Journal of Computers Vol. 32 No. 2, 2021, pp. 149-163
doi:10.3966/199115992021043202013

Personalized Learning Resource Recommendation Based on Course Ontology and Cognitive Ability

Xiuli Diao[1], Qingtian Zeng[1*], Hua Duan[2], Zhengguo Song[1], Chonghong Zhou[3]

[1] College of Computer Science and Engineering, Shandong University of Science and Technology, Qingdao, China
{dxlszg, szgdxl}@126.com, qtzeng@163.com

[2] College of Mathematics and Systems, Shandong University of Science and Technology, Qingdao, China
huaduan59@163.com

[3] College of Ecnomics & Management, Shandong University of Science and Technology, Qingdao, 266590, China
zhouchanghong@163.com

Received 1 May 2020; Revised 15 May 2020; Accepted 30 May 2020

Abstract. As an important way to solve the learner's information loss within an e-learning system and support personalized learning, learning resource recommendation has attracted more and more attention. A personalized learning resource recommendation framework based on course ontology and the learner's cognitive ability is proposed in this paper. Firstly, course ontology is constructed with C language course as an example, and semantics reasoning rules are defined based on course ontology. Then, according to the test results, the learner's cognitive ability is dynamically estimated using maximum likelihood estimation and joint probability, and a learner model based on learning preference and cognitive ability is constructed. Finally, it explores the personalized learning resource recommendation method that integrates course ontology, the learner's cognitive ability and learning preference. In the experimental part, the proposed recommendation method is applied to the e-learning system, and the experiment is carried out in the C language course teaching to verify the feasibility and effectiveness of the proposed recommendation method.

Keywords: course ontology, cognitive ability, e-learning, learning resource, personalized learning

1 Introduction

Personalized learning resource recommendation is a research hotspot in the field of e-learning, which can help the learner quickly find suitable learning content from the huge and complex learning resource database. However, due to some special requirements, learning resource recommendation is different from product or film recommendation. First of all, the recommended learning content must cover all knowledge points oriented to the learner's learning objective, so as to ensure the integrity and coherence of course knowledge learning. Secondly, in order to enhance the learning experience, the recommended learning content must match the cognitive ability of the target learner. Where, the cognitive ability is calculated and updated according to the learner's test feedback results. According to the above requirements, a personalized learning resource recommendation framework based on course ontology and the learner's cognitive ability is proposed. The framework not only considers the coverage of knowledge points oriented to learning objective, but also helps the learner to find appropriate learning content according to the dynamic cognitive ability in the learning process, so as to ensure the mastery of the target knowledge points.

* Corresponding Author

According to the recommendation framework, the learner firstly needs to select the target knowledge point according to the course ontology in order to obtain the suitable course knowledge point set for his or her learning objective. Secondly, test must be used to judge the learner's mastery of each knowledge point and his or her cognitive ability. Thirdly, based on the learner's cognitive ability and learning preferences, appropriate knowledge points and learning resources are recommended. The feasibility and effectiveness of the personalized learning resource recommendation framework are verified by the development of prototype recommendation system and teaching practice.

2 Related Work

The concept of recommendation system can be traced back to the late 1980s [1]. Nowadays, personalized recommendation system has been applied in many fields, among which e-commerce is the most typical application. In recent years, with the popularization of educational information and the development of Web 2.0 technology, personalized recommendation has been gradually applied to the learning resource recommendation. The research mainly bases on the learner's characteristics and learning resources, and combines the existing and typically recognized recommendation strategies (For example, collaborative filtering recommendation, content-based recommendation, knowledge-based recommendation, etc.) to achieve personalized learning resource recommendation. For example, user-based or project-based collaborative filtering could achieve personalized learning resource recommendation of for a learner [2]. [3] made use of resource attributes and the learner's attributes as well as the learner sequential pattern of acquiring resources in the recommendation process, and combined collaborative filtering based on implicit and explicit attributes with BIDE algorithm to recommend learning resources. [4] based on user interests, learning preferences and knowledge model, structured ubiquitous learning resources were synthetically recommended by using the characteristics of semantic description, generative information, KNS network and learning activities of ubiquitous learning resources. In[5], through mining the learner's learning data to identify different learning styles and patterns and learning habits, the personalized recommendation of learning content was completed. [6] combined individual preferences of different learners to get group characteristics, and researched how to recommend learning resources to a group of learners. In order to improve the adaptability and diversity of recommendation system, [7] introduced learning object-oriented recommendation mechanism into learner-oriented recommendation system, and proposed a self-organizing recommendation method based on learning object. In the recommendation process, the transfer of the learner's explicit characteristics and implicit preferences are considered. The above recommendation model is mainly based on user characteristics, which can help a learner quickly acquired the required learning resources, but it was not suitable for the course knowledge learning with strong logical structure.

Some studies of learning resource recommendation utilize the learner's competence characteristics. [8] dynamically evaluated the learner's abilities using modified project response theory to provide personalized course sequence services for a learner, taking into account the matching degree between the difficulty level of courseware and the learner's abilities, as well as the conceptual correlation between courseware. In [9], according to the learner's various characteristics and behavioural tendencies, such as learning style, media tendencies and cognitive levels, the corresponding teaching strategies were adopted to realize the recommendation of personalized learning path and learning resources, and the adaptive presentation of learning objects and learning activity sequences was realized based on the course ontology model. In [10], before a learner began to learn, the hierarchical recommendation algorithm was used to generate personalized learning content for the learner based on the teaching plan and the learner's multi-dimensional characteristics (including knowledge level, ability level and goal characteristics). In the learning process, genetic algorithm was used to update the personalized course content dynamically according to a learner's dynamic needs. The above recommendation methods paid attention to the logic of knowledge itself, but most of them lacked the consideration of the integrity of learning objective, which affected the value of recommendation methods.

In the research process of personalized learning resource recommendation, new entry points are constantly emerging. [11] took into account social relationships such as the trust among learners, recommended user relationship and learning resources of common interest by using collaborative filtering technology, and analysed the comments of individual users and groups on resources by affective analysis technology, so as to recommend high-quality resource for users. [12] proposed a learning resource recommendation model and algorithm based on situational awareness. In the recommendation process, learner preferences, historical sequence patterns of acquiring resources, multi-dimensional attributes and correlation of resources were taken into account. In [13], based on the learner's reading content, Learning Assistant was designed to recommend additional resources to supplement or explain the original text in order to ensure that the learner's online reading process can proceed smoothly. [14] presented a content-based recommendation algorithm. The convolutional neural network (CNN) could predict the potential factors of multimedia resource information from text. The main novelty of this algorithm was that it directly used text information for content-based recommendation without mark-ups. [15] recommended personalized learning resources based on collaboration and social labeling, using a variety of different technology methods. [16] proposed a method of applying collaborative annotation technology to online teaching system, which combined social tagging and sequential pattern mining to generate learning resources for a learner. The above recommendation methods can realize the personalized learning resource recommendation, but ignore the logic of knowledge and the learner's learning goal, and are not suitable for the course knowledge learning with strong logical structure.

The ontology helps to ensure the logic of the recommended learning resources knowledge. [17] presented a knowledge-based hybrid recommendation system for online learning resource recommendation based on ontology and sequential pattern mining. In the proposed recommendation method, ontology is used to model and represent the domain knowledge about the learner and learning resources whereas SPM algorithm discovers the learner's sequential learning patterns. [18] organized learning resources by using course ontology, and realized self-adaptive personalized learning based on the learner's learning style and changing behavior. [19] organized exercises based on the knowledge set of the course, considers the knowledge level of the learners, and recommends personalized exercises according to the learning objectives and homework feedback, thus ensuring the interpretability of the recommendations. The above recommendation methods generally lack the consideration of the integrity of learning objective and the learning ability characteristics.

To sum up, in order to ensure the integrity of the learner's learning objectives and the internal logical structure of the recommended personalized learning resources, this research uses course ontology to organize and describe course knowledge points and learning resources. In order to ensure the effective completion of the target knowledge points, this research focuses on the learning process information, such as the mastery of knowledge points, the feedback results of tests and the dynamic changes of the learner's cognitive ability, which are the key factors affecting learning effectiveness. Therefore, according to the big data of learning behavior such as knowledge point information browsed by a learner in online course learning, feedback information of participating tests and dynamic evaluation information of learning results, the recommendation mechanism of personalized learning resources has explored in this paper, and provided personalized learning support services for a learner, so as to help the learner improve learning efficiency, enhance learning experience and optimize learning effect.

This research addresses two main issues: (1) Whether the recommended learning content covers all the necessary knowledge points to accomplish the learning objective; (2) Whether the recommended knowledge points match the learner's current cognitive ability, and whether the recommended learning resources are consistent with the learner's preference.

Therefore, a learning resource recommendation framework has been proposed based on course ontology and the learner's cognitive ability, which aims to help the learner find appropriate learning content by considering the coverage of knowledge points and cognitive ability. In the recommendation framework, the learner's learning objective must be identified before, he or she can acquire the knowledge points of course objective suitable for his or her learning. Then, according to the test feedback results, the mastery of knowledge points can be immediately judged, and finally appropriate learning content and resources based on cognitive ability and learning preference are recommended to the learner.

3 A Framework of Personalized Learning Resource Recommendation Based on Course Ontology and the Learner's Cognitive Ability

The research framework includes five functional modules: course ontology construction, description and organization of learning resources, learner behavior big data, learner model construction with dynamic updating of cognitive ability and recommendation mechanism of personalized learning resources. It aims to recommend appropriate learning resources according to a learner's individual learning goal, as shown in Fig. 1.

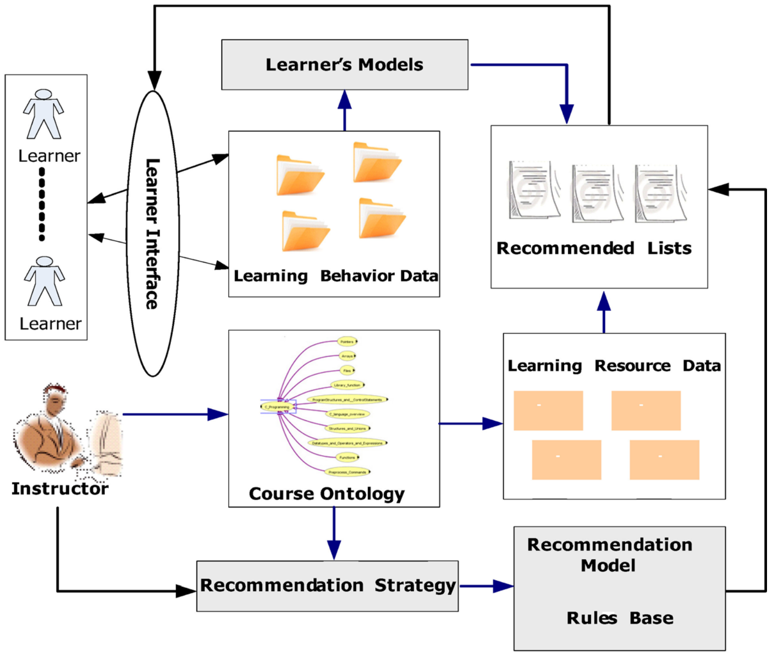

Fig. 1. Framework of personalized learning resource recommendation based on course ontology and cognitive ability

(1) Course ontology construction: The course is an important educational resource in online education platform and the basic premise for the smooth development of online education. The course ontology regards a course as a field, and a knowledge point as a concept. It is constructed according to the logical relationship between the course chapters and knowledge points, and described with the formal language recognized by the computer [20]. The aim is to form a common understanding and understanding of course knowledge structure between human and computer, and lay a foundation for the realization of e-learning personalized course learning.

(2) Description and organization of learning resources based on course ontology: Through the organization and description of learning resources based on course ontology, the semantic association between learning resources is established. In order to meet the different learning preference of a learner, knowledge points are presented in various ways, which include text, pictures, courseware, video, audio, test questions and other presentation types. In order to meet the needs of a learner with different cognitive abilities, the difficulty attributes of test questions are graded to achieve effective description and management of learning resources.

(3) The learner behaviour big data: There are abundant big data of learner behaviour in the e-learning platform, which can be divided into static data and dynamic data according to the degree of data updating. Among them, static data refers to the learner's basic personal information (e.g. user ID, specialty, etc.), dynamic data includes the learner's individual learning trajectory data (e.g. courses taken, types of resources learned and feedback data from tests), and the re-engineering knowledge generated in the learning process (e.g. annotations, questions, evaluations, notes, etc.). Based on the big data of the learner behaviour in answering test questions accumulated in the process of learning, the difficulty of test questions and the learner's cognitive ability is calculated, and his or her real learning needs are dynamically captured.

(4) Learner model construction with dynamic updating cognitive ability: A learner's cognitive ability is reflected in the testing process after learning the knowledge points. Through statistical analysis of the learner's dynamic behaviour data in answering the test questions, his or her cognitive ability is calculated by maximum likelihood estimation and joint probability method. Because the learner's feedback is dynamic, the difficulty of the test is dynamic, and the cognitive ability will be updated dynamically, so as to build an adaptive and dynamically adjustable learner model, which lays the foundation for different cognitive ability learners to recommend different learning content.

(5) Recommendation mechanism of the personalized learning resources:This module firstly implements the recommendation of knowledge points set needed to achieve the learning goal based on the rule reasoning of course ontology. After each knowledge point is completed, the learner needs to take part in the test. Then, the learner's cognitive ability is dynamically calculated according to the behaviour data of the test questions, and adaptive teaching strategies are defined. Follow-up knowledge points are recommended according to the current situation of knowledge point's mastery and the learner's cognitive ability. Then, learning resources are recommended according to the learner's learning preference.

4 Course Ontology Construction

Regarding course as a small field, course ontology is used to describe the hierarchical and semantic relations between knowledge points in a course. The definition of course ontology is detailed in [20]. The course ontology database takes knowledge points as the smallest information unit to construct the system. Each knowledge point can be as a learning goal. Its construction process includes three steps: determining the top concept set of ontology, establishing conceptual hierarchical structure relations and establishing various relationship attributes. Next, take the C language course as an example to construct course ontology.

4.1 Determining the Top Concept Set of Ontology

Based on the C language programming textbook, according to the teaching steps, the course knowledge are divided into granularity, and the C_programming.owl document of C language course knowledge ontology is established by using Protégé tool. The whole document is divided into three levels, and the core concept set T is summarized and sorted out. T={C language overview, Data types and Operators and Expressions, Library function, Arrays, Program Structures and Control Statements, Functions, Pre-process Commands, Pointers, Structures and Unions, etc.}. As shown in Fig. 2.

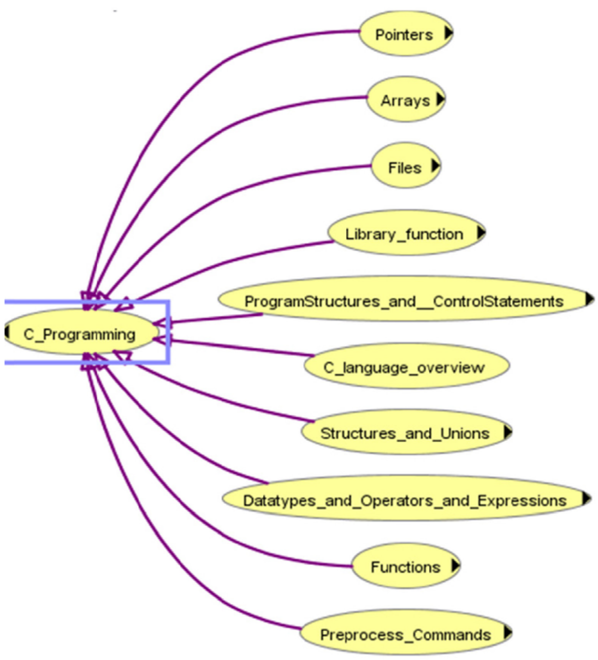

Fig. 2. Top-level classification structure chart

4.2 Conceptual Hierarchical Structure Relations

After establishing the top-level concepts, we extend them and build the whole course ontology model, which reflects the father-son structural relationship between concepts, that is "is-a". This process is also a top-down process, that is to say, according to the pre-defined abstract parent class of the upper level, the next level of subclasses are gradually elaborated.

The hierarchical structure of course class "C_programming" is based on concepts as nodes. It takes "C_programming" as the root of course ontology and extends downward to top concepts such as "Arrays", "Program Structures and Control Statements", "Functions". Each top concept has its own sub-concepts, which are extended to the next level. As follows:

T (Library function) = {Input function, Output function, String function};

T (Arrays) = {Character array, Single dimensional array, Two dimensional array};

T (Structures and Unions) = {Structure, Union, Linked list, Enum}.

The conceptual hierarchy is presented as a tree structure. The organizational structure of the course knowledge has a clear main line, which ensures the systematization of the course knowledge. The learner can gradually refine the concepts along the top-down structure. Fig. 3 is a *C_programming* part of the classification structure.

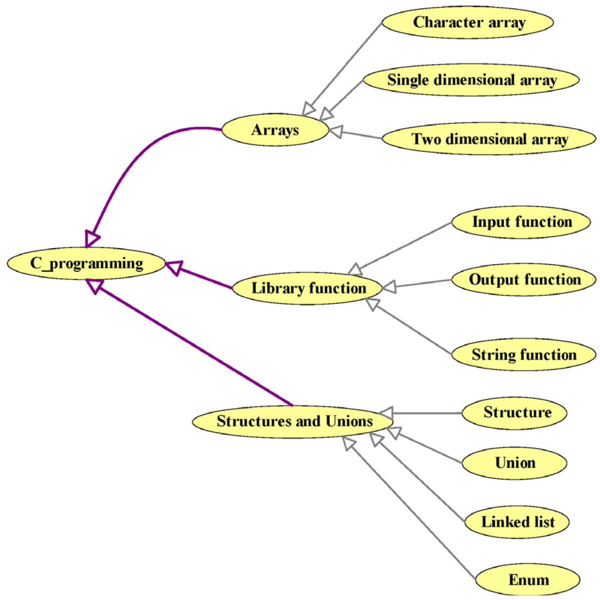

Fig. 3. C_programming part of the classification structure

4.3 Establishing Relational Attributes

In order to prepare for the definition of reasoning rules, the course ontology mainly establishes four relationship attributes: the relationship between knowledge points, the relationship between resources and knowledge points, the relationship between learners and knowledge points, and the relationship between learners and resources attributes. The defined relational properties are shown in Fig. 4.

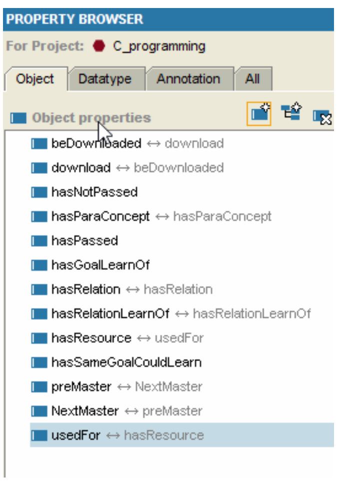

Fig. 4. Relational attribute establishment

(1) Relational attributes among knowledge points: There are the prerequisite relationship “preMaster”, the successor relationship “nextMaster”, and the parallel relationship “hasParaConcept”. Among them, “preMaster” attribute and “nextMaster” attribute have reversibility, and “hasParaConcept” attribute itself has symmetry. These attributes determine the relationship between learning resources, the position and order in the learning process, and the use of the relationship attributes of knowledge points can provide the learner with personalized learning sequence.

(2) Relational attributes between resources and knowledge points: There are the knowledge point relations of resource ownership “usedFor”, the related resource relation of knowledge point possesses “hasResource”, and the type relation of resource belongs to “belongTo”. The “usedFor” attribute and “hasResource” attribute are reversible. The semantic relationship between knowledge points and learning resources is established through these relational attributes. The classification of “Resource” can be divided into PPT courseware file “PPT file”, “Text file”, “Video file”, “Test file” and so on.

(3) The relationship between the learner and knowledge points: “HasSameGoalCouldLearn” represents the relationship between the target knowledge point that can be learnt by the learner and is similar to the current knowledge point. “HasPassed” represents knowledge point relationships that have been mastered by the learner. “HasGoalLearnOf” represents the relationship between target knowledge points that can be learned by the learner.

(4) The attributes of the relationship between the learner and resources: “Download” represents the learner to download resources. “BeDownloaded” means that resources are downloaded by learners. The “download” and “beDownloaded” attribute are reversible.

5 Learner Model Construction with Dynamic Updating Cognitive Ability

The learner model gives an overview of personality characteristics based on the learner’s learning preferences and cognitive ability, including the learner’s static and dynamic information. Static attributes include name, age, specialty and learning preferences (referring to resource preferences, text, video, audio and other resource types), and dynamic information includes cognitive ability, knowledge learning status, and so on. Among them, the static attributes of the learner remain unchanged in the learning process. For example, the learner can be recommended their favorite learning resource types according to their learning preferences, which are generally collected when the learner logs in the e-learning system for the first time.

The initial learner model information is established by filling in the registration information when the learner logs into the system, and the subsequent information is added and updated by recording the learner’s learning behavior. Where, cognitive ability is calculated by using the learner’s answers to the test. The calculation process is divided into three steps.

Set n to represent the difficulty level of the test questions and m to represent the learner’s cognitive ability level. According to the calculated value of n, the difficulty of the subject can be divided into three levels (1-3): *difficult* (n = 3), *medium* (n = 2), *easy* (n = 1); according to the calculated value of m, the learner’s cognitive ability can be divided into three levels (1-3): *high* (m = 3), *medium* (m = 2), *low* (m = 1).

(1) Computing the difficulty of test questions: The difficulty of a test is calculated based on the result of all learners answering the question. $Diff_{(t)}$ is set to indicate the difficulty of test t, $Accept_{(t)}$ is used to indicate the number of times that all learners have done a test t, and $Submit_{(t)}$ is used to indicate the number of times that all learners have submitted the answer to the test t. The calculation method is shown in Equation (1). Then, according to the value of $diff_{(t)}$, the test is divided into three levels: difficult, medium and easy.

$$diff_{(t)} = 1 - (Accept_{(t)} / Submit_{(t)}) \qquad \textbf{(1)}$$

Equation (1) shows that the difficulty of a test will be updated dynamically with the cumulative number of answers submitted.

(2) Acquiring the learner’s cognitive competence matrix: In order to estimate the learner’s cognitive ability more scientifically and pertinently, this study not only calculates the learner’s cognitive ability based on the correct rate of individual answers, but also estimates their average cognitive ability based on the test results of all learners.

$a_{[m][n]}$ is used to express the probability of the learner with cognitive ability m to answer the test questions with difficulty *n*. Its value is the average value of the ratio of correct times to submission times of the test questions with difficulty *n* for all learners with ability *m*. It is obtained by counting the answers to the test questions before. The calculation method is shown in Equation (2). Where, $N(User_{m\_}(accept, dif_n))$ is the number of questions of difficulty *n* that students of ability *m* can answer correctly, $N(User_{m\_}(submit, dif_n))$ is the number of questions of difficulty *n* submitted by learners of ability *m*.

$$a_{[m][n]} = \sum_{i=1}^{n} N(User_{m\_}(accept, dif_n) / N(User_{m\_}(submit, dif_n)) / n \quad \textbf{(2)}$$

Set *Ability* to represent the learner's cognitive ability matrix. According to the value of $a_{[m][n]}$, calculate the learner's ability by Equation (3).

$$Ability = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad \textbf{(3)}$$

The following example illustrates the calculation method of $a_{[m][n]}$. Compute $a_{[2][3]}$, which indicates the probability that the learner with medium ability ($m = 2$) will make a correct answer to a test question with high difficulty ($n = 3$). Assuming that three learners (*Zhang*, *Wang and Li*) all have medium abilities, the test results of difficulty $n = 3$ are shown in Table 1.

Table 1. The results of three learners' answers to n=3 test questions

Name	Number of submission	Number of correct answers
Zhang	20	5
Wang	10	3
Li	5	4

Then, $a_{[2][3]} = (5/20 + 3/10 + 4/15) / 3 = 0.272$.

(3) Using maximum likelihood estimation and joint probability to calculate the learner's cognitive ability: Maximum likelihood estimation (MLE) is a parameter estimation method used when the parent type is known. In an experiment, events with high probability are more likely to occur than those with low probability. According to the maximum probability, we can deduce the cause of "events".

When the observed value of a given sample is given, the likelihood function is defined as Equations (4) and (5).

$$L(\theta) = L(\theta; x_1, x_2, ..., x_n) = f(x_1, x_2, ..., x_n; \theta) \quad \textbf{(4)}$$

$$L(\theta) = \prod_{i=1}^{n} (x_n; \theta) \quad \textbf{(5)}$$

$L(\theta)$ is regarded as a function of parameter θ, and it can be used as a measure of how likely θ will produce subsample observations of $x_1, x_2, ..., x_n$.

The maximum likelihood estimation method is to estimate θ by $\hat{\theta}_L$, which maximizes $L(\theta)$, i.e. Equation (6).

$$L(\hat{\theta}_L) = \max_{\theta} L(\theta) \quad \textbf{(6)}$$

Then it calls $\hat{\theta}_L$ the maximum likelihood estimate (MLE)of θ.

Therefore, according to the situation that the learners with different cognitive abilities a_i do test questions for (t_1, t_2, ..., t_n), the cognitive ability matrix is calculated by Equations (2) and (3), and the joint probability of cognitive ability is obtained. When x_i is used to represent the right and wrong situation of question *i*, the maximum likelihood function is as follows by Equation (7):

$$L(a) = \prod_{i=1}^{n} f(x_i; a). \tag{7}$$

Then, according to the maximum likelihood estimation theory and Equation (7), when the learner's corresponding cognitive ability is a_i at the maximum L (a_i), the probability is the highest, and then the cognitive ability is a_i at this time.

Example: Suppose the learner *S* does a test question correctly. According to the results of this question, if *S*'s cognitive ability is 1, the probability of the current result is 0.1; when *S*'s cognitive ability is 2, the probability of the current result is 0.4; when *S*'s cognitive ability is 3, the probability of the current result is 0.5. It can be seen that when *S*'s cognitive ability is 3, the probability of doing this test correctly is the greatest. According to the maximum likelihood estimation theory, *S*'s cognitive ability is updated to 3.

Every time a learner completes a test, his or her cognitive ability is updated. When the number of test questions accumulates to a certain extent, the learner's cognitive ability tends to be stable and the more accurate his or her cognitive ability is judged.

(4) Examples of calculating the learner's cognitive ability: Assuming that the cognitive abilities of each learner are low, medium and high probability P_{low}, P_{mid}, P_{high} respectively, then their initial values are equal, all of which are 1/3. A learner's cognitive abilities are calculated in two cases.

・**In the case of a learner doing a test question correctly**

Assuming that the learner's ability is 1 and the probability of doing the right test is P_{low}, then $P_{low} = P_{low} * a_{[1][i]}$;

Assuming that the learner's ability is 2 and the probability of doing the right test is P_{mid}, then $P_{mid} = P_{mid} * a_{[2][i]}$;

Assuming that the learner's ability is 3 and the probability of doing the right test is P_{high}, then $P_{high} = P_{high} * a_{[3][i]}$.

・**In the case of a learner doing a test question wrongly**

Assuming that the learner's ability is 1 and the probability of doing the right test is P_{low}, then
$P_{low} = P_{low} * (1 - a_{[1][i]})$;

Assuming that the learner's ability is 2 and the probability of doing the right test is P_{mid}, then
$P_{mid} = P_{mid} * (1 - a_{[2][i]})$;

Assuming that the learner's ability is 3 and the probability of doing the right test is P_{high}, then
$P_{high} = P_{high} * (1 - a_{[3][i]})$.

Judging the maximum of P_{low}, P_{mid} and P_{high}, if P_{high} is the largest, the learner's cognitive ability is set to 3. Every time a learner completes a test, his or her ability is updated once for the *high*, *medium* and *low* probability.

6 Recommendation Method Based on Course Ontology and Cognitive Ability

In this section, we propose a recommendation method based on course ontology and cognitive ability, which includes two stages: one is to define reasoning rules based on course ontology; the other is to propose personalized learning resource recommendation algorithm based on the learner's cognitive ability.

6.1 Definition of Reasoning Rules Based on Course Ontology

Ontology-based reasoning can mine explicit definitions and implicit knowledge. For this reason, based on the concepts and relationships in the course ontology, SWRL (Semantic Web Rule Language) is used to define a series of reasoning rules for adaptive teaching strategies, and the reasoning engine is used to recommend suitable knowledge points and learning resources for different learners. The reasoning rules based on course ontology not only conform to human cognitive habits, but also help the learner to grasp the target knowledge points comprehensively with the formal definition of course ontology. The defined SWRL rules are shown in Table 2.

Table 2. SWRL reasoning rules

Name	Expression
Rule-download1	hasNotPassed(?x,?y) ^ hasResource(?y,?z)→download(?x,?z)
Rule-download2	Uer(?x)^C_Programming(?y)^Resources(?z)?sqwl:equal(?x.preferLearnigBy?z.belongTo) ^hasGoalLearnOf(?x,?y)→download(?x,?z)
Rule-learn1	hasPassed(?x,?y) ^ NextMaster(?y,?z)→hasGoalLearnOf(?x,?z)
Rule-learn2	hasPassed(?x,?y)^hasParaConcept(?y,?z)→hasSameGoalCouldLearn(?x,?z)
Rule-learn3	hasNotPassed(?x,?y)^hasParaGoncept(?y,?z)→hasSameGoalCouldLearn(?x,?z)
Rule-learn4	hasNotPassed(?x,?y)^preMaster(?y, ?z)→hasGoalLearnOf(?x,?z)

(1) Rule-download1 indicates that if the learner x does not grasp the knowledge point y currently learned, and the knowledge point y has the relevant learning resource z, then the learner x can download z to learn.

(2) Rule-download2 indicates that if the learner x needs to learn the knowledge point y in the next step and the knowledge point y has relevant learning resource z. And it is exactly the resource type of z which x likes, the learner x can download z to learn.

(3) Rule-learn1 indicates that if the learner x has mastered the knowledge point y that he or she has learnt at present and the next knowledge point z that he or she has learnt x, he or she can further learn the knowledge point z.

(4) Rule-learn2 indicates that if the learner x has mastered the current knowledge point y, and the knowledge point y has the parallel knowledge point z, then the learner x can choose the learning knowledge point z.

(5) Rule-learn3 indicates that if the learner x does not grasp the current knowledge points y, and the knowledge point y have the parallel knowledge point z, then the learner x can choose the learning knowledge point z.

(6) Rule-learn4 indicates that if the learner x do not grasp the knowledge point y which he or she is currently learning, and the learning knowledge point y must firstly grasp the knowledge point z, then the learner x should firstly learn z.

Based on the above reasoning rules, we can recommend the following knowledge points set according to the learner's mastery of the current knowledge point. Where, the mastery of the knowledge point is calculated according to the situation of the learner completing the test questions. Detailed calculation methods and process are shown in [21]. In this research, "Complete mastery" and "Basic mastery" are recorded as learner's mastery of a knowledge point.

6.2 Personalized Learning Resource Recommendation Method Based on The Learner's Cognitive Ability

In this stage, the recommendation method recommends appropriate knowledge points for the learner according to his or her current cognitive ability. For example, according to the inference rule in 6.1, the learner can choose to continue learning the knowledge point without mastering the knowledge point *X*, or to choose the prerequisite knowledge points of *X*. What knowledge points are finally recommended for the learner depends on the current cognitive ability. Specific recommendations are as follows:

(1) If the learner has mastered the current knowledge points and his or her current cognitive ability is "high" or "medium", the successor knowledge points or the parallel knowledge points will be recommended; if the current cognitive ability is "low", the current knowledge points or the parallel knowledge points will be recommended.

(2) If the learner does not grasp the current knowledge points, and the current cognitive ability is "high", then the current knowledge point or the parallel knowledge points will be recommended; if the current cognitive ability is "medium" or "low", the prerequisite knowledge points will be recommended.

In summary, the knowledge recommendation algorithm based on the learner's cognitive ability (*Algorithm 1*) is presented as follow.

```
Algorithm 1. Knowledge point recommendation algorithm based on the learner's
cognitive ability.
Input: Course ontology, mastery of the knowledge point and the learner's
cognitive ability.
Output: A set of knowledge points recommended for learning.
   If (the current knowledge point has be mastered)  Then
       If (the current cognitive ability is  "high" or "medium")  Then
       The successor knowledge points or the parallel knowledge points will
be recommended
       Else If (the current cognitive ability is "low")   Then
       the current knowledge point or the parallel knowledge points will be
recommended.
       End if
   Else If (the current knowledge point has not be mastered)  Then
       If (the current cognitive ability is "high")   Then
       the current knowledge point or the parallel knowledge points will be
recommended.
       Else If (the current cognitive ability is "low" or "medium")  Then
       the prerequisite knowledge points will be recommended.
  End if
End if.
```

Through the above two recommendation links, a list of knowledge points suitable for the learning objective can be recommended for the learner, and then the preferred resource can be automatically recommended when his or her chooses the recommended knowledge points for learning. Every time when the learner completes the content learning of a knowledge point, he or she needs to take part in a test to judge the mastery status of the knowledge point and update his or her cognitive ability.

7 Experiments

In this section, the recommended method is applied to the e-learning system of C language. The overall framework of the improved personalized learning system is shown in Fig. 5, which includes three function modules: course learning function, recommendation function and management function. Based on this platform, experiments are carried out in C language teaching to evaluate the feasibility and effectiveness of the recommended method.

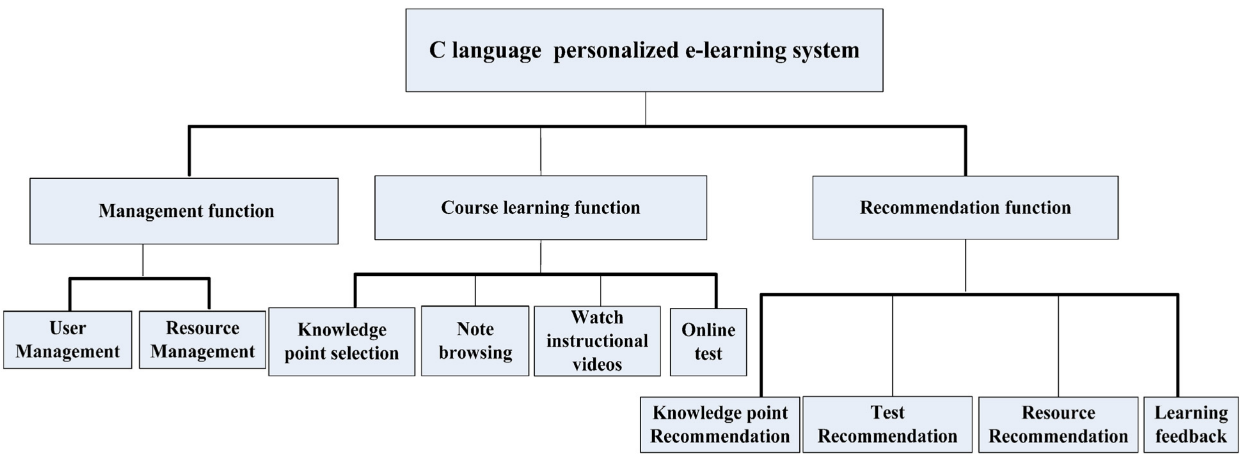

Fig. 5. Overall architecture of C language personalized e-learning system

7.1 Experiment Design

Method Application. The proposed recommendation method is applied to the existing C language e-learning system. When the learner logs on to the e-learning system, the system automatically captures the learner model information, such as name, specialty, learning preference and cognitive ability, learning knowledge points, etc. After the target knowledge point is selected, the system automatically recommends the list of knowledge points and the learning resources preferred by the learner. As shown in Fig. 6, learner S can learn the corresponding knowledge points after choosing “The character data” of the target knowledge point, if there is no learner behavior data, and then it can present preferential text resources. At the same time, based on the reasoning rules of course ontology in 6.1, “Integer data” and “Float data” as prerequisite knowledge points and “Data type conversion” as successor knowledge point is recommended. After learning the current knowledge point, the learner needs to click on the “test section” hyperlink at the bottom of the page. The system will enter the test page to evaluate the learner’s learning situation. In the test feedback page, the system will judge the learner’s mastery of the knowledge point based on his or her test results, and calculate the learner’s cognitive ability. Then, Algorithm 1 is used to recommend knowledge points and learning resources for the learner to follow up. As shown in Fig. 7, the feasibility of the recommendation mechanism is verified.

Fig. 6. Knowledge point and learning resource recommendation

Fig. 7. Test feedback and subsequent knowledge points and resource recommendation

Experimental data. In this study, 70 students in Shandong University were randomly divided into two groups with 35 students in each group, the experimental group and the control group. As this course is a basic course of programming, students have strong learning needs and interests. Under the careful preparation and guidance of the teachers, the students in the experimental group and the control group were able to skillfully carry out learning activities based on the online learning system. Since the experimental subjects were newly enrolled freshmen, the impact of learning experience on the learning effect was negligible.

Experimental methods. In this experiment, the experimental group and the control group were set up. The students in the experimental group conducted their learning activities on the online learning platform using the proposed recommendation method, while the students in the control group conducted their learning activities on the online learning platform without the recommendation function. The resources on both platforms were the same. The content of C language course is divided into 10 chapters and 30 sections, 264 multimedia learning resources are designed, 60 sets of exercises and 1 test feedback discussion area. At the same time, each learner is required to complete knowledge points, exercises and test feedback.

At the end of the course, the two groups were given a final test at the same time. The study performance and study efficiency of the two groups were statistically and comparatively analyzed, and the satisfaction of the experimental group in three aspects of learning experience, study performance and study time was evaluated (Yes/No).

7.2 Experimental Results

Fig. 8 compares and analyses the learning efficiency of knowledge points between the experimental group and the control group (KP is the abbreviation of knowledge points in the figure). The results show that the average learning time of the former is significantly less than that of the latter, and the learning efficiency is higher.

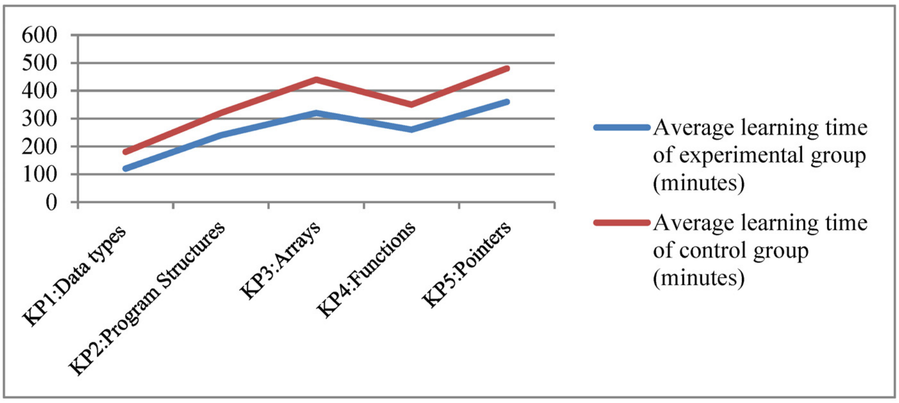

Fig. 8. Learning efficiency of experimental group and control group

Table 3 shows the comparative analysis data of the two groups of students after the end of the course. Since the experimental subjects were freshmen, it was assumed that the knowledge level of the two groups before the experiment was basically the same, with no significant difference. After one semester of study, the average score of the experimental group was 7.81 points higher than that of the control group, and $p<0.01$, indicating that the learning effect of the experimental group was significantly better than that of the control group.

Table 3. Learning effect statistics

	Final test			
	N	Mean value	Standard deviation	Sig. (two-sided test)
Experimental group	35	78.68	9.835	0.009
Control group	35	70.87	10.003	

After the end of the course, the students in the experimental group were evaluated on their satisfaction with learning motivation, learning experience and learning time (yes/no). After investigation and statistical analysis, the results were 89.2%, 80.4% and 92.5%, respectively. t can be seen that students give high recognition on whether it is beneficial to enhance learning motivation, improve learning experience and shorten learning time.

7.3 Discussion

This study was applied to a small range of C language course, and 35 students in the experimental group experienced the “knowledge recommendation” and “resource recommendation” functions of the C language personalized learning system. On the surface of the results, students in the control group had significantly higher gpas. In terms of satisfaction, most students affirmed the role of the recommendation mechanism, and believed that recommendation based on personalized resources could enhance learning motivation and improve learning efficiency. This is because the proposed recommendation method can recommend suitable and personalized learning resources for learners and realize personalized learning.

In addition, through interviews with students and teachers in the experimental group, it is found that students above the average are more likely than those with higher scores to accept the guidance of the recommendation method. Most of these students learn knowledge points and do test questions according to the systematic recommendation, so that they can carry out the learning process step by step and smoothly. On the other hand, some excellent students with high scores are more independent, do not fully believe in the role of system recommendation, and sometimes choose their own learning content to study, resulting in a relatively low degree of satisfaction in learning experience.

To sum up, compared with the typical recommendation strategies based on collaborative filtering [2], content-based [14] and knowledge-based [18], the recommendation method in this paper can recommend knowledge points based on the relationship between fine-grained knowledge points, dynamically calculate the learner's cognitive ability based on the feedback data of his or her test, and then recommend personalized learning content and resources based on the learner's cognitive ability, so as to ensure the completion of his or her personalized learning objectives. This recommendation method can be widely applied to online platforms in the complete learning process (including knowledge points, exercises and test feedback), such as the popular Massive Open Online Courses (MOOC) and Small Private Online Course (SPOC) platforms.

8 Conclusions

This research proposes a personalized learning resource recommendation method based on course ontology and the learner's cognitive ability, and applies it to online learning of C language course. Firstly, the teaching content of C language course is described and packaged by using Protégé which is a visual ontology modeling tool, and the course knowledge ontology database is defined. Then, the learning resources are described and organized based on the course ontology. Lastly, the recommendation method of personalized learning resource integrating the course ontology, the learner's cognitive ability and learning preference are discussed. A personalized learning resource recommendation system is designed and implemented, and the practice is carried out in real teaching to verify the feasibility and validity of the proposed recommendation framework.

The next step is to apply the C language personalized learning system on a large scale, collect the learner's online learning behavior data, further verify the recommendation effect, analyze the factors affecting the learner's online learning effect, and improve the proposed recommendation method.

Acknowledgements

This research is supported by the National Science Foundation of China (61472229, 31671588 and 61602278), the Education Ministry Humanities and Social Science Project of China (16YJCZH012, 16YJCZH041, 16YJCZH154), Sci. & Tech. Development Fund of Shandong Province of China (2016ZDJS02A11, 2014GGX101035 and 2014BSB01020), the Opening Fund Key Laboratory of Ministry of Civil Affairs (NDRCCPICC201602), the Taishan Scholar Climbing Program of Shandong Province, SDUST Research Fund (2015TDJH102), Qingdao City Philosophy and Social Science Planning Project (QDSKL1701093), Education Department's Cooperative Educational Project of School and Research (201801037127), SDUST Excellent Teaching Team Project (JXTD20180505 and JXTD20170503), and SDUST Research on Education and Teaching (QX2018M27).

References

[1] T.W. Malone, K.R. Grant, F.A. Turbak, S.A. Brobst, M.D. Cohen, Intelligent Information Sharing Systems, Communication of the AVM 30(5)(1987) 390-402.

[2] F. Yang, M.J. Wang, R.M. Shen, P. Han, Community-Organizing Agent: An Artificial Intelligent System for Building Learning Communities Among Large Numbers of Learners, Computers & Education 49(2)(2007) 131-147.

[3] M. Salehi, Application of Implicit and Explicit Attribute Based Collaborative Filtering and BIDE for Learning Resource Recommendation, Data & Knowledge Engineering 87(1)(2013) 130-145.

[4] C. Min, et al., The personalized recommendation model design of content in the ubiquitous learning——taking “Learning Cell” for example, Modern Educational Technology 21(21)(2011) 13-18.

[5] A.K. Milicevic, B. Vesin, et al., E-Learning personalization based on hybrid recommendation strategy and learning style identification, Computers & Education 56(3)(2011) 885-899.

[6] P. Dwivedi, K. K. Bharadwaj, E-learning recommender system for a group of learners based on the unified learner profile approach, Expert Systems 32(2)(2013) 264-276.

[7] S.S. Wan, Z.D. Niu, An E-learning recommendation approach based on the self-organization of learning resource, knowledge-based Systems, S0950705118303204 (2018) 71-87.

[8] Wan, Shanshan, Z. Niu, An e-learning recommendation approach based on the self-organization of learning resource. Knowledge Based Systems 160(NOV)(2018) 71-87.

[9] C.M. Chen, C.Y. Liu, M. H. Chang, Personalized curriculum sequencing utilizing modified item response theory for web-based instruction, Expert Systems with Applications 30(2)(2006) 378-396.

[10] Q. Jiang, Research on support model and implementation mechanism of adaptive learning system, [dissertation] Northeast Normal University, 2012.

[11] X.H. Tan, Personalized course generation & evolution based on a recommendation system and genetic algorithms, [dissertation] Shanghai Jiao Tong University, June 2013.

[12] P. Karampiperis, A. Koukourikos, G. Stoitsis, Collaborative filtering recommendation of educational content in social environments utilizing sentiment analysis techniques, Recommender Systems for Technology Enhanced Learning (2014) 3-23.

[13] J. Luo, F, Dong, J. Cao, et al., A context-aware personalized resource recommendation for pervasive learning, Cluster Computing 13(2)(2010) 213-239.

[14] L. Liu, G. Koutrika, S. Wu, Learning assistant: a novel learning resource recommendation system, 2015 IEEE 31st International Conference on Data Engineering, 2015.

[15] J. Shu, X. Shen, H. Liu, A content-based recommendation algorithm for learning resources, Multimedia Systems 1(2017) 1-11.

[16] K. Aleksandra, et al., Enhancing E-learning systems with personalized recommendation based on collaborative tagging techniques, Applied Intelligence 1(2017) 1-17.

[17] K. Aleksandra, B. Vesi, I. Mirjana, Social tagging strategy for enhancing E-learning experience, Computers & Education 118 MAR (2018) 166-181.

[18] J.K. Taru, Z. Niu, A. Yousif, A hybrid knowledge-based recommender system for E-learning based on ontology and sequential pattern mining, Future Generation Computer Systems 72(JUL)(2017) 37-48.

[19] M. Rani, O.P. Vyas, An ontology-based adaptive personalized E-learning system, Assisted by Software Agents on Cloud Storage, Knowledge-based Systems 90(DEC)(2015) 33-48.

[20] J.L. Xia, Z.H. Cao, Personalized exercise recommendation algorithm combining learning objective and assignment feedback, Journal of Intelligent & Fuzzy Systems 35(3)(2018) 2965-2973.

[21] Q. Zeng, Z. Zhao, Y. Liang, Course ontology-based user’s knowledge requirement acquisition from behaviors within E-learning systems, Computers & Education 53(3)(2009) 809-818.

[22] X.L. Diao, Q.T. Zeng, H. Duan, F.M. Lu, C.H. Zhou, Personalized exercise recommendation driven by learning objective within E-learning systems, International Journal of Performability Engineering, 14(10)(2018) 2532-2544.