A Hybrid Learning Object Recommendation Algorithm in E-Learning Context

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Abstract

In adaptive e-learning system, the researchers focused on how to provide the learners with learning objects depending on their preferences and needs. This makes the process of filtering unwanted learning objects an increasing challenge for the learners. Content recommendation systems can suggest the users what they should learn. People have made great efforts on research about recommendation systems using content-based recommendation and collaboration-based recommendation. In this paper, the authors proposed a hybrid learning object recommendation method to improve the accuracy of the recommendation. The experiment result shows that recommendation precision of hybrid recommendation method is higher than content-based recommendation method and collaboration-base recommendation method.

Keywords: Learning Object, Recommendation, E-Learning, Hybrid Learning Object Recommendation Algorithm

1. Introduction

The term e-learning refers to online learning delivered over the World Wide Web via public internet or private intranet [1]. It is concerned with the computer based implementation of an educational system, thus it is a result of a computer oriented analysis and design of such system. [2, 3] The traditional learning systems follows “one size fits all” approach where all the learners are provided with same learning content. But the learners’ requirements and goals dynamically change over time which can’t be addressed by the traditional approach. However, the main challenge of the most recent research is to provide efficient and adaptive e-learning systems. To achieve efficiency, the e-learning systems are modeled as a directed graph where each node represents a Learning Object [4, 5]. A learning object is a collection of content items, practice items, and assessment items that are combined based on a single learning objective. Each learning object may contain one concept, one object, an image, or an audio session. The adaptive learning provides an alternative to the traditional approach, where learning objects can be provided dynamically as per learner preferences and needs. By considering such learner contexts and providing the learning objects depending up on these contexts will significantly improve the efficiency of the e-learning [6]. This makes the process of filtering information an increasing challenge for the learners. Instead of aimlessly browsing through large amounts of data, learners fall back on using recommendation services. Filtering systems remove unwanted learning objects while recommender systems suggest to the users what they should learn [7]. People have made great efforts on research about recommendation systems using content-based recommendation and collaboration-based recommendation [8].

Wang et al. proposed an adaptive personalized recommendation model in order to help recommend SCORM-compliant learning objects from repositories in the Internet. The model adopted an ontological approach to perform semantic discovery as well as both preference-based and correlation-based approaches to rank the degree of relevance of learning objects to a learner’s intension and preference [9]. Chen proposed 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 [10]. Tsai et al. proposed a learning object
recommendation mechanism which uses both preference-based and neighbor-interest-based approaches in ranking the degree of relevance of learning objects to a user’s intension. By this model, a tutoring system is able to provide easily and efficiently for active learners suitable learning objects [11].

In the above research work, content-based recommendation method or collaboration-based recommendation method were used to filter the unwanted learning objects. But both of the methods have their advantages and disadvantages. Some other researches proposed the models based on the learner’s level of knowledge and the learning style. Chen’s proposal is to match the difficulty of the learning object with the learner’s knowledge level [12]. After that, many researchers believe that the learning content should satisfy the learner’s characters of learning style. Chang et al. proposed a method to recognize the learner’s learning style in order to improve the system’s ability of adapting the user’s personalized requirements [13]. The above methods focused on measuring the similarity of the learning objects and the requirements of the learners. Because the learners have strong subjective feelings on the learning objects, these methods can’t be very exact. In this paper, a hybrid learning object recommendation method to improve the accuracy of the recommendation was proposed.

2. Description of the related concepts

There are two main concepts in this research, the learner and the learning object. The authors use two parameters to describe the learner: the learner’s learning style and the learner’s level of knowledge. The authors also use two parameters to describe the learning object: the characters of the learning object and the difficulty of the learning objects. Then, the learners and the learning objects can build the relationship.

2.1. Description of the learners’ characteristics

2.1.1. The types of learning style

All Learning styles are various approaches or ways of learning. They involve educating methods, particular to an individual that are presumed to allow that individual to learn best. Here are brief descriptions of the four Kolb learning styles.

- Diverging style - These people are able to look at things from different perspectives. They are sensitive. They prefer to watch rather than do, tending to gather information and use imagination to solve problems. These learners prefer to learn learning object like graphs, charts, animation and vivid symbol. [14]

- Assimilating style- The Assimilating learning preference is for a concise, logical approach. Ideas and concepts are more important than people. These people require good clear explanation rather than practical opportunity. They prefer to learn learning object such as audio and video. [14]

- Converging style- People with a Converging learning style can solve problems and will use their learning to find solutions to practical issues. They prefer technical tasks, and are less concerned with people and interpersonal aspects. They prefer to learn learning object in Text format. [14]

- Accommodating style- The Accommodating learning style is “hands-on”, and relies on intuition rather than logic. These people use other people’s analysis, and prefer to take a practical, experiential approach. They prefer to learn learning object such as simulation software. [14]

A learner will show the tendency of the various types of learning style. Different learners will show different tendency in every type of the learning style. [15] The authors use the vector $C = (c_1, c_2, c_3, c_4)$ to describe the tendency of the learning style of the learner $s_1, s_2, s_3, s_4$. And $s_i$ stand for the degree of the learners belong to the Diverging style, Assimilating style, Converging style and Accommodating style. And $0 \leq s_i \leq 1(i=1,2,3,4), s_1 + s_2 + s_3 + s_4 = 1$. 

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2.1.2 The learner’s level of knowledge

According to the breadth and depth of the learners have mastered the knowledge (concept), a simple test can be used via online learning system to analyze the level of knowledge of the learner. The authors use $d(0 \leq d \leq 1)$ to describe the learner’s level of knowledge. If $l$ is close to 0, it means that the learner’s level is close to the beginner; If $l$ is close to 1, it means that the learner’s level is close to the expert. [15]

2.2 Description of the learning object

2.2.1 Description of the characters of the learning object

Learning objects can use many ways to express knowledge, such as text, video, audio, format and interactive learning software. The authors use $C = (c_1, c_2, c_3, c_4)$ to describe the extent of the using different expressing ways. $c_1, c_2, c_3$ and $c_4$ stand for the proportion of text, symbol(for example graph and animation), video(audio) and interactive software in a learning object. And $0 \leq c_i \leq 1 (i = 1, 2, 3, 4), c_1 + c_2 + c_3 + c_4 = 1$. [15]

2.2.2 The difficulty of the learning object

The designers of the learning object can define the difficulty of the breath and depth of the knowledge of the learning object. The difficulty is defined $d(0 \leq d \leq 1)$. If $d$ is close to 0, it is suitable for beginners to learn; If $d$ is close to 1, it is suitable for an expert learner to learn. [15]

3. Hybrid learning object recommendation algorithm

The problem of personalized recommending according to personal needs has been studied extensively. Two fundamental major paradigms have emerged. In the content-based recommendation paradigm, one tries to recommend learning objects that are similar to those ones the user was interested in the past; while in the collaborative recommendation paradigm, one identifies the “users” whose interests are similar to the user and then recommend the learning objects those similar users are interested. The major difference between content-based recommendation and collaboration-based recommendation is that collaboration-based recommendation only uses the user-item ratings data to make predictions and recommendations, while content-based recommender systems rely on the features of users and items for predictions. Both content-based recommendation and collaboration-based recommendation have limitations. While collaboration-based recommendation does not explicitly incorporate feature information, content-based recommendation do not necessarily incorporate the information in preference similarity across individuals.[16, 17] While each approach has its own advantages and disadvantages, this paper focuses on the exploration of combining the two mechanisms to recommendation.

3.1 Content-based recommendation

Content-based recommender systems make recommendations by analyzing the content of textual information and finding regularities in the content [16]. Content-based recommendation techniques are based on content analysis of the target items. For examples, the technique of term frequency analysis for text documents is a well-known content analysis method. In content-based filtering systems, recommendations are provided to a user based solely on a user profile built up by analyzing the content of items that the user rated in the past and/or user’s personal information and preferences [18].
The learning object in the learning object set can be described as a vector of character item set. 

\[ q_i = \langle w_1, w_2, \ldots, w_n \rangle \]

where \( w_i \) is the weight of character item \( t_i \) in learning object \( q \).

\[ w_i = \frac{f_i}{qf_i} \]

where \( f_i \) is the frequency of \( t_i \) in learning object \( q_i \). \( qf_i \) is the amount of character item \( t_i \) in learning object \( q_i \).

The description of the learner’s character is similar to the learning objects. The learner’s character can be seen as a text document and described as vector \( U \). The Cosine similarity of the learning object vector \( V \) and user vector \( U \) can be computed as follows [19]:

\[ \text{sim}(i, j) = \frac{u \cdot q}{||u|| \cdot ||q||} \]

It need to set a threshold of \( \text{sim}(i, j) \) and recommend the top(n) to the users.

### 3.2 Collaboration-based recommendation

Collaboration-based recommendation is the technique of using peer options to predict the interest of others. Users indicate their opinions in the form of ratings on various pieces of information, and the collaborative filter correlates the ratings with those of other users to determine how to make future predictions for the rater [20].

In collaboration-based recommendation, items (e.g., learning object) are recommended to a particular user when other similar users also prefer them. The definition of “similarity” among users depends on applications. A collaboration-based recommendation algorithm collects all information about users’ characters and calculates the similarity among the users. If some users have similar characters, they will be categorized to the same user group.

The authors set the learning objects which user i and user j are both interested in as \( U_{ij} \). The similarity of user i and user j can be measured by the following formula:

\[ \text{sim}(i, j) = \frac{\sum (R_{i,c} - \bar{R}_{j})(R_{j,c} - \bar{R}_{j})}{\sqrt{\sum (R_{i,c} - \bar{R}_{j})^2 \cdot \sum (R_{j,c} - \bar{R}_{j})^2}} \]

\( R_{i,c} \) is the degree of the interest of user i in item c. According to the similarity of the two users, the authors can predict the use’s interest degree to the learning objects they have not selected and learned yet, then recommend the learning objects of high interest degree. [19]

\( NBS_u \) is the closest neighbors set of user \( u \). \( P_u \) is the user \( u \)'s interest degree of learning object i.

\[ P_{u,i} = \frac{\sum_{v \in NBS_u} \text{sim}(u, v) \times R_{v,i}}{\sum_{v \in NBS_u} (|\text{sim}(u, v)|)} \]

### 3.3 A hybrid recommendation algorithm

The content-based recommendation and the collaboration-based recommendation both have their advantages. The authors proposed a hybrid algorithm to consider both of their advantages. On the one hand, recommend the learning objects to the user according to the similarity of the learning object and the user’s characters such as learning style. On the other hand, find the user’s close set of neighbors through computing the similarity of the users, and then recommend the learning objects which the neighbors are most interested in [19]. The process of the method is below (see figure 1):
The algorithm is as follows:

Step 1: initialize the parameters: learner’s level of knowledge, learner’s learning style, the characters of the learning object, the difficulty of the learning object, the learning objects prepared for selection, the threshold of content-based recommendation, and the threshold of collaboration-based recommendation.

Step 2: Content-based recommendation.

(1) The similarity of learner’s level of knowledge and the difficulty of the learning object. \( I_o \) is the level of the target learner \( L_o \)’s level of knowledge. \( d_j \) is the difficulty of the learning object \( O_j \). The similarity of \( I_o \) and \( d_j \) is \( \text{sim}(I_o, d_j) = 1 - |I_o - d_j| \geq \alpha_1 \).

(2) The similarity of learner’s learning style and the characters of the learning object. The learner \( L_o \)’s learning style \( s^o = (s^o_1, s^o_2, s^o_3, s^o_4) \), the characters of the learning object \( O_j \) is \( c = (c_1, c_2, c_3, c_4) \). The similarity of \( L_o \) and \( O_j \) is \( \text{sim}(L_o, O_j) \geq \alpha_2 \). \( \alpha_1 \) and \( \alpha_2 \) are both the thresholds of the similarity.

(3) Generate the set of the recommended learning object \( X \).

Step 2: Collaboration-based recommendation.

(1) The similarity of the neighborhood learners and target learner. \( L \) is the set of the learners who have finished the learning task. \( L_j = \{l_1, l_2, \ldots, l_m\} \). \( l_j \) is the level of the knowledge of learner \( L_j \). \( I_o \) is the target learner. \( I_o \) is \( L_o \)’s level of knowledge. \( \text{sim}(I_o, l_j) = 1 - |I_o - l_j| \geq \beta_1 \).

(2) The learner \( L_o \)’s learning style \( s^k = (s^k_1, s^k_2, s^k_3, s^k_4) \) and \( \text{sim}(L_o, L_k) \geq \beta_2 \). \( \beta_1 \) and \( \beta_2 \) are both the thresholds of the similarity.

(3) Generate the set of the recommended learning object \( Y \).

Step 3: Recommend the set of learning object \( X \cap Y \) to the target leaner.

4. Experiment results

The effectiveness of an information recommendation system is usually measured by two criteria, the “Recall” and the “Precision” rate. In this paper, the authors choose “Precision” criteria to measure the effect of the hybrid recommendation method.

\[
\text{precision} = \frac{\text{number of relevant learning objects}}{\text{number of recommended learning objects}}
\]

The authors select 3 learners A, B and C randomly to participate the experiment. They use content-based recommendation method, collaboration-base recommendation method and hybrid recommendation method respectively to verify the precision of the recommendation process. The result is below (see figure 2):
Figure 2. The recommendation precision by using three recommendation methods among the learners A, B and C.

The figure shows that for learner A and C, the recommendation precision of hybrid recommendation method is the highest, and the recommendation precision of content-based recommendation method is the lowest. For learner B, the recommendation precision of hybrid recommendation method is the highest, and the recommendation precision of collaboration-based recommendation method is the lowest. For all three learners, the recommendation precision of hybrid recommendation method is higher than content-based recommendation method and collaboration-base recommendation method.

5. Conclusion and future work

In most e-learning systems, content-based recommendation method or collaboration-based recommendation method was used to filter the unwanted learning objects. Then the learners can acquire the learning objects which they really need. But both of the methods have their disadvantages. The authors proposed a hybrid learning object recommendation method to improve the accuracy of the recommendation. The hybrid recommendation method shows high recommendation precision than the two above methods. But the results show that the recommendation precision is also need to be improved. In the future work, the authors will select more learners to verify the effectiveness of the algorithm and improve it continuously.

6. References

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