Research on the Strategy of E-Learning Resources Recommendation based on Learning Context

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***Abstract*—E-learning has gradually become an important learning modality in modern society. How to present the suitable and high-quality learning resource to students from massive learning resources is particularly important. Personalized recommendation technology is one of the effective solutions. However, because of the lack of consideration of learning context information, the existing learning resource recommendation methods cannot effectively solve the problems such as knowledge navigation loss and learning topic drift. In order to solve these problems, this paper proposes an e-learning resource recommendation method based on learning contexts. By constructing the learners' learning context map and "knowledge-resource" context correlation model, combining with the personalized recommendation technology, the learners are treated with learning resources that fit their learning goals, knowledge ability and individual preference. This strategy can help learners to grasp the knowledge system and learning direction, and improve their learning efficiency.**

Keywords—E-learning; Personalized Recommendation; Learning Context

I. Introduction

With the development of E-learning and E-learning systems, learners are provided with a large number of various learning resources, which greatly enriched their cognitive level. However, when learners face quality uneven and widely distributed learning resources, they may face the problem of knowledge navigation loss and learning subject drift. How to help learners to obtain the appropriate learning resources from the massive data and improving the learning efficiency have become a research hotspot. At present, personalized recommendation is considered as one of the effective method to solve this problem. Besides, many researchers have done a lot of research about the personalized recommendation. Yu Z, Nakamura Y, Jang S, et al proposed a Strategy of Ontology-Based Semantic Recommendation for Context-Aware E-Learning [1]. L Sabine Graf proposed a method based on Felder-Silverman learning style table for personalized learning resources recommendation [2]. Yang Y J and Wu C proposed an AACS method, which used the ant colony algorithm and the Kolb learning style model [3]. Yang Lina have constructed a contextual learning resource recommendation method by studying the formal representation of ubiquitous learning context [4]. Li Hui and his Research team proposed a context-based collaborative filtering recommendation algorithm, which improved the user similarity calculation formula by introducing the learning context information [5]. Although the above researches improve the recommended quality by taking account the introduction of context information, there are deficiencies in predicting learners' learning behavior and propping learners' learning path due to the lack of context information and neglecting the relationship of each learning context. This paper analyzes the context information from the three aspects of learners, domain knowledge and learning resources. By constructing the learning context map and the knowledge-resource context correlation model and combining with the personalized recommendation technology, the learners can be provided with learning resources which meet their learning goal, knowledge ability and personality preference, so as to further solve the problem of information overload, knowledge trek and learning topic drift.

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II. Related Works

A. Personalized Recommendation Methods

Personalized recommendation methods can be mainly divided into content-based method, collaborative filtering method and hybrid recommendation method. Different recommended methods have their own advantages and disadvantages.

The core of content-based recommendation is to produce the recommendation by analyzing the user model and calculating the similarity of feature of content about recommended object [6]. This recommendation algorithm has strong adaptability, without user's historical data is not required and the problem of data sparseness cannot acquire, but there are some shortcomings such as poor recommendation effect on complex structures such as audio and video resources.

Collaborative-Filtering(CF) algorithm is the most widely used recommendation method. It is divided into user-based CF and item-based CF. Its core idea is to find the user’s or item’s nearest neighbor by the user-project scoring matrix, and to predict the target user's rating on the recommended resources based on the nearest neighbors’ score [7]. Therefore, the core problem is the users’ similarity calculation. Most commonly, the formula of the Pearson correlation coefficient is used. For example, user-based

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CF, The Similarity $sim(u_i, u_j)$[6] represents the similarity of user i and user j.

$$sim(u_i,\ u_j) = \frac{\sum_{i\in I_{ij}}(R_{i,c}-\overline{R_\iota})(R_{j,c}-R_j)}{\sqrt{\sum_{c\in I_{ij}}(R_{i,c}-\overline{R_\iota})^2}\sqrt{\sum_{c\in I_{ij}}(R_{j,c}-\overline{R_J})^2}} \quad (1)$$

I_{ij} represent the items, which are scored by user i and user j. The score $R_{i,C}$ is that user i evaluates the item c. The score $R_{j,C}$ is that user j evaluates the item c. $\overline{R_\iota}$ and $\overline{R_J}$respectively represent the score of user i and user j.

When the similarity of the users is gained by the eq. (1), the target item' score of the user can be calculated by the equation (2)[6]. Thus, every target item's predicted rating is acquired. The most highly rated items are recommended to the user.

$$PR_{u,c} = \overline{r_u} + \frac{\sum_{i\in N_u} sim(u,\ i)(\gamma_{i,c}-\overline{r_i})}{\sum_{i\in N_u}|sim(u,\ i)|} \quad (2)$$

$PR_{u,c}$ is user u's predicted rating for item c. $\gamma_{i,c}$ is the score of item c evaluated by user i . $\overline{r_u}$ and $\overline{r_i}$ each represents the average score of user i and user j.

Collaborative filtering algorithm can push complex unstructured resources, and is also good at discovering new interests of users. But it has problems of "cold start" and "matrix sparse".

Hybrid recommendation method combines two or more recommendation methods to achieve better performance with fewer of the weaknesses than other individual recommendation method. There are two main ideas for the hybrid recommender, they are hybrid recommendation results and hybrid recommendation strategy. In the first one, the results are produced by two or more recommended methods, and processed by some methods to get the finally preferable results. Such as, the weighted hybrid recommendation strategy, the mixed hybrid [9]. In the second one, recommender uses a recommendation strategy as a framework and mixes additional recommendation strategies [8,9]. The most common practice is to combine collaborative filtering recommendation techniques with other recommended techniques to overcome the "cold start problem", such as Claypool's proposed combination of content filtering and collaborative filtering [10].

B. Context

So far, there are many definitions of the context. In 1994, SCHILIT and THEMER firstly proposed the word "context-aware", they think the context is based on the location, the surrounding people and objects around the iconic objects, as well as the changes of these objects [11]. Brown PJ, who think that the context is a number of specific factors, such as location, time, temperature, etc. [12]. Ryan defined the context as the user's location, environment, logo, and time [13]. What is widely accepted and cited now is the definition proposed by Dey [14] in his doctoral thesis in 2000: "Context is any information that can be used to characterize the situation of an entity. An entity is a person, place or object that is considered relevant to the interaction between a user and an application, including the user and application themselves". According to Dey's definition of context, this study considers that context is a combination of information used to characterize the entity that participates in the interaction.

III. LEARNING CONTEXT INFORMATION

Learning context refers to the learning situation. Based on the Dey's definition of context [14], this study expands this definition and divides learning context-related entities into three categories: "learners related context", "learning resource related context" and "domain knowledge related context".

A. Learners Context Information

Learners refers to users of an e-learning system. From the perspective of learners, this study divides the learning context information into personal information, current knowledge abilities and learning behaviors. The user's personal information represents the user's static information. The current knowledge abilities and learning behaviors indicate the dynamic information of learners. To express the learner's context information, we defined it as eq. (3).

$$L_C = \{L_p,\ Ls_n,\ Lm_n\} \quad (3)$$

Where, L_C is the learner's contextual information.

L_p is the personal information, In the learning system, there are a lot of personal contextual information which can be obtained. This study suggests that they are the most easy-obtain information of the learners' academic information including: school, professional, grade and subject information, and using quaternion formalized representation, that is, L_p = {school, profession, grade, subject}.

Ls_n represents the learner's current knowledge abilities context element set. The learner's current knowledge abilities [15] reflects the learner's knowledge of the domain of knowledge and the grasp of the context. It's also an important basis for learning resources recommended. A context information record of knowledge state is recorded by the following formula.

$$S_i = \{ID_i,\ Score_i\} \quad (4)$$

$$Ls_n = \{S_1, \ldots S_i, \ldots S_n\} \quad (5)$$

Where S_i is one context record of learner's current knowledge abilities. ID_i is the knowledge points that the learner learns. $Score_i$ is test scores of knowledge points. Ls_n is a set of S_i.

Lm_n represents the learner's learning behavior context set, which is mainly the behavioral record of the learner's access to the resource, that is, the information of resources accessed and the behavior of the resource accessing, including: downloading, printing, collecting and browsing time information. A record of learning behavior context is represented by the following formula.

$$M_i = \{R_i, A_i\} \quad (6)$$

$$Lm_n = \{M_1\ ,\ \ldots\ ,\ M_i\ ,\ \ldots\ ,\ Mn\} \quad (7)$$

where R_i represents the resource accessed by the learner accesses and A_i represents the behavior that occurs when the learner accesses the resource. Lm_n is a set of M_i.

B. Domain Knowledge Context Information

Discipline domain knowledge refers to all knowledge within a particular discipline [16]. The context information of domain knowledge is composed by knowledge point information and knowledge association rules. Where the knowledge point information is composed by basic information such as knowledge subject label and subject, course, chapter of knowledge points. The relationship between knowledge points includes generational relations, dependencies, reference relationships, fraternal relations and free relationships [17]. This study simplifies the relationship between knowledge points into parent-child relationship and brotherhood. A knowledge points context is represented by the following formula.

$$N_i = \{ N_{info}, N_{fath}, N_{child}, N_{bro} \} \tag{8}$$

$$LN_n = \{N_1 , \dots , N_i , \dots , N_n\} \tag{9}$$

Where N_i is a record of domain knowledge context information. N_{info} is current knowledge point information. N_{fath} is N_{info}'s paternal knowledge context. N_{child} is N_{info}'s child knowledge context. N_{bro} is N_{info}'s brotherly knowledge context. LN_n is a set of N_i.

C. Learning Resource Context Information

Learning resources are closely related to learner context and domain knowledge context. So, this paper chooses the keywords, discipline, and the knowledge topic of the resource as the resource context information. We defined it as eq. (10).

$$R_i=\{R_{key} , R_{disci} , R_{subj}\} \tag{10}$$

$$LR_n = \{R_1 , \dots , R_i , \dots , R_n\} \tag{11}$$

Where R_i is learning resources context information. R_{key} is learning resource's keywords. R_{disci} is the subject of the learning resource. R_{subj} is knowledge topic of learning resource. LR_n is a set of R_i.

IV. A HYBRID RECOMMENDATION MODEL BASED ON LEARNING CONTEXT

This study adopts a hybrid recommendation strategy based on content-based recommendation and collaborative filtering recommendation. The general process of this hybrid strategy model is as follows. Firstly, by the learner's current knowledge abilities context information, learning context map and the "knowledge-resource" contextual correlation model, we can analyze and predict the learner's learning paths.

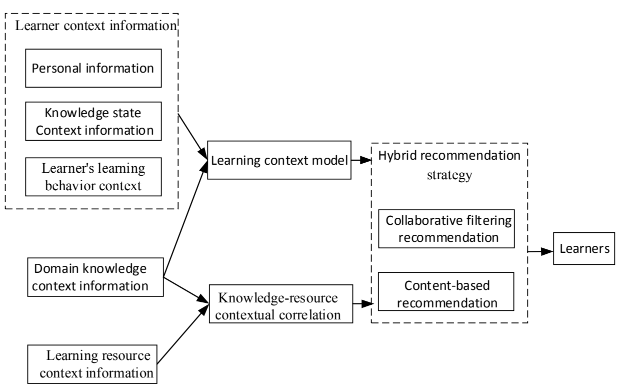

Fig. 1. A hybrid recommendation model based on learning context.

Secondly, we use the content-based recommendation method to recommend learning resources which meet the learning paths. Finally, the collaborative filtering recommendation can get the preferable resources which meet the learner's learning goal and preference. This hybrid recommendation model correctly guides the learners' learning behavior and improves their learning efficiency. The recommendation model is shown in Figure 1.

A. The Construction of Learning Context Model

The learning context model is a generalization, summary and analysis of learners' learning knowledge by the learner's knowledge abilities context and domain knowledge context map, including learners' knowledge points hash area and the tree of learning knowledge context. The knowledge point hash area represents the scattered knowledge points which learners have been mastered. The knowledge context tree is composed of the learners' learning points and the relationship between them. Therefore, the model can clearly reflect the distribution of knowledge points which the learners have learned. It is helpful to analyze and predict the learning behavior of learners.

In the learning context model, we get the learner's context information L_C in the learning system, and locate the discipline area of the learner's current study according to the personal contextual information L_p. We also can get the learner's current knowledge abilities in the field by the learner's knowledge abilities context Ls_n. Then, according to the location of the disciplines, from the knowledge database to get the knowledge points and the knowledge of the relationship between the context of the information set N_n, according to the domain knowledge map construction methods and processes, we construct domain knowledge context map, and show the correlation between knowledge points [18]. Finally, the learner's knowledge abilities context Ls_n is mapped into the domain knowledge context map, thus we can get the learners' learning context model in this domain knowledge field. The model of learning context is shown in Figure 2.

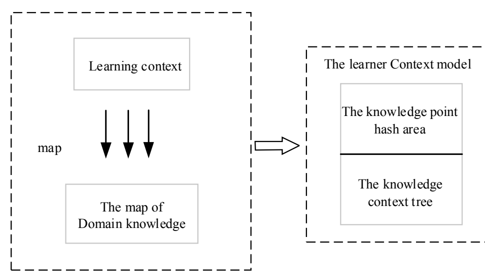

Fig. 2. The constructive mechanism of learning context model.

B. The Construction of Correlative Model of "Knowledge-Resource" Context

In the learning system, resources are closely related to the knowledge points, and each resource has the basic information properties of its learning subject, chapter and learning object when it is created. In this study, the TF-IDF [19] algorithm is used to extract the knowledge subject and the weight vector set contained in the resource, and the resource keyword and its subject are obtained from the resource basic information database. Thus, the context vector set LR_n of the learning resources is obtained by eq. (10). And then the knowledge subject of the learning resource is matched with the domain knowledge context set $LN_n$to construct the association relation model of n: n between learning resources and knowledge points. The model of "knowledge-resource" context is shown in Figure 3.

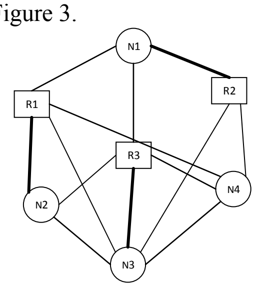

Fig. 3. The model of "knowledge-resource" context

C. The Implementation of Recommendation Algorithm

The recommendation algorithm is the most important part of the whole recommendation system. The specific algorithm of this paper is as follows:

Step one, the learner's personal contextual information Lp is obtained from the learner's context database, and the current subjects of the learner's learning is positioned according to the Lp. Thus, we can acquire the domain knowledge context information N_n and the learning resource context information R_c.

Step two, according to the learning context map construction mechanism and the "knowledge - resource" context correlation mechanism, we construct the learning context map and knowledge - resource association model.

Step three, the knowledge state information set Ls_n in the current subject field of the learner is obtained. It contains the learning knowledge, the historical knowledge and the unit-test information.

Step four, if Ls_n is empty, proceed to step eight. Otherwise, obtaining the knowledge of the current learning or the latest learning knowledge of the learner, analyzing the learning path of the learner according to the learner's learning profile and the domain knowledge map, predicting the collection of knowledge units NT_n that the learner will learn or should learn.

Step five, if the predicted knowledge point NT_i is in the learner knowledge hash area, it will be directly added into the collection NT_n. If the knowledge point NT_i is in the learner's knowledge context tree, it will be added into NT_n , at the same time, determining whether there is knowledge NT_i that unqualified in the survey on the path of the context tree associated with the knowledge point, if it exists, then, it also will be added to the collection NT_n.

Step six, according to the knowledge unit set NT_n and the "knowledge-resource" context correlation model, the learning resource set R_n is obtained by the content-based recommendation arithmetic. And the learning behavior information related to all the R_n in the system is also obtained.

Step seven, the "learner-resource" scoring matrix of R_n is constructed using the implicit score [20] by the learning behavior. The R_n will be filtrated and sorted again. Thus, R'_n is gained and recommended to learner, which conforms to learner's learning objective and also accords with personal interests of the learner.

Step eight, if Ls_n is empty, that is, the current learner is a new user. At this time, according to the learner's contextual information, we use the content-based recommendation arithmetic to recommend appropriate resources for the learner. Those resources are gained by the field of domain knowledge spectrum and "knowledge - resource" context correlation model, and, which are also closely associate with the knowledge Points.

V. Design and Implementation of Hybrid Recommender System Based on Learning Context

The proposed hybrid recommendation model shows the learning resource recommendation should take account the following aspects in the design. The first one is to acquire contextual information, including learners' contextual information, contextual information of learning resources and domain knowledge, which is the basis of recommendation system. The second is to build knowledge resource association and learners learning context map. Finally, it is necessary to recommend resources that both meet the learner learning objectives and the learner's personal preferences. In view of the above requirements, a hybrid recommendation system framework based on the learning context is shown as figure 4:

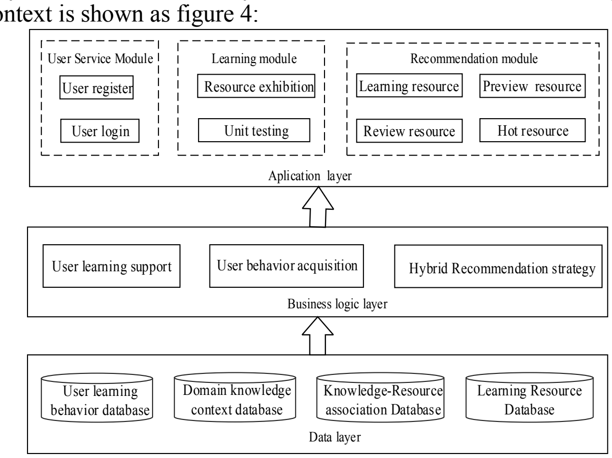

Fig. 4. A hybrid recommendation system framework based on learning context

The entire recommendation system consists of three modules: user service module, user learning module and user recommendation module. The user recommendation module includes the learning resource recommendation area, the review resource recommendation area, the preview resource recommendation area and the popular resource recommendation area. The learning resource recommendation area is a high-quality learning resource recommended for the learners' current learning knowledge. The review resource recommendation area is the relevant learning resource recommended for the unqualified knowledge on the learners' current learning route. The preview resource recommendation area is predicted the knowledge that most likely to learn by users and recommend the relevant learning resources based on the learner's current knowledge, state, context and domain knowledge. Popular resource recommendation area, according to the relevant areas of learning and recommend the highest heat in this area and meet the personal preferences of the relevant resources.

The whole system structure is developed by using MVC design framework, and java web development technology is adopted. The front end of the system is mainly the presentation of the page and the window of user's operating. System background service is responsible for business logic processing, including the acquisition and processing of learning context user learning context and domain knowledge map construction, knowledge resources associated strategy, and the implementation of hybrid recommendation mechanism. The database is the storage of system-related data.

VI. Conclusion and Future Work

This paper analyzes the theory of context and personality recommendation, and the learning context information that should be considered in the recommendation of learning resources. It expounds the relationship between learner context and domain knowledge context and also describes the relationship between domain knowledge context and learning resource context. This article puts forward a method of constructing a learner's context map model and a "knowledge - resource association" model, which combines with the hybrid recommendation technology to construct a hybrid recommendation strategy model based on learning context. According to this model, this paper has shown the design solution of the intelligent recommendation system based on learning context. The practice has proved that this recommendation model can analyze learners' learning context in a comprehensive way, and provide learners with learning resources that conform to learners' learning goals, knowledge systems and personality preferences. In the process of learning resources recommendation, how to acquire more advanced user context elements such as learners' emotional status, mediate learners' psychological state by pushing related resources is the difficulty of follow-up research.

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