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Computers & Education 44 (2005) 237–255

COMPUTERS & EDUCATION

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Personalized e-learning system using Item Response Theory

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Accepted 16 January 2004

Abstract

Personalized service is important on the Internet, especially in Web-based learning. Generally, most personalized systems consider learner preferences, interests, and browsing behaviors in providing personalized services. However, learner ability usually is neglected as an important factor in implementing personalization mechanisms. Besides, too many hyperlink structures in Web-based learning systems place a large information burden on learners. Consequently, in Web-based learning, disorientation (losing in hyperspace), cognitive overload, lack of an adaptive mechanism, and information overload are the main research issues. This study proposes a personalized e-learning system based on Item Response Theory (PEL-IRT) which considers both course material difficulty and learner ability to provide individual learning paths for learners. The item characteristic function proposed by Rasch with a single difficulty parameter is used to model the course materials. To obtain more precise estimation of learner ability, the maximum likelihood estimation (MLE) is applied to estimate learner ability based on explicit learner feedback. Moreover, to determine an appropriate level of difficulty parameter for the course materials, this study also proposes a collaborative voting approach for adjusting course material difficulty. Experiment results show that applying Item Response Theory (IRT) to Web-based learning can achieve personalized learning and help learners to learn more effectively and efficiently.

Keywords: Distance education; Learning strategies; Intelligent tutoring systems; Collaborative learning

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0360-1315/$ - see front matter
doi:10.1016/j.compedu.2004.01.006

1. Introduction

In recent years, numerous Web applications have been developed, such as portal websites (AltaVista; Google; Yahoo; YAM), news websites (CNN; Google News; Taiwannews), various commercial websites (Amazon; eBay), and so on, demonstrating the increasing maturity of the Internet. Consequently, the rapid growth of information on the Web (Lawrence & Giles, 1998) has created a problem of information overload (Berghel, 1997; Borchers, Herlocker, Konstanand, & Riedl, 1998), such that Internet users are unable to find the information they require (Arasu, Cho, Garcia-Molina, Paepcke, & Raghavan, 2001; Kobayashi & Takeda, 2000; Lawrence & Giles, 1999). To help Internet users to search more efficiently, many powerful search tools (Brin & Page, 1998; Chidlovskii & Glance, 2000; Direct Hit, 2000; Kleinberg, 1998) have been proposed, such as the Google search engine (Google), or the Citeseer website (NEC Research Institute ResearchIndex). Most of these search tools provide personalized mechanisms to enable users to filter out uninteresting or irrelevant search results. Restated, personalized service has received considerable attention (Rashid, Albert, Cosley, Lam, McNee, & Konstan, 2002; Herlocker & Konstan, 2001; Mobasher, Cooley, & Srivastava, 2000) recently because of information needs different among users.

Furthermore, recent surveys of network behaviors by Yam (The investigation of Yam) have shown that most users apply search engines to find information, and moreover Web learning is a growing trend. Learning via electronic appliances on the Internet is called e-learning (Barker, 2002), also known as distance learning, on-line learning (training) or Web-based learning, and helps learners learn by themselves through the Internet. According to the analysis of International Data Corporation (IDC) (International Data Corporation), the worldwide corporate e-learning market will exceed US$ 24 billion by 2004. The reason for the growth of is that it provides a convenient and efficient learning environment and practical utilities at anytime and anywhere. Many universities (E-learning in the University of Maryland), corporations (E-learning in Cisco), and educational organization (Distance Learning Resources Network (DLRN)) are developing distance learning platforms to provide course materials for Web-based learning. They also are often used for on-line employee training in business (E-learning in Cisco). Similar to online searching, Web-based learning also needs personalized mechanisms to help learners learn more efficiently. Therefore, many researchers have recently endeavored to provide personalization mechanisms for Web-based learning (Brusilovsky, 1999; Chou, Chang, & Jiang, 2000; Kao, 2001; Khan, 1997; Lin, 2001; Liu, Chen, Shou, & Lin, 1999; Papanikolaoum & Grigoriadou, 2002; Myung-Geun, 2001; Hongchi Shi, Spyridon Revithis, & Su-Shing Chen, 2002). Therefore, to provide personalized learning strategy is urgently needed for most e-learning systems currently. Nowadays, most recommendation systems (Rashid et al., 2002; Balabanovic & Shoham, 1997; Fu, Budzik, & Hammond, 2000; Kao, 2001; Papanikolaoum & Grigoriadou, 2002; Lee, 2001) consider learner/user preferences, interests, and browsing behaviors when analyzing learner/user behaviors for personalized services. These systems neglect the importance of learner/user ability for implementing personalized mechanisms. On the other hand, some researchers emphasized that personalization should consider different levels of learner/user knowledge, especially in relation to learning (Brusilovsky, 1999; Lin, 2001; Liu et al., 1999). That is, the ability of individuals may be based on major fields and subjects. Therefore, considering learner ability can promote personalized learning performance.

Item Response Theory, IRT (Baker, 2001; Baker & Frank, 1992; Hambleton, 1985; Horward, 1990; Hulin, Drasgow, & Parsons, 1983; Hsu & Sadock, 1985; Lord, 1980 Wang, 1995), is a robust theory in education measurement. Item Response Theory usually is applied in the Computerized Adaptive Test (CAT) domain (Baker, 2001; Baker & Frank, 1992; Hambleton, 1985; Horward, 1990; Hsu & Sadock, 1985; Hulin et al., 1983; Lord, 1980; Wang, 1995) to select the most appropriate items for examinees based on individual ability. The CAT not only can efficiently shorten the testing time and the number of testing items but also can allow finer diagnosis at a higher level of resolution (Horward, 1990). Presently, the concept of CAT has been successfully applied to replace traditional measurement instruments (which are typically fixed-length, fixed-content and paper–pencil tests) in several real-world applications, such as GMAT, GRE, and TOEFL.

Based on the previous analyses, the adaptive testing theory in the CAT inspires us to transfer IRT into the personalized e-learning domain. This study proposes a personalized e-learning system based on IRT, termed PEL-IRT, to provide Web-based personalized e-learning services. This novel approach applies the single parameter logistic model with difficulty parameter proposed by Georg Rasch in 1966 (Hambleton, 1985; Horward, 1990; Hulin et al., 1983) to model various difficulty levels of course materials. Furthermore, PEL-IRT can dynamically estimate learner ability based on the maximum likelihood estimation (MLE) by collecting learner feedback after studying the recommended course materials. Based on the estimation of learner abilities, the novel system can recommend appropriate course materials to learners. Restated, learner ability and the difficulties of course materials are simultaneously taken into account when implementing the proposed personalization mechanism.

In summary, the proposed personalized e-learning system based on IRT provides benefits in providing learning paths that can be adapted to various levels of difficulty of course materials and various abilities of learners. The system prevents the learner from becoming lost in the course materials by providing personalized learning guidance, filtering out unsuitable course materials to reduce cognitive loading, and providing a fine learning diagnosis based on an individual's user profile. Experimental results also confirm that the proposed personalized e-learning system can indeed recommend appropriate course materials to learners based on individual ability, and help them to learn more efficiently and effectively.

2. Personalized course recommendation system

This section describes the novel system architecture and the personalized mechanism implemented using IRT. First an overview of the system architecture is presented in Section 2.1. Sections 2.2 and 2.3 then describe the system components in detail.

2.1. System architecture

This study proposes a personalized e-learning system based on Item Response Theory (PEL-IRT) to provide adaptive learning. Fig. 1 illustrates the proposed system architecture, which can be divided into two main parts according to system operation procedures, that is front-end and back-end parts. The front-end part manages communication with learners and records learner

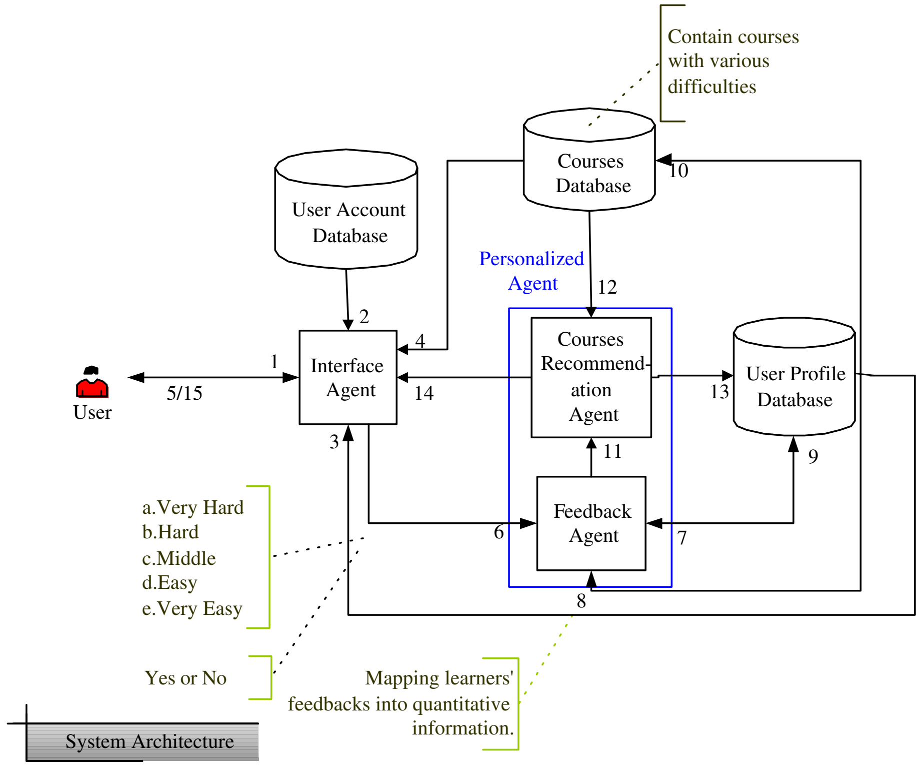


Fig. 1. System architecture (the number of $1, 2, \ldots, 15$ indicates the procedure of system operation).

behavior. Meanwhile, the back-end part aims to analyze learner ability and select appropriate course materials for learners based on estimated learner ability.

The interface agent in Fig. 1 belongs to the front-end part. It identifies learner status, transfers learner queries and returns the suggested course materials to learners. It can serve as a human-machine interactive interface. Besides, a personalized agent manages back-end operation which can be divided into two separated agents, namely the feedback agent and course recommendation agent. The feedback agent aims to collect learner feedback information, update learner ability, and adjust the difficulty parameters of course materials. Moreover, course recommendation agent aims to select appropriate course materials for learner from the course database.

In the proposed system, each course material item is classified into a predefined course unit. This system also provides a searching and browsing interface to help learners retrieve course materials in a specified course unit. Learners thus can select course units of interest or use keywords to search for course materials that they need or interested in. While all learners browse course materials, only registered learners are provided personalized service. Initially, learners can login to this system via registered accounts to obtain personalized services. Course materials with a moderate difficulty level are assigned to learners visiting the system for the first time. Personalized learning services are provided if learners click course materials and reply to the predefined questionnaires. Moreover, the feedback agent estimates learner abilities and adjusts the difficulty parameters of the course materials based on explicit learner feedback information. Course recommendation agent then use the new abilities of learners to select appropriate course materials for learners. The information function (Baker & Frank, 1992; Hambleton, 1985; Hambleton, Swaminathan, & Rogers, 1991; Wang, 1995) mentioned in Section 2.5 is applied to select appropriate course materials based on the new abilities of learners. When learners click the recommended course materials, a personalized agent repeats the recommended action until learners give other query terms or logout of the system.

Additionally, PEL-IRT includes three databases, namely the user account database, user profile database and courses database. To identify the learner's status, the user account database records learner e-mail addresses. The user profile database contains learner query terms, clicking behavior, responses to questionnaires, learner abilities and the difficulties of the clicked course materials. That is, all learners related browsing information is stored in the user profile database. The courses database contains the courses materials, and their corresponding difficulty levels. Furthermore, Section 2.3 details the difficulty parameters of course materials determined by the experts and collaborative voting by learners.

Based on the system architecture, the details of system operation are described as follows:

Step 1. Collect learner personal information and accept the given query term to search interested course units via the interface agent.
Step 2. Identify learner status based on personal information via the user account database.
Step 3. Load learner initial ability based on the selected course unit from the user profile database (if the learner is a beginner, then the system assigns them course material with a moderate difficulty level).
Step 4. Select recommended course materials from the course database for individual learners based on learner ability in the selected course unit.
Step 5. Display the recommended course materials to learners and wait for their explicit feedback response (after learners browse the course material, they are asked to reply to two assigned questionnaires).
Step 6. Collect learner feedback responses using the feedback agent.
Step 7. Re-evaluate learner abilities based on their explicit feedback responses on the selected course unit.
Step 8. Modify the difficulty parameters of course materials in the course database.
Step 9. Store learner new abilities into the user profile database.
Step 10. Store the modified course material difficulty parameters into the course database.
Step 11. Send re-evaluated learner abilities to the course recommendation agent for course recommendation.
Step 12. Select course materials for individual learners from the course database based on the ranking of their provided information degree described in Section 2.5 in detail.
Step 13. Record the recommended course ID to avoid making redundant course recommendations.
Step 14. List recommended course materials in the content display-area of the interface agent.
Step 15. Learners perform further learning processes based on the recommended course materials.

Repeat Steps 5 to 15 until the learners either select other course units or give new query terms to search for further course material learning; the process can also be ended if learners logout of the system.

Fig. 2 displays the entire learning process of the proposed system. First, the system must identify learner status; if learners are using the system for the first time, the system provides the

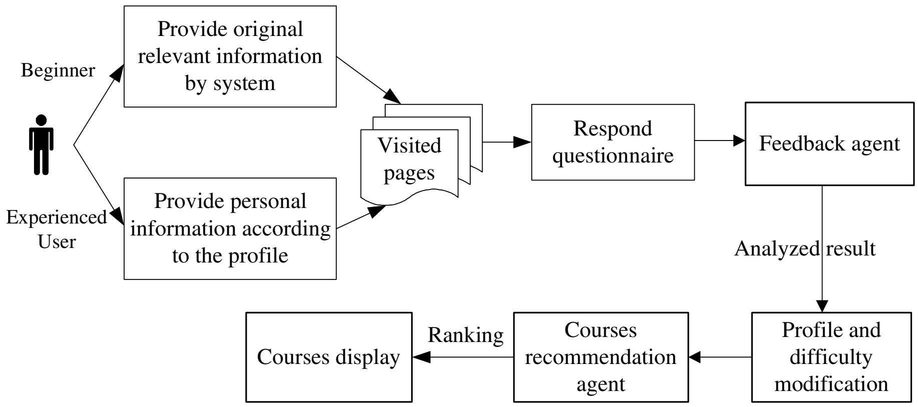


Fig. 2. The learning process of PEL-IRT.

original course material list (non-personalization list) to learners based on learner query terms. After learners visit some course materials and respond to the assigned questionnaires, the proposed system re-evaluates learner abilities, adjusts the difficulty parameters of the selected course material, and recommends appropriate course materials to learners. The following section describes the system components in detail.

2.2. System components

Based on the proposed system architecture shown in Fig. 1, this section describes the system components in more detail.

2.2.1. Interface agent

The interface agent provides a friendly interface for interacting with learners and also serves as an information channel for communicating with the personalized agent. The interface agent provides the functions of account management, authorization and query searching. When learners visit this system, they can select course categories and units of interest from the course database, and can use appropriate keywords to search course materials of interest. Learners visiting this system for the first time must register. Initially, the system recommends course materials to learners based on query term as well as selected course category and unit. After learners login to the system successfully and browse some course materials of interest, they are asked to complete two assigned questionnaires. These replies are then sent to the personalized agent and use to determine learner new abilities, tune difficulty parameters and suggest appropriate course materials to learners.

The questionnaire contains two brief questions: "What do you think about the difficulty of this course material?", and "Do you understand the content of the course material? " The first question requires respondents to select from a five levels degree scale: "very hard", "hard", "moderate", "easy" and "very easy". The second question has two crisp options: "yes" or "no". Learner responses are sent to the personalized agent for re-evaluation of learner abilities and modification of the difficulty parameters of the browsed course materials. Section 2.3 illustrates the description of the two questionnaires.

2.2.2. Personalized agent

After learners respond to the assigned questionnaires, their responses are forwarded to the personalized agent. This personalized agent contains the feedback agent and courses recommendation agent, as shown in Fig. 1. The feedback agent records learner responses, analyzes learner abilities, and adjusts course material difficulty. The feedback agent can communicate with the interface and course recommendation agents simultaneously. Furthermore, the feedback agent contains three main operations: collecting learner feedback information, re-evaluating learner abilities based on feedback information and updating course difficulties in the course database. Fig. 3 shows the detailed flowchart of the feedback agent. The information gathered from the interface agent includes learner e-mail addresses, the IDs of clicked courses, and the answers of learners to the assigned questionnaires. In the PER-IRT system, courses material difficulty is tuned using the collaborative voting approach (Jiang, Tseng, & Lin, 1999; Lin, Tseng, & Jiang, 2000) and new abilities of learners are re-evaluated by applying maximal likelihood estimation method as mentioned in Section 2.4 (Hambleton, 1985; Hambleton et al., 1991; Walope, Myers, & Myers, 1998). The corresponding updated information is sent to modify the user profile and courses databases, respectively. Meanwhile, the abilities of new learners are also sent to the course recommendation agent as an index to rank course materials in the course database based on

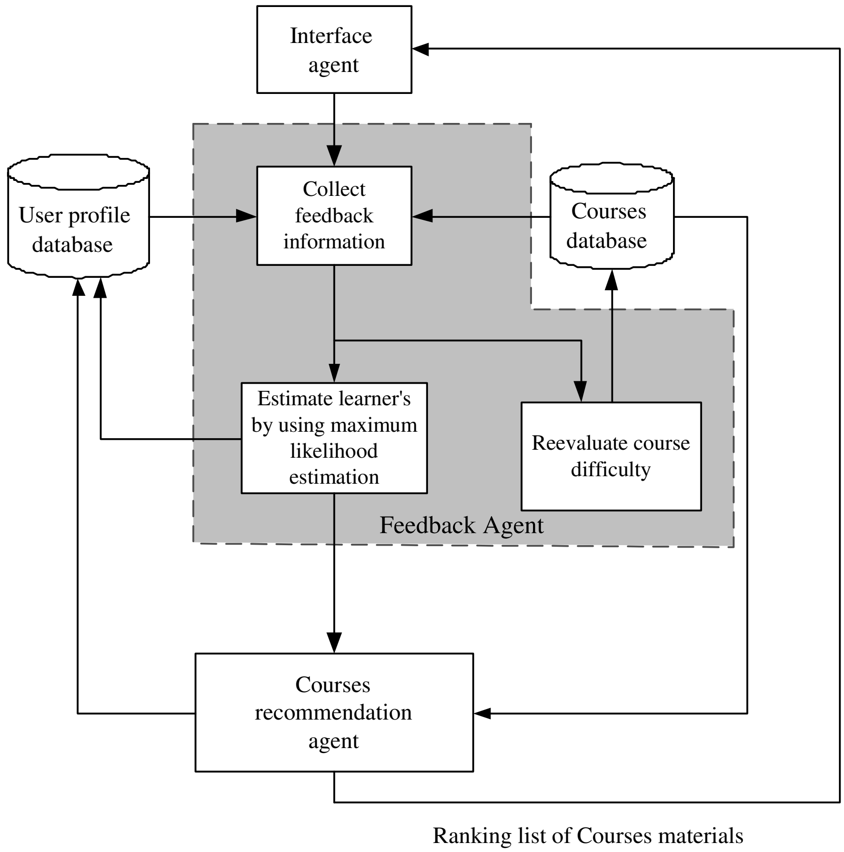


Fig. 3. Operation flowchart of feedback agent.

information function (Hambleton et al., 1991). The following section describes how to adjust course material difficulty and estimate learner abilities.

2.3. Tuning difficulty parameters of course materials

To recommend appropriate course materials to learners based on their individual requirements, the item characteristic function proposed by Rasch with a single difficult parameter is used to model a course material. The system presented here considers both course material difficulty and learner ability because these variables affect learner interests and learning results. Generally, excessively difficult course materials can frustrate learners. On the contrary, excessively easy course materials can cause learners to lack any sense of challenge and thus waste time. Thus, providing appropriate course materials to learners is important for Web-based learning systems. In most Web-based learning systems, course experts determine the difficulty parameters of course materials. However, this approach is not appropriate because most learners are not course experts. To satisfy real needs, the system presented here automatically adjusts course materials difficulty based on the collaborative voting approach (Jiang et al., 1999; Lin et al., 2000). Namely, course experts first initialize course material difficulty, then adjust the difficulty of course materials according to the learner feedback information. After many learners use this system, course material difficulty gradually becomes reasonable and stable. In fact, the system presented here can effectively reduce the effect of noise or abnormal learner feedback information due to the proposed collaborative voting approach.

The following describes the procedure for adjusting the difficulties of course materials. The 5-point Likert scale proposed by Likert in 1932 (Likert, 1932) defined scaled answers relating to the learner collaborative voting approach from "strongly disagree" to "strongly agree", based on individual degree of agreement or disagreement with the question. The reason for using a 5-point Likert scale is that too many options items will confuse learners. Meanwhile, too few options items will prevent learners from being able to distinguish the various difficulties of course materials. The most common scale measure is defined from 1 to 5. Generally, 1 indicates "strongly disagree", 2 is "disagree", 3 is "unsure", 4 is "agree" and 5 is "strongly agree". In a variation of standard Likert scale, this study uses a scale where −2 indicates "very easy", −1 is "easy", 0 is "moderate", 1 is "hard" and 2 is "very hard". Furthermore, the tuned difficulty of course material is a linear combination of the course difficulty as defined by experts and assessed by learners, with a different weight assigned to each. To describe the proposed method, three definitions related to the proposed collaborative voting approach are described below:

Definition 3.1 *(Difficulty levels of course material)*. Assume that $D = \{D_1, D_2, \ldots, D_i, \ldots, D_5\}$ is a set of course material difficulty levels which includes five different difficulty levels. D_1 represents very easy, quantified as -2; D_2 represents easy, quantified as -1; D_3 represents moderate, quantified as 0; D_4 represents hard, quantified as 1, and D_5 represents very hard, quantified as 2.

Definition 3.2 *(Average difficulty of the jth course material based on learner collaborative voting)*.

$$b_j(\text{voting}) = \sum_{i=1}^{5} \frac{n_{ij}}{N_j} D_i, \tag{1}$$

where b_j(voting) denotes the average difficulty of the jth course material after learners give collaborative voting, n_{ij} represents the number of learners that give feedback responses belonging to the i^{th} difficult level for the jth course material, and N_j is the total number of learners that rate the jth course material, and $N_j = \sum_{i=1}^{5} n_{ij}$.

Definition 3.3 *(The tuned difficulty of course material).*

$$b_j(\text{tuned}) = w \times b_j(\text{initial}) + (1 - w) \times b_j(\text{voting}), \tag{2}$$

where b_j(tuned) is the tuned difficulty of the jth course material based on learner collaborative voting, b_j(initial) is the initial difficulty of the jth course material given by course experts, and w is an adjustable weight.

The system presented here can use Eq. (2) to automatically adjust the difficulty of course materials in the course database based on the linear combination of the course difficulties as defined by course experts and the course difficulties determined from learner collaborative voting. Additionally, the time complexity of the tuned difficulty of course material remains constant because the present system preserves all old voting results.

2.4. Estimation of learner abilities

Before describing how to estimate learner's ability, we first assume that a randomly chosen learner responds to a set of n course materials with response pattern $(U_1, U_2, \ldots, U_j, \ldots, U_n)$, where U_j is either 1 or 0 for the jth course material. In this study, $U_j = 1$ represents that learners can completely understand the selected course material. On the contrary, $U_j = 0$ represents that learner cannot completely understand the selected course material. Next, the maximum likelihood estimation (MLE) widely used in CAT domain (Horward, 1990) is applied to estimate learner's ability in this study. Based on the assumption of local independence (Baker & Frank, 1992; Hambleton et al., 1991; Wang, 1995), the estimated formula of learner ability based on the tuned difficulty of course material thus is illustrated as follows:

$$L(u_1, u_2, \ldots, u_n | \theta) = \prod_{j=1}^{n} P_j(\theta)^{u_j} Q_j(\theta)^{1-u_j}, \tag{3}$$

where

$$P_j(\theta) = \frac{e^{(\theta - b_j(\text{tuned}))}}{1 + e^{(\theta - b_j(\text{tuned}))}},$$

and $Q_j(\theta) = 1 - P_j(\theta)$, $P_j(\theta)$ denotes the probability that learners can completely understand the jth course material at a level below their ability level θ, $Q_j(\theta)$ represents the probability that learners cannot understand the jth course material at a level below their ability level θ, and U_j is the answer of yes or no obtained from learner feedback to the jth course material, i.e. if the answer is yes then $U_j = 1$; otherwise, $U_j = 0$.

Since $P_j(\theta)$ and $Q_j(\theta)$ are functions of learner ability θ and course material difficulty parameter, the likelihood function is also a function of these parameters. Learner ability θ can be estimated by computing the maximum value of likelihood function (Hambleton et al., 1991). Restated, learner ability equals the θ value with maximum value of likelihood function. The method of maximum likelihood function estimation requires two input parameters to evaluate learner abilities: the tuned difficulties of the course materials based on the collaborative voting approach, and the yes or no responses of learners to the assigned questionnaires. Restated, learners must give crisp yes or no responses after browsing a course material.

In the system presented here, learner abilities are limited to between −3 and 3. That is, learners with ability $\theta = -3$ are viewed as the poorest, those with ability $\theta = 0$ are viewed as having moderate abilities, and those with ability $\theta = 3$ are viewed as having the best abilities. This system adaptively adjusts learner abilities based on learner feedbacks. If learners can understand completely the content of the suggested course material, then learner abilities will be promoted based on the estimated formula of learner abilities mentioned in Eq. (3), otherwise learner abilities will be descended. The present system sends the abilities of new learners to the course recommendation agent, after which the course recommendation agent ranks a series of appropriate course materials in the course database according to the new ability. The next subsection introduces how to recommend appropriate course materials to learners based on learner abilities.

2.5. Recommendation of personalized courses materials

After the feedback agent re-evaluates learner abilities, the course recommendation agent can recommend course materials to learners based on new learner abilities as estimated by the feedback agent. Fig. 4 shows the relationship between the course recommendation agent and the feedback agent. In this study, the information function (Hambleton et al., 1991), shown in Eq. (4),

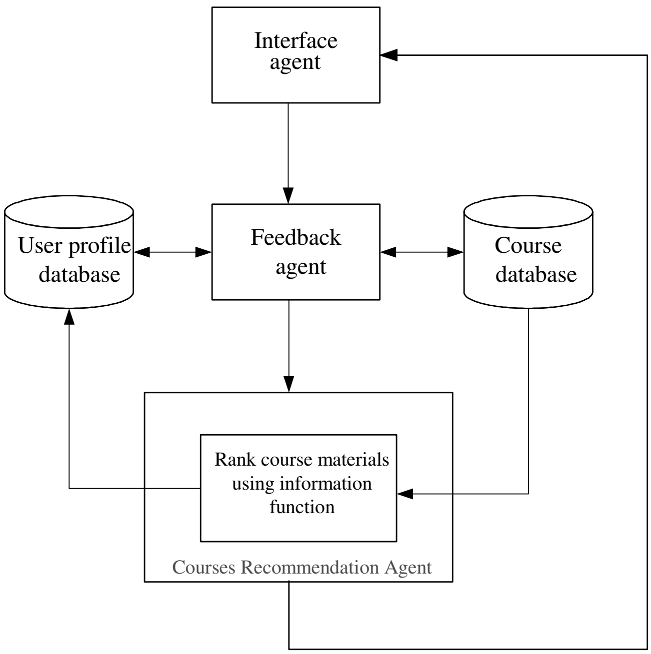


Fig. 4. Operation flowchart of courses recommendation agent.

is applied to compute the matched degree for recommending appropriate course materials to learners:

$$I_j(\theta) = \frac{(1.7)^2}{[e^{1.7(\theta - b_j(\text{tuned}))}][1 + e^{-1.7(\theta - b_j(\text{tuned}))}]^2}, \tag{4}$$

where θ denotes learner new abilities estimated after n preceding course materials, $P_j(\theta)$ represents the probability of a correct response to the jth course material for learners with ability θ, $b_j(\text{tuned})$ is the tuned difficulty of the jth course material.

That is, course recommendation agent can recommend a series of course materials to learners with ability θ according to the ranking order of information function value. A course material with a maximum information function value under learner with ability θ indicates that the system presented here gives the highest recommendation priority.

3. Experiments

The prototype of PEL-IRT was published on the web-site http://203.64.142.234:5647/ to provide personalized e-learning services and enable the performance of the proposed e-learning system in recommending personalized course material to be evaluated. Detailed experimental results and the evaluation of the degree of satisfaction for learners are described as follows.

3.1. Course terminology

Various course terminology related to course design are first explained to describe experimental results. Courses created by teachers using the course management interface, can be categorized as titles of "Neural Networks" and "C Language Programming", etc. Moreover, a course can be further divided into several course units by analyzing teaching content. Furthermore, a course unit involves many relevant course materials that convey similar concepts, but such course materials are associated with different levels of difficulty. Course experts initially determine the difficulty parameter of each piece of course material. The difficulty level is slightly tuned in response to feedback from learners. Restated, course material organized on a single Web page is the smallest course element in the proposed system. For example, the course unit, "Perceptron", in the course category, "Neural Network", includes many similar course materials with various levels of difficulty, to convey the concept of the Perceptron.

3.2. Experimental environment

The proposed prototype is implemented in Microsoft Windows 2000 using a IIS 5.0 Web server. The front-end script language PHP 4.3 and MySQL server are used to implement the system. Fig. 5 presents the entire layout of the user interface. The left frame displays the course categories, the course units and a list of all course materials in the course database. When a learner clicks on a course material, the content of the selected course material will be shown in the upper-right window. The bottom-right window presents the feedback interface. The system

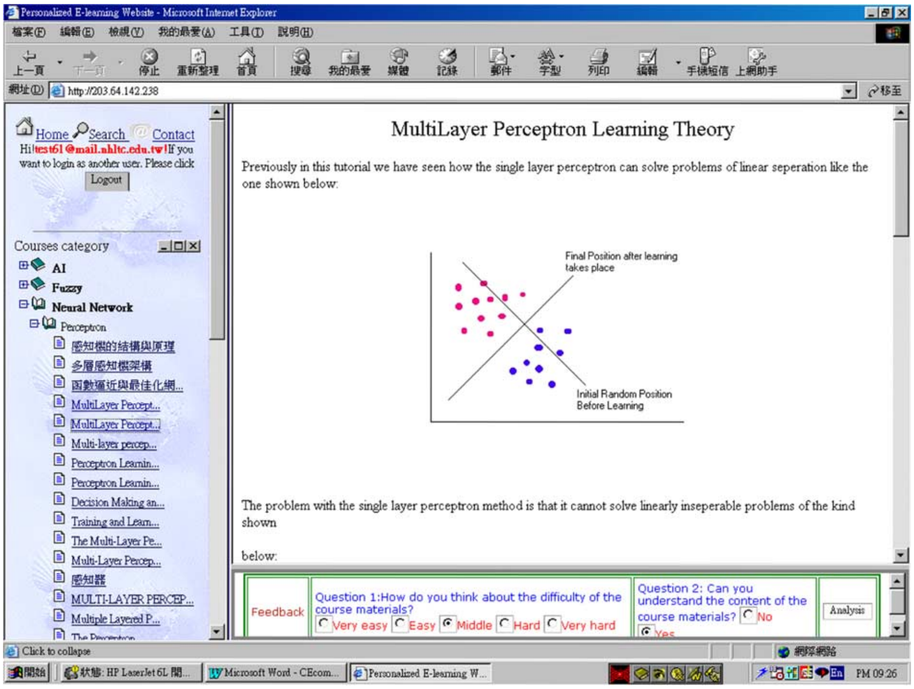


Fig. 5. The entire layout of user interface.

obtains the learner's feedback through the feedback interface in the form of replies to two predesigned questionnaires. This system currently contains only few course materials in most course units because designing course materials of high quality is time-consuming. Moreover, high-quality course materials are also difficult to obtain from the Internet. Consequently, developing a large quantity of high-quality course materials for use in the proposed personalized e-learning system is important future work. Currently, under the course category, "neural network", the proposed system defines three course units and includes 58 course materials taken from the Internet. Moreover, each course material has a corresponding difficulty parameter, initially determined by course experts and each learner has a different ability in working through each course units. Fig. 6 depicts an example of a course material recommendation based on a learner's ability according to the feedback offered by the learner. The title (標題) indicates the subject of the course material; the recommendation index (推薦指數) denotes the recommended degree of course material, and the description (描述) briefly describes the content of corresponding course material. The length of the bar line in the recommendation column specifies the recommended degree of the corresponding course material. A longer bar corresponds to that the course material is better suited to the learner.

3.3. Experimental results and analysis

The course unit, "Perceptron" under the course category, "Neural Network" (NN), is used to obtain the experimental results because this course unit presently contains more course materials

Fig. 6. An example of course material recommendation based on learner ability.

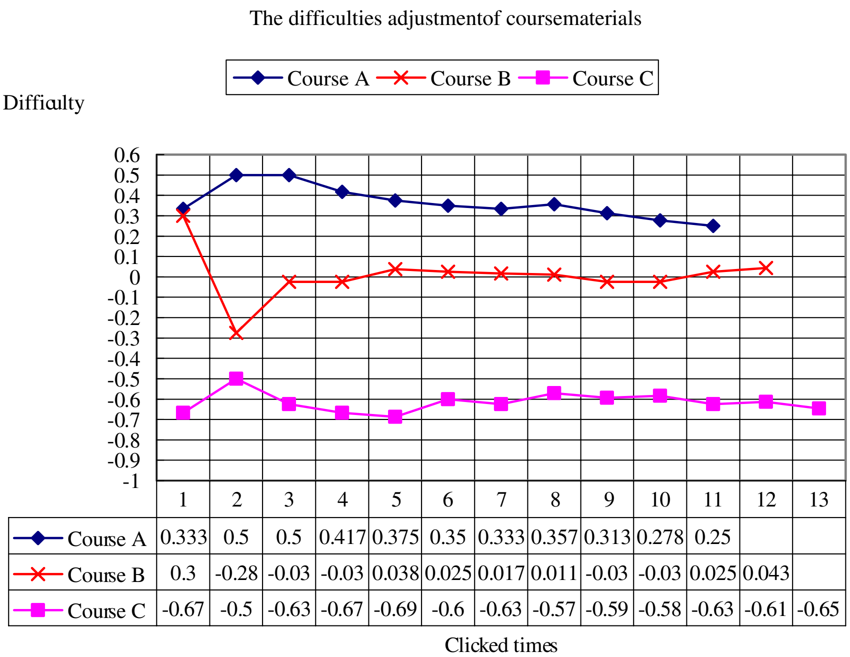
to support providing personalized e-learning services. Currently, the ''Perceptron'' unit includes a total of 35 course materials with various levels of difficulty, conveying similar concepts; 210 learners logged in to the system, and the user profile database includes 2525 records. All of the learners are studying for a Masters' degrees and are taking courses on neural networks.

3.3.1. Adjusting the difficulty of course material

In the proposed system, the difficulty of the course material can be dynamically tuned using the proposed collaborative voting approach after learners offer feedback. In this experiment, three course materials taken from the course unit ''Perceptron'', named as Material A, Material B and Material C, are employed to illustrate the process of adjusting the difficulty of the course material. Materials A, B and C are difficult, moderately difficult, and easy, respectively. The difficulty parameter and the ability of the learner are normalized to be between −1 and 1. Fig. 7 presents the tuned curves of the difficulty parameters for three different course materials. The tuned margin in the initial stage is large because the difficulty of the course material, as determined by the course experts may not suit the ability of the learners. The three tuned curves of the difficulty parameters slowly approach a steady value as the number of visiting learners increases; that is, difficulty of the course material can be correctly determined by a large amount of collaborative voting by learners.

3.3.2. Adapting to ability of learners

The ability of learners can be dynamically re-evaluated according to feedback by learners who have examined the recommended course materials. That is, the evaluated ability of



	1	2	3	4	5	6	7	8	9	10	11	12	13
Course A	0.333	0.5	0.5	0.417	0.375	0.35	0.333	0.357	0.313	0.278	0.25		
Course B	0.3	-0.28	-0.03	-0.03	0.038	0.025	0.017	0.011	-0.03	-0.03	0.025	0.043	
Course C	-0.67	-0.5	-0.63	-0.67	-0.69	-0.6	-0.63	-0.57	-0.59	-0.58	-0.63	-0.61	-0.65

Fig. 7. The tuned curves of the difficulties of course materials.

learners is increased or reduced based on the learners' feedback. According IRT, a learner's ability is increased if he or she can understand all of the content of the recommended course materials. The ability of the learner will be reduced if the learner cannot understand some of the content of the recommended course materials. In this study, the learning paths of the three learners of various learning abilities are selected from the database of user profiles to demonstrate experimental results. Fig. 8 presents the three curves tuned to the abilities of the three learners during a learning process. Learner ability is dramatically tuned in the initial stage. When learners learn the appropriate course materials recommended by the proposed system during a learning process, their abilities will gradually approach a stable value. Furthermore, Fig. 9 plots the relationship between the difficulty parameters of the clicked course materials with the adjustment of the learner A's ability. In this figure, the learner is assumed to respond "yes" to the question, "Do you understand the content of the recommended course materials?" asked of the 20 clicked course materials. If learners completely understand the more difficult recommended course materials, then the tuned value of learner ability will be large. In contrast, if learners understand less difficult course materials, the tuned value of learner ability will be small.

Fig. 10 presents the relationship between the ability of the learner to the difficulty parameter of the recommended course material. The difficulty parameter of the recommended course material is strongly correlated with learner ability. This result implies that the proposed system can indeed recommend appropriate course materials to learners, according to their abilities.

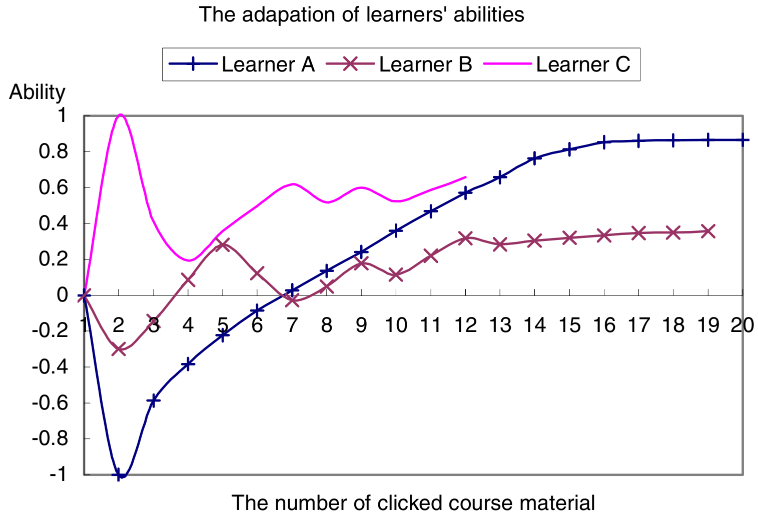


Fig. 8. The adaptation of learner ability.

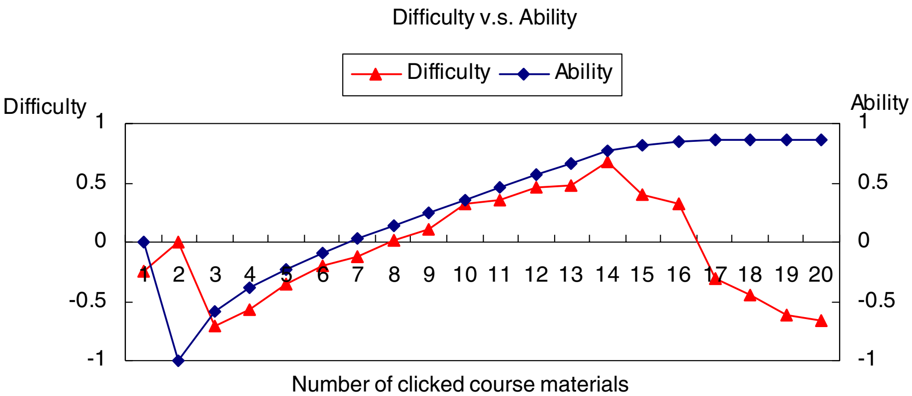


Fig. 9. The relationship between the difficulty parameter of the clicked course material and the adjustment of the learner A's ability.

3.4. Evaluating degree of satisfaction

Next, two methods are applied to evaluate learners' satisfaction for the personalized e-learning services provided by the proposed system. The first method involves the collection of learner responses to determine whether the recommended course materials meet most learners' requirements. The personalized mechanisms of the proposed system are evaluated from two different perspectives - those of the learner and the course material. Table 1 lists the results. The proposed system collects learners' responses to the question, "Do you understand the content of the course material?", submitted through the user interface agent. According to the learners, their average degree of understanding of the recommended course materials is 0.825, which is close to one,

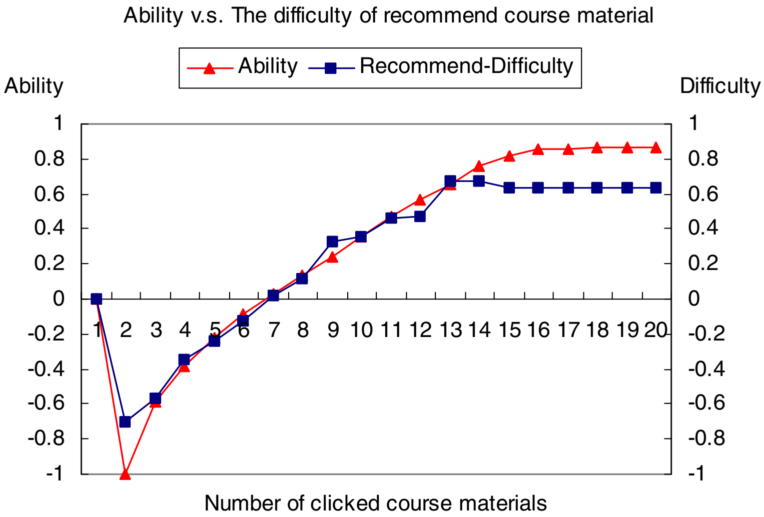


Fig. 10. The relationship between learner A's ability and the difficulty parameter of the recommended course material.

Table 1
The learner satisfaction evaluation for the recommended course materials during a learning process

Viewpoint	The learners' comprehension degree for the course material recommended by our system
(a) Do you understand the content of the recommended course materials? (1: yes, 0: no)	
Learner views	0.825
Course material view	0.837
Viewpoint	The average difficulty of the first recommended course material
(b) How do you think about the difficulty of the recommended course material? (0: very easy, 1: easy, 2: moderate, 3: hard, 4: very hard)	
Learner view	1.815
Course material view	1.573

which result shows that the learners' comprehension of the recommended course material is high. From the perspective of the course material, the average proportion of the recommended course material that can be comprehended by learners is 0.837, which is also close to one, which result shows that learners can comprehend most recommended course materials. Furthermore, from these two different perspectives, the average difficulties of the course materials recommended by the proposed system are 1.815 and 1.573, respectively, which values are close to two, indicating that most learners agree that the recommended course materials are moderately difficult. The result also demonstrates that the proposed system recommends suitable course materials to learners. Therefore, this system satisfies most learners' requirements of a personalized e-learning service. The second method is to investigate learner satisfaction using the four designed questionnaires, answered after a learner has finished a learning process. This study applies a five-point Likert scale (Likert, 1932) to evaluate the degree of satisfaction with the proposed system. Answers on the five-point scale are, very satisfactory, satisfactory, neutral, unsatisfactory or very

Table 2
The satisfaction evaluation after learning

Question	Answer: Learner choices				
	Very suitable	Suitable	Moderate	Unsuitable	Very unsuitable
(1) How do you feel that the top five course materials recommended by our system are appropriate?	20 (9.5%)	93 (44.3%)	87 (41.4%)	10 (4.8%)	0 (0%)
(2) How do you feel that our system gives lower ranking order for inappropriate course materials?	5 (2.4%)	120 (57.1%)	65 (31%)	20 (9.5%)	0 (0%)
	Very satisfactory	Satisfactory	Moderate	Unsatisfactory	Not very satisfactory
(3) Do the personalized services provided by our system satisfy your requirement?	18 (8.6%)	95 (45.2%)	82 (39%)	15 (7.1%)	0 (0%)
(4) Do the learning process provided by our system satisfy your requirement?	0 (0%)	55 (26.2%)	130 (61.9%)	25 (11.9%)	0 (0%)

unsatisfactory. Table 2 evaluates the learners' responses. Experimental result shows that learner satisfaction with the personalized services of the proposed system is very high.

4. Conclusion

This study proposes a personalized e-learning system based on Item Response Theory, termed PEL-IRT, which estimates the abilities of online learners and recommends appropriate course materials to learners. PEL-IRT provides personalized Web-based learning according to course materials visited by learners and their responses. Moreover, course material difficulty can be automatically adjusted using the proposed collaborative voting approach. Experimental results show that the proposed system can precisely provide personalized course material recommendations on-line based on learner abilities, and moreover can accelerate learner learning efficiency and effectiveness. Importantly, learners only need to reply to two simple questionnaires for personalized services.

Acknowledgements

The authors would like to thank the National Science Council of the Republic of China for financially supporting this research under Contract No. NSC92-2520-S-026-002.

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