to automatically update learning objectives in the learning process. According to the learning state data, a method is proposed to accurately describe the learner’s learning needs. To realize the personalization of e-learning, three kinds of influencing factors, including learning objective, grasp state of knowledge point and answer preferences, are taken into account for the exercises recommendation. The knowledge trees are used to visualize the complete knowledge structure in...
the learning process so that the learner can see his or her progress and deficiencies of knowledge. In this way, the cognitive load and Trek phenomenon brought about by text messages are reduced greatly. A running example is used to evaluate the proposed approach in the paper, and the feasibility and effectiveness of the method are demonstrated.

In the future work, the time factor of the learner’s answering exercises will be introduced to describe the learner’s needs by building a more precise learner’s cognitive model. Furthermore, the selection of the parameters used in the calculation will be explored with more experiments.

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