Learning Object Recommendation Services in Interactive E-learning Systems

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Abstract The traditional teaching method is already show its limitations that students from different backgrounds are still given the same contents at the same time, and they may only interest in part of a whole learning content. Such these contents couldn't be used to provide the exact content to the learners and reused by other authoring tools and content management systems. In this paper, we propose a novel weighted-based recommendation mechanism to compute recommendation priority for learning objects and develop the interactive e-learning system with learning content recommendation services. It can dynamically provide adaptive learning contents to different learners.

Key-words: Digital Learning, Recommendation Service, Learning Object

1 Introduction

Web-based applications always provide people a huge of information at any time. For all that, numbers of websites, users and digital contents are still created increasingly. The network traffic in Internet is also to grow up trendily [2, 10]. From these aplenty and various contents made by using a new design technology, we usually can't find the need data quickly. The situation will cause users to search the need data confusedly. To effectively address the problem of information overload, many tools are developed and presented for accesses data used by indexed, searched and filtered [7, 13]. Such these information tools often have a common drawback and provide too munch irrelative data [3]. Hence, the mechanism of recommender system is advocated and used widely. The recommender system will help users make a correct choice from many kinds of source data [8]. However, the different valuations of quality may be found from the viewpoint of user and recommendation mechanism on the recommendation result. In other words, a learning object with high valuation is recommended to users but the user's valuation of recommendation may differ from that of the recommendation mechanism. This concept has been shown in Fig. 1 [11]. From the viewpoint of the user, how well a recom mendation satisfies him is termed the user perceived quality. The relevance score it computes for a recommendation mechanism is termed its internal quality from the viewpoint of recommendation service. Reducing the difference of user perceived quality and internal quality is challenge for many recent approaches.

A new era of digital learning is on the horizon, hundreds of learning contents are created and more and more people begin to acquire knowledge through digital learning platform. The traditional teaching method is already show its limitations that students from different backgrounds are still given the same co-

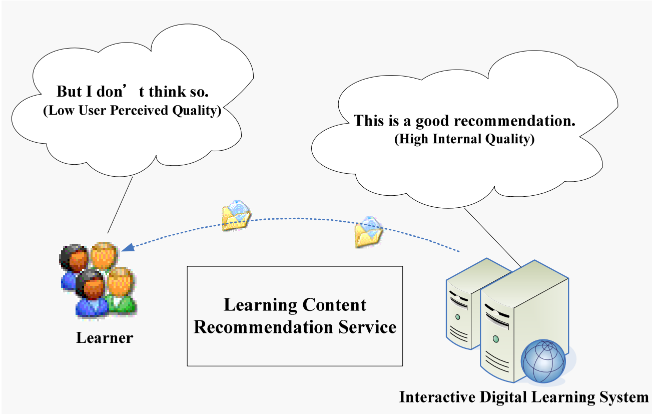

Fig. 1. Different valuations of quality [11].

ntents at the same time, and they may only interest in part of a whole learning content. More recently, many digital learning contents consisted of huge continuing presentation and the explanations in detail for contents are not attached. Such these contents couldn't be used to provide the extra contents to the learners and reused by other authoring tools and content management systems. In this paper, we concerns how to realize personal learning through recommendation services and share learning objects each other among learning platforms. A novel weighted-based recommendation mechanism is proposed to develop the interactive e-learning system with learning content recommendation services. This interactive e-learning platform satisfy that the system provides the adaptive learning materials to different learners in shorter time, and (2) learning contents consists of smaller learning objects based on SCROM standards to achieve the purpose of share and reusability.

2 Related Work

Nowadays adaptive algorithms established by information recommendation systems can be classified into three categories. The first category is traditional data mining that finds association rules between a set of co-purchased items. The quality of association rules is commonly evaluated by looking at their support and confidence [1]. The second category is collaborative filtering. It will identifies users whose tastes are similar to those of a given user and recommends items the have liked. The entire process of collaborative filter recommendation has consisted of representation, neighborhood formation, and recommendation generation [9]. The last category is content-based filtering that the features of items can be useful in recommending items. It assumes that the degree of relevance of an item can be determined by its content. The content-based recommendation approach tries to recommend items similar to those a given user has liked in the past [11].

Many noticeable research results on recommending algorithms have been presented. However, most of these algorithms have mostly designed for E-commerce applications. Additionally, these recommending algorithms must depend on statistical computing to evaluate what is of value for users. That implies the longer computing time will be occurred. The learning object recommendation service often dynamically provides adaptive learning contents to different learners in real-time. Therefore, these approaches are not suitably used in interactive e-learning systems.

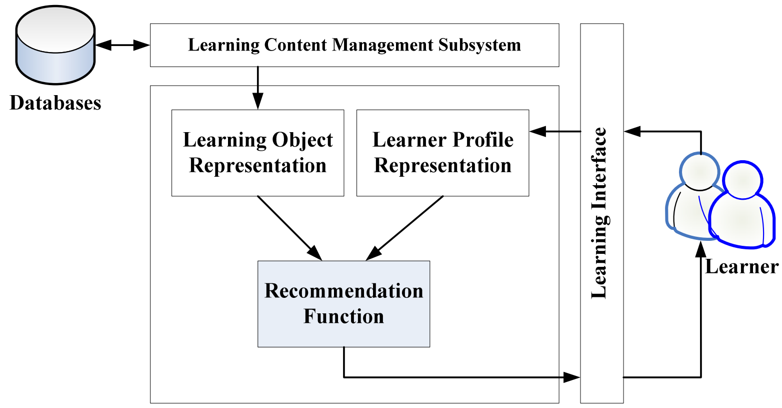

Fig. 2. The process of learning object recommendation mechanism

Table 1. Characteristics in learning objects

attribute items	attribute values
class	{web design, multimedia animation, linux concept, database}
style	{theory, foundation, application}
difficulty	{simple, average, advance}
learning time	{less 10 min., 11-20 min., 21-30 min., more 30 min.}
applied value	{low, middle, high}

3 Weighted-Based Recommendation Service Mechanism

Against the above background, we will develop the research architecture of learning object recommendation services based on text filtering system model proposed by [6] as shown in Fig. 2. From the theory foundation, this architecture is comprised of learning object representation, learner profile and recommendation function as explained below:

3-1. Learning object representation

The vector-based representative method is used according to the characteristic of recommended learning objects. The distinguishing characteristic indicates the use of adaptive attribute items for detail information descriptions. To achieve successfully learning object recommendation services, each value of attribute item will be transferred to the form of $[0,1]^n$. The characteristics of learning objects are exemplified in Table 1. Each characteristic has its prevailing values, such as theory, basic and application in the style attribute. Combing the values of attribute items is become to the vector for a learning object representation. The learning object representation is shown in Fig. 3 where n is the total number of characteristics in learning object; m_i represents the number of values for the *i*th characteristics. For instance, the value of (class, style, difficulty, learning time, applied value) for a learning object is (multimedia animation, application, simple, 11-20 min., middle). Hence, this learning object is represented as the vector (0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0). This learning object contains about multimedia animation so that the value of (A_1V_1, A_1V_2, A_1V_3, A_1V_4) is (0, 1, 0, 0) respectively.

3-2. Learning profile representation

All records for learning profile are toward the favorite degree of attribute values from the viewpoint of learners. The vector-based representative method is also used in learning profile representation. The learning profile representation is shown in Fig. 3 where n is the total number of characteristics in

(a) Learning Object Representation = $(A_1V_1, A_1V_2, \ldots, A_1V_m, A_2V_1, A_2V_2, \ldots, A_2V_m, \ldots A_nV_1, A_nV_2, \ldots, A_nV_m)$,

$$A_iV_j \in \{0,1\},\ 1 \le i \le n,\ 1 \le j \le m$$

$$\text{if } A_iV_j = \begin{cases} 1 & \text{if a learning object possesses the } j\text{th value of the } i\text{th characteristic} \\ 0 & \text{otherwise} \end{cases}$$

(b) Learner Profile Representation = $(W_{A1V1}, W_{A1V2}, \ldots, W_{A1Vm}, W_{A2V1}, W_{A2V2}, \ldots, W_{A2Vm}, \ldots, W_{AiV1}, W_{AiV2}, \ldots, W_{AiVm})$,

$$0 \le W_{AiVj} \le 1,\ 0 \le i \le n,\ 0 \le j \le m$$

(c) Recommendation Score = $\sum_{i=1}^{n}\sum_{j=1}^{m} W_{AiVj} \times A_iV_j,\ 1 \le i \le n,\ 1 \le j \le m$

Fig. 3. Weighted-based recommendation service mechanism

learning object; m_i represents the number of values for the *i*th characteristics. W_{AiVj} indicates a degree of learner's interest in the *j*th value of the *i*th characteristic. For instance, a learner is interested in the class of linux concept, style of applied material, difficulty of average and learning slowly. Hence, this learner may is represented as the vector (0, 0, 0.65, 0, 0, 0, 0.55, 0, 0.7, 0, 0, 0, 0, 0.83, 0, 0, 0).

3-3. Recommendation function

If learning object representation and learner profile representation are prepared, the system will execute the recommendation function to calculate recommendation score for each learner. The learning object with highest recommendation score is firstly recommended to learner. The design of recommendation function based on the weighted principle is by multiplication of learning object representation and learner profile representation. The recommendation function is shown in Fig. 3. For instance, the value of learning object representation and leaner profile representation are (0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1) and (0, 0, 0, 0.475, 0, 0, 0.515, 0, 0.69, 0, 0.27, 0, 0, 0, 0, 0, 0.4), respectively. Thus, the recommendation score is 2.35.

4. Conclusions

Researches on personal learning have gained more and more attention thanks to the explosive use of e-learning environment. However, most recommending mechanisms must depend on statistical computing to evaluate what is of value for users. That implies the longer computing time will be occurred. The learning object recommendation service often dynamically provides adaptive learning contents to different learners in shorter time. Therefore, this paper proposes the weighted-based recommendation mechanism to develop the interactive e-learning system with learning content recommendation services. From the experiments results, it's justified to show its ability in furnishing effective personal recommendation services.

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