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## Study on and Realization of Hybrid Recommendation-Based Adaptive Learning System

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### ABSTRACT

Adaptive Learning System (ALS) is an effective solution for the supporting service to personalized learning. Recommending personalized contents according to the differences of learners is the core mechanism of ALS. Based on the modeling of learners and domain knowledge, this study uses the content and collaborative filtering-based hybrid recommendation to realize a new-type personalized proactive recommendation mechanism. Experiment results show that the findings of this research could well recommend proper learning contents suitable for learners to improve their learning effect.

**Key words:** ALS, learner model, domain knowledge model, hybrid recommendation

### INTRODUCTION

With the development of computer network technologies and the socialization and life-long trend of learning, the online learning systems emerge as time requires. However, traditional online learning systems are usually oriented on the systems themselves without enough consideration of the differences between learners in their personalized demand, ignoring the teaching theory of “focusing on learners”, furthering presenting the problem of no obvious effect of online learning. ALS is an effective solution to support personalized learning that could well make up for the shortage of traditional online learning systems. Targeting the individual differences of learners, this system mainly relies on personalized recommendation mechanism to realize effective screening and reorganization of learning contents and provide personalized contents suitable for current learners in a dynamic manner.

ALS evolves from the Intelligent Teaching System (ITS) and adaptive super-media system and has got the attention of multiple domestic and foreign researchers. Currently, studies on ALS mainly focus on user modeling, personalized navigation and Web semantics. Among typical research findings are ELM-ART (Weber and Brusilovsky, 2001), AHA (De Bra *et al.*, 2006), ApeLS (Conlan, 2008) and A-Tutor (Pinde and Kedong, 2002), etc.

The core of ALS is to recommend personalized learning contents based on the differences of learners, making the recommendation technology the most critical part in the ALS system. To a great extent, the recommendation technology decides if the system is a good one or a bad one. Currently, major recommend technologies include collaborative filtering recommendation, contents-based recommendation, association rules recommendation and hybrid recommendation

technology (Zhou, 2009). Of them, collaborative filtering is the earliest and most frequently used technology in the recommendation system. It mainly uses the similarity value of the target user to adjacent user groups to determine suitable contents for the target user (Kim *et al.*, 2006; Sarwar *et al.*, 2001). Currently, this technology is adopted in recommendation systems such as Amazon, CDNow and MovieFinder, etc. (You and Ye, 2006). The contents-based recommendation which is the continuance and evolvement of the collaborative filtering technology, recommends products to target users based on the matching value between the users and the resources in the system and the similarity of resource information. Currently many commercial movie websites choose this technology (Adomavicius and Tuzhilin, 2005; Li, 2012). Hybrid recommendation is a new type of recommendation technology integrating multiple types of recommendation to exert their advantages.

Judging from all researches above, it can be seen that, currently, studies on ALS are still in the exploration stage with many vacant fields requiring further work. Personalized recommendation technology, thought quite mature, is mainly centered on e-commerce field. Therefore, how to effectively integrate the recommendation technology into the ALS system to improve the recommendation accuracy of the system is worth our study. This study mainly studies how to use contents-based and collaborative filtering-based hybrid recommendation technology in ALS to realize the system's recommendation mechanism.

## **METHODOLOGY**

**Design of overall structure of hybrid recommendation-based ALS:** According to the demand of learning, the roles in users in ALS mainly include learners and course teachers (also working as administrators). Therefore, an ALS system could be divided into two major modules, course learning and course management. Course learning is the system's core module and learners usually need a series of works which include systematic user modeling, hybrid recommendation and pre-treatment of learning contents, before starting personalized learning under the support of learning tools and relevant service components of the system. Course teachers or administrators could conduct uniform set-up and management on user models, learning logs, course contents, teaching strategy and learning resources through various managerial functions provided by the system. The overall structure is shown below in Fig. 1.

The operation mechanism of this system mainly includes five steps below.

When a learner logs on the system to learn for the first time, he/she is required to fill in his/her personal information (mainly including password, name, gender, age and profession) to complete registration. Afterwards, under the guidance of the system navigation, the learner could select the learning style suitable for him/her or could complete a testing questionnaire of the learner's learning style-Felder-Silverman Index of Learning Styles, ILSs) (Felder and Silverman, 1988). Then, through the learner modeling component, the system would process such information and store the information in the user model database.

In the learning process, the system would use the logger for real-time analysis and record of the learner's current access route and update the learner's learning record data timely.

Course teachers use the management component to define the course's knowledge point structure, teaching strategy and learning resource, etc, to establish the domain knowledge model and store the information in the database, providing data support for following system recommendation service.

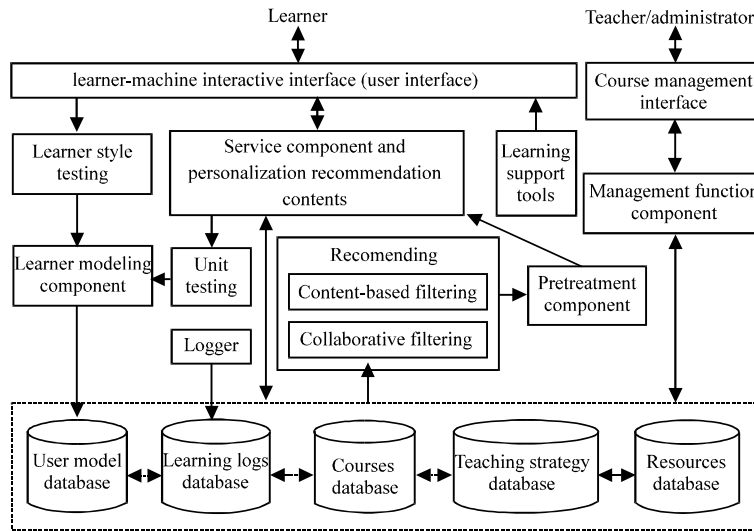


Fig. 1: Overall structure of ALS

Based on current model characteristics of the learner, the system would use contents-based and collaborative filtering-based hybrid recommendation technology to match the knowledge object of the course and the users and identify proper knowledge object, forming the segment sequence of the learning contents. Afterwards, through contents pretreatment component, these learning contents segments are reorganized and would provide personalized learning to learners with the support of the system’s learning tools and relevant service components.

After completing each knowledge unit, the learner is expected to complete the dynamic unit testing presented by the system. Afterwards, the system would use learner modeling component analysis to process the learner’s testing score and update the user model database in a timely manner, providing referential grounds for further personalized recommendation service.

**Hybrid recommendation-based ALS system modeling:** In ALS, system modeling is a particularly important step and the basic guarantee for the system to realize personalized recommendation mechanism. This study mainly conducts modeling from two dimensions, the learner model and the domain knowledge model.

**Learner modeling:** Learners are the target of personalized recommendation of the ALS system and also the reference model of system recommendation. Arguably, the accuracy of the contents of ALS recommendation is subject to the influence of the learner model to a great extent. In this system, by collecting and processing learner-personalizing information on a real-time basis, the learner modeling component could realize learner modeling. To truly reflect the current learning state of the learners, this study establishes the learner model in the form of quadruples:

$$\text{Learner model} = (\text{Base info, Learning style, Cognitive level, Learning records})$$

where, BaseInfo stands for basic static information of a learner, mainly including the learner’s login name, password, student number, name, gender, age and profession, etc.

Learning style refers to a learner's learning style. This system mainly adopts the famous Felder learning style model which includes four dimensions: Intuitive-Sensitive, Visual-Verbal, Active-Reflective, Global-Sequential. Concrete representing methods of learning styles could be: LearningStyle(Student) = ( $\langle D_1, ls_1 \rangle, \langle D_2, ls_2 \rangle, \langle D_3, ls_3 \rangle, \langle D_4, ls_4 \rangle$ ). Where,  $\langle D_i, ls_i \rangle (1 \leq i \leq 4)$  stands for the value of a dimension of the Felder learning style;  $D_i$  represents the styles of the four dimensions;  $ls_i$ , a fuzzy value ( $ls_i \in [0, 1]$ ), represents the value of  $D_i$ , the dimension of the learning style.

CognitiveLevel represents the learner's current cognitive level which contains how well the learner masters relevant knowledge points. This value domain could be initialized as "understanding", "comprehending", "mastering" and "applying" and would be updated dynamically based on the learning of each unit by the learner.

LearningRecords stands for the learner's learning records and highlights the access route of the learner in the learning process, mainly including number, access time, access duration, visitor, access address, number of knowledge point and access description, etc.

In this model, BaseInfo is of stable static information usually provided by a learner directly while registering; LearningStyle could be set up by the learner during registration or could be obtained through the learner completing online Felder learning style scale; CognitiveLevel and LearningRecords would both be dynamically updated during the learning process to lay the foundation for further providing satisfactory personalized learning resources to learners.

**Domain knowledge modeling:** The domain knowledge model is about the structurization of the domain knowledge and providing data resource to learners for their personalized learning. The establishment of a domain knowledge model requires decent knowledge structure system so that learners could build up the cognitive system for discipline knowledge. Under normal conditions, domain knowledge consists of several knowledge points with any two knowledge points having certain relations. Thus a directed graph is formed by the relations among these knowledge point (Garzotto *et al.*, 1995). Here we could use the form of an association table to represent the relations among the knowledge points. The directed graph formed by the knowledge points and the association table is  $G = (K, \{ \langle k_i, k_j \rangle, a_{ij} \})$ , where,  $K = \{k_1, k_2, \dots, k_n\}$  represents the knowledge point set;  $a_{ij} \in [0, 1]$  is the weight value of directed arc  $\langle k_i, k_j \rangle$ , representing the correlation level between knowledge points  $k_i$  and  $k_j$ . Therefore, the association table among knowledge points could be described as a square matrix of order  $n \cdot P_{n \times n}$ .

In the domain knowledge model, teaching strategy database could be used to store such information of the knowledge points as the importance, difficulty coefficient, styles and association rules, etc. The system could extract characteristics information of the knowledge points from the teaching strategy database and transform them into the forms of directed graph and matrix in turn for the calculation of the value of the similarity to the user model, providing data model to following system recommendation.

**Procedure and algorithm of hybrid recommendation-based ALS recommendation:** In the process of ALS recommendation, characteristics information of the learners and the domain knowledge would be extracted from the user model database and domain model database separately and association rules would be applied to calculate the value of the similarity of characteristics which would be effectively integrated through matrix rating method. Finally, based on the calculated similarity value, the system would recommend to learners the set of knowledge object

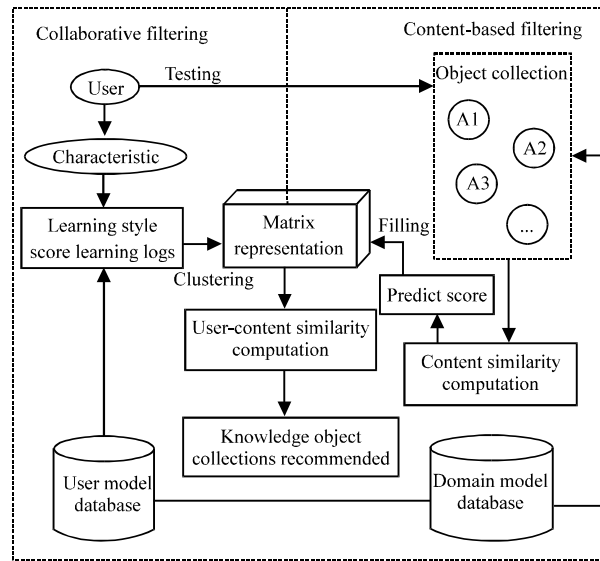


Fig. 2: Procedure of hybrid recommendation

suitable for their personal demand. In the learning process, learners usually need to go through a test after completing the learning of a knowledge unit and the system would update the learner's cognitive level parameter on a real-time basis according to the test score. The recommendation procedure is shown below in Fig. 2.

In this research, the algorithm of the ALS system's core recommendation is described below:

The system's input items: user's registration information, matrix of object characteristics values and the maximum value of the quantity of recommendation knowledge objects-N.

The system's output items: the recommendation results list: Top-N:

- According to the requirement of the contents filtering algorithm on well-structuring, the vacant values of the user-knowledge object testing score matrix would be filled and knowledge unit that have not been tested would have the initialized value of 0
- The user model would be established based on four dimensions: basic user information, learning styles, cognitive levels and learning records and  $Sim(LO)$ , the similarity of the target user, will be calculated. On this basis, the K-Means clustering algorithm is used to complete the clustering of users and the results are described in the form of  $User = \{u_1, u_2, u_3, \dots, u_n\}$
- Calculate the average score of the test scores of all users  $u$  in the User sequence and use it as the clustering center. Calculate the distance of current target user with the clustering center  $Sim(u_i)$ . Find out the category to which the target users belongs and the set of all other fictive users-the Fictive User-in the category
- Call in the knowledge contents characteristics values matrix algorithm to calculate the test score of each knowledge object  $k$
- Judge if this target users would go through knowledge unit test. If the judgment result is True, go to Step 7. If it is False, turn to Step 6
- Calculate the similarity of the target users and all users in Fictive User based on basic characteristics of the user (background information) and turn to Step 6
- Calculate the similarity of target users and to all users in Fictive\_User according to the knowledge unit test score of target users

- Calculate the neighbor user set of the current target users -- Neighbor\_User--according to the order of the sorting order of the similarity
- Calculate  $Sim(UO)$ , the similarity of Neighbor User with the knowledge object based on the clustering analysis on u.LearningRecord, the Neighbor\_User's learning records
- Recommend to the target users the first Nx knowledge object lists according to the sorting calculation of  $Sim(UO)$ , the similarity

**Experiments:** To test the efficacy of the system, we designed a series of experiments. The experiment object is 30 students randomly selected from the undergraduate computer education program. In the experiment process, these 30 students were randomly categorized into groups S1 and S2 with equal group members. Group S1 was the experiment group (registered users of the system); S2 was the comparison group (non-registered users of the system); then students of the two groups learned at the same time within the valid time of 100 min. The learning content was the first chapter, "Operators and Representations". After the learning they could make online test.

## RESULTS

**System realization:** After a series of pre-stage processes such as demand analysis, system modeling, database design and programming, we were able to develop a preliminary prototype of the ALS system. The system adopted B/S structure and MVC development mode with the development environment being Eclipse+JDK+Tomcat+SqlServer2010 and the development languages including Java, Xml, C language, VB, JavaScript and T-SQL, etc. Afterward, the system was tested with the content of the C Programming Language course: After a learner entered into this system, the system would, based on the current learner's learning style, cognitive level and learning records, present personalized contents and recommend relevant learning resources on a real-time basis. Because of the differences among learners in interface preference, learning styles and cognitive levels, the system would also present interfaces to learners with personalized characteristics. Figure 3 below shows the learning interface effect of a learner named Limin.



Fig. 3: ALS system interface

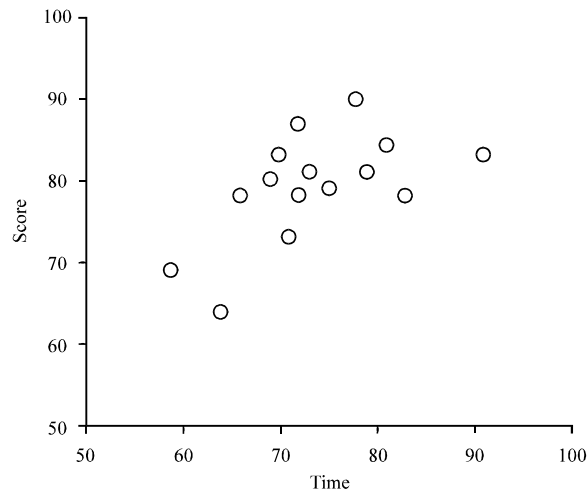


Fig. 4: Duration-score scatter points distribution of group S1

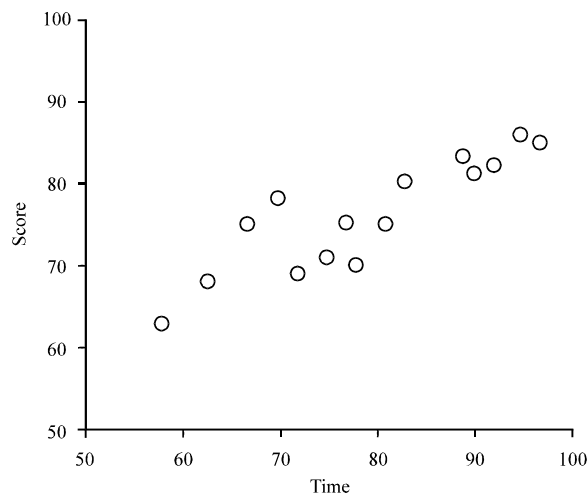


Fig. 5: Duration-score scatter points distribution of group S2

Figure 3 shows that this system mainly consists of four parts: (1) The upper column presents the system's major function menu, including course introduction, learning space, recommendation resource, online answers and student works, (2) The left column lists out current personalized learning information in the form of module, including the learner's login status (clicking on "learning management" could modify the learning style and submit works, etc), learning records and system recommendation resources, (3) The central column includes four sub-items, the learning target, knowledge structure, knowledge contents (able to be presented in multiple forms such as words, pictures, PPT and video, etc.) and the expanding knowledge and (4) The right column includes course announcement, learning calendar (clicking on days could show their own learning records) and the learning tools.

Finally, we collected the data of the learning duration and test scores of the students from the system and analyzed the distribution status of the data from the viewpoint of "duration-score" dimension. The results are shown in Fig. 4 and 5.



Table 1: Results of t-test

Group statistics						t-test for equality of means	
Group	N	Mean	Std. deviation	Std. error mean	t	Sig. (2-tailed)	
Time	S1	15	73.80	8.143	2.103	-1.468	0.153
	S2	15	79.27	11.907	3.074		
Score	S1	15	79.58	5.735	1.481	2.052	0.049

## DISCUSSION

Currently, studies on ALS mainly focus on user modeling, personalized navigation and Web semantics. Among typical research findings are ELM-ART (Weber and Brusilovsky, 2001), AHA (De Bra *et al.*, 2006), ApeLS (Conlan, 2008) and A-Tutor (Pinde and Kedong, 2002), etc.

The comparison between Fig. 4 and 5 shows that the duration and scores of students from Group S1 are relatively centralized with the duration-score dimension basically falling within the scope between (65.85) and (70.85). On the other hand, Group S2 students have a larger span and the learning scores and learning duration generally have a positive proportional relation. To further analyze the differences between students of the two groups, we used SPSS to conduct a t-test analysis with the results shown in Table 1.

Table 1 tells us that the average learning duration of students from the two groups were both over 70 minutes, with the standard deviation of Group S1 a little smaller than that of Group S2 ( $8.143 < 11.907$ ), showing that the average learning duration of Group S1 had smaller separation degree. Regarding the learning scores, students of the two groups both registered scores slightly above average, with the score of Group S1 outperforming Group S2 a little ( $79.58 > 76.37$ ,  $5.735 < 6.850$ ). Combining the t value and the Sig. (2-tailed) value we could further find out that learning duration  $t = -1.468$ ,  $\text{Sig} = p = 0.153 > 0.05$ , showing that students from the two groups did not differ much in learning duration; for the learning score,  $t = 2.052$ ,  $\text{Sig} = p = 0.049 < 0.05$ , showing that students of the two groups differed in learning scores. Therefore, out of comprehensive consideration, this system could improve the learner's learning effect to a certain extent.

## CONCLUSION

Combining the advantages of hybrid recommendation, this study introduces the contents-based and collaborative filtering-based hybrid recommendation technology into ALS, realizing a new-type proactive recommendation mechanism. This study describes ALS' system structure, operation mechanism, system modeling methods, recommendation procedure and algorithm as well as the realization method of the ALS system. Finally, this research designs a series of experiments to verify the efficacy of the system from the dimension of "duration-score". Experiments results show that the system could recommend personalized learning resource and further improve the learners' learning effects.

## ACKNOWLEDGMENT

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