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Enhanced Learning Resource Recommendation Based on Online Learning Style Model

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Abstract: Smart learning systems provide relevant learning resources as a personalized bespoke package for learners based on their pedagogical needs and individual preferences. This paper introduces a learning style model to represent features of online learners. It also presents an enhanced recommendation method named Adaptive Recommendation based on Online Learning Style (AROLS), which implements learning resource adaptation by mining learners' behavioral data. First, AROLS creates learner clusters according to their online learning styles. Second, it applies Collaborative Filtering (CF) and association rule mining to extract the preferences and behavioral patterns of each cluster. Finally, it generates a personalized recommendation set of variable size. A real-world dataset is employed for some experiments. Results show that our online learning style model is conducive to the learners' data mining, and AROLS evidently outperforms the traditional CF method.

Key words: smart learning; e-learning; online learning style; adaptive recommendation; Collaborative Filtering (CF)

1 Introduction

Smart learning systems offer new ways of acquiring knowledge and have been expanding their popularity and influence over recent decades. Popular e-learning websites, such as Moodle or Coursera, are incessantly digitalizing materials for learners with different educational backgrounds and needs. However, without proper guidance, learners may experience difficulty in choosing suitable materials in the face of massive information during their learning process[1].

The development of adaptive learning systems, which give instructions and learning resource recommendations based on different levels of expertise, interests, goals, educational backgrounds, and personal traits of learners, has become an important research direction. To represent learners' traits and features on the web, the most popular direction of research is the integration of learning styles[2]. Learning styles are unique manners in which learners begin to concentrate on, process, absorb, and retain new and difficult information[3]. Gaining insights into different learning styles can offer means to design and provide recommendations that are adapted to individual needs.

Selecting an appropriate model is the key of integrating learning styles into adaptive learning systems. However, doing so is a challenge as at least 70 learning style theories or models have been proposed by experts from various domains[4]. The Felder-Silverman model is the most widely used theory[5,6], as it is a compromised combination of other classical theories and convenient to be implemented into computer programs with its data collection instrument called index of learning styles. Other notable studies include Dunn and Dunn's theory[7], which posits that a learner's learning style can be influenced by many factors; Kolb's learning style inventory[8], which describes

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learner's internal cognitive processes as a four-stage cycle of learning; and Myers-Briggs Type Indicator (MBTI)[9], which indicates psychological preferences in how people perceive.

In this paper, an enhanced recommendation method named Adaptive Recommendation based on Online Learning Style (AROLS) is proposed. This method is integrated with a comprehensive learning style model for online learners. The method makes recommendations by considering the learning style as prior knowledge. First, it generates learner clusters of different learning styles. Second, the behavioral patterns represented by learning resource similarity matrix and association rules of each cluster are extracted using learners' browsing history. Finally, our enhanced method creates a personalized recommendation set of variable size according to data mining results of previous steps. Experiments on real data show that the proposed method offers recommendation results with better precision while maintaining a computational advantage compared with traditional item-based Collaborative Filtering (CF) recommendation.

The paper is organized as follows. Section 2 discusses previous research related to our topic. Section 3 introduces an online learning style model to represent features of online learners. Section 4 presents the enhanced recommendation method that applies CF and association rule mining. The experimental results are discussed in Section 5, and Section 6 concludes this work.

2 Related Work

2.1 Learning styles

Learning style theories have proven their impact in optimizing learners' performance[10]. However, given the subversive changes and freedom to the acquisition of knowledge brought by e-learning, classical theories based on traditional, systematic, and linear teaching environments may no longer be suitable. Studies have also been made to analyze behavioral patterns of online learners. Keefe[11] proposed a hybrid model, which combines literature-based detection and automatic detection to identify a learner's learning style. Sharma[12] extracted learning preferences and styles by analyzing the content of web pages. Chou and Chen[13] used a learning progress bar to measure learning styles in MOOCs. Amir et al.[14] employed a literature-based method and support vector machine to predict learning styles. An increasing number of researchers are using learning style models in e-learning activities. However, many people ignore the fact that learners' behaviors and their learning styles differ in traditional learning and online learning. Only few studies have been dedicated to online learning style, and the models are mostly in the design level. In our study, we aim to design a comprehensive model based on classical theories and online learner behavior. We also include a proven recipe for the application of learning styles in adaptive learning.

2.2 Adaptive learning resource recommendation

The objective of Recommender Systems (RSs) is to provide useful advice by helping individuals identify content of interest from a set of choices[15]. Three main recommendation algorithms are considered to build a successful RS: content-based recommendation analyzes contents' properties and recommends ones with similar properties[16], CF uses opinions of a cluster of similar users or items to help identify items of interest [17], and combined recommendation improves the performance and efficiency by combining different algorithms[18–20].

Appropriate suggestions may not only make the best use of learning materials, but also enable learners to learn rapidly and easily[21]. Student Course Recommender (SCR)[22] offers suggestions after analyzing learners' information based on Bayesian network modeling; the Course Recommender[23] applies CF methods with C4.5; Recommender system based on Association RulEs (RARE)[24] improves the recommendation mechanism by incorporating the data mining process with user ratings; and context models are designed to characterize learning context and provide support[25]. Protus[26] processes learner clusters based on different learning styles and mines frequent sequences of learners.

All these learning resource RSs think highly of contents, but most of them use recommendation techniques without considering the distinction of learning styles, which is a crucial part of learner-centered learning. In our point of view, learners with similar learning styles have similar preferences and learning behaviors, so our enhanced method considers the concept of learning style and focuses on group-based collaborative learning.

3 Online Learning Style Model

Traditional learning and online learning differ in many ways. For example, students in a classroom environment may have preferences on sound, light, and temperature, whereas those factors do not suit online learning environments as the main element of the environment is an interactive web page. Thus, an online learning style model of eight dimensions has been proposed in our previous work[27]. This work compares traditional and online learning in four categories: emotion, sociology, physiology, and psychology. Subsequently, eight features are designed to characterize online learners, and an investigation of online learning behaviors related to these features is conducted and analyzed. Results show that our new online learning style model differentiates online learners and helps understand their behavior.

Table 1 shows the eight features and corresponding behaviors of our online learning style model.

(1) Emotion. The emotion category centers around the extent to which online learners are self-directed learners. According to Entwistle's model[28], motivated online learners monitor and pace themselves until finishing the course, so they may have more interactive records with e-learning systems and tend to click unpopular learning resources than their unmotivated counterparts. By contrast, inactive learners simply finish the necessary materials and assessments.

(2) Sociology. Online learners differ also in how they react to peer interaction and communication. Some dislike discussions and prefer to study by themselves; others thrive on the support provided by group work.

(3) Physiology. The visual and verbal features refer to the Felder-Silverman model. Online learners receive information from different sources: visual (e.g., sights, pictures, diagrams, and symbols) and auditory (e.g., sounds and words). Visual learners are more visually sensitive and have a better comprehension of materials visually presented, whereas auditory learners acquire information with improved performance when they listen to or read the materials. Other learners adapt to how the materials are presented.

Table 1 Online learning style model.

Category	Feature	Learning behavior
Emotion	Motivational	Long duration of study, doing a lot of assessments, etc.
Sociology	Communicational	Being active in the forum, etc.
Physiology	Visual	Prefer videos and pictures
	Verbal	Prefer text and audio materials
Psychology	Sensory	Prefer facts, data, and experimental materials
	Intuitive	Prefer principles and theories
	Sequential	Browse materials in a logically ordered progression
	Global	Jump from one material to another

(4) Psychology. The psychology category refers to the strategies that students use for the comprehension of information. The sensing and intuitive features, which refer to Myers-Briggs Type Indicator (MBTI), reflect what learners focus their attention on. Sensing learners prefer detailed materials based on facts, whereas intuitive learners prefer concepts, meanings, and associations. Moreover, we introduce the sequential and global features from Felder-Silverman's model as the presentation order of materials affects the learning efficiency. Some of them learn sequentially in a logically ordered progression, and others learn by making intuitive leaps until they understand eventually.

In most traditional models, features are mutually exclusive. For example, in Felder-Silverman's model, a learner cannot be sequential and global at the same time. On the contrary, our model combines those features by using a vector of eight dimensions to characterize learners. For instance, if a learner obtains high scores in both sequential and global features, then we can say that the learner is very flexible in choosing learning strategies.

Our online learning model provides a comprehensive way to represent features of online learners and explain how they differ from one another. In the following section, we develop our recommendation method based on this model.

4 Adaptive Recommendation Based on Online Learning Style Model

On the basis of our online learning style model, we introduce an enhanced CF recommendation method called AROLS. The basic idea is to mine data of generated learner clusters and filter item-based collaborative recommendation results by association rules. AROLS consists of three steps: learner clustering, learning preference mining, and learning resource recommendation.

4.1 Learner clustering

Clustering is a data mining technique that creates groups of similar data to extract useful patterns. As suggested in an investigation on how to incorporate data mining into e-learning environments[29], we use the clustering algorithm to promote group-based collaborative learning. K-means is a classical clustering algorithm based on partition for learner clustering and is still widely used in research[30]. It scales well to large number of samples and has been used across a large range of application areas in many different fields.

Given a set of N learners $X = \{x_1, x_2, \ldots, x_N\}$, where each learner x_N can be replaced by a vector $\{\boldsymbol{d}_{n1}, \boldsymbol{d}_{n2}, \ldots, \boldsymbol{d}_{n8}\}$ according to the online learning model, $\boldsymbol{d}_{nj}$ represents the value of j-th feature of the learner x_n. We use Euclidean metric to calculate the distance between two learners,

$$d(x_m, x_n) = \sqrt{\sum_{j=1}^{8} (\boldsymbol{d}_{mj} - \boldsymbol{d}_{nj})^2} \tag{1}$$

By measuring the distance, K-means algorithm can divide N learners into K disjoint clusters $C = \{c_1, c_2, \ldots, c_K\}$, each cluster c_k is a set of learners and can be described by the mean (or centroid) μ_k of the learners in the cluster. The main idea of K-means is to update the centroids by iterative computation until some criteria for convergence are met.

4.2 Mining learning preferences

To extract useful information from learners' browsing data, we calculate similarities and association rules between learning resources for each learner cluster c_k.

Having a set of M learning resources $I = \{i_1, i_2, \ldots, i_M\}$, we apply cosine similarity metric to determine the similarity $\text{sim}(i_m, i_n | c_k)$ between i_m and i_n accroding to browsing history of learners in cluster c_k,

$$\text{sim}(i_m, i_n | c_k) = \frac{|S(i_m|c_k) \bigcap S(i_n|c_k)|}{\sqrt{|S(i_m|c_k)||S(i_n|c_k)|}} \tag{2}$$

where $|S(i|c_k)|$ represents the number of learners in cluster c_k who clicked item i and $|S(i_m|c_k) \bigcap S(i_n|c_k)|$ is the number of learners in cluster c_k who both clicked i_m and i_n.

Let I_j be a subset of I such that $I_j \subseteq I$. For cluster c_k, the support of I_j is the percentage of learners in cluster c_k that browsed learning resource set I_j,

$$\text{support}(I_j | c_k) = \frac{|S(I_j|c_k)|}{N_{c_k}} \tag{3}$$

An association rule is an implication of the form $I_i \to I_j$, which means the presence of I_i may infer the presence of I_j. For cluster c_k, the support of a rule $I_i \to I_j$ or a set $I_i \bigcap I_j$ is the percentage of learners in cluster c_k who clicked both I_i and I_j,

$$\text{support}(I_i \to I_j | c_k) = \frac{|N(I_i|c_k) \bigcap N(I_j|c_k)|}{N_{c_k}} \tag{4}$$

Support is a measure that indicates the frequency of a rule applying to the data; high support corresponds to a strong correlation between the items. We also compute confidence for association rules such as $I_i \to I_j$, which is the fraction of learners in cluster c_k who clicked I_i and I_j,

$$\text{conf}(I_i \to I_j | c_k) = \frac{\text{support}(I_i \to I_j | c_k)}{\text{support}(I_i | c_k)} \tag{5}$$

Confidence refers to the reliability of the rule, which also indicates the significance of the correlation between items. In this paper, we use the Apriori algorithm[31] to generate association rules that satisfy a minimum confidence from frequent item sets, whose support exceeds a user-specified minimum support threshold.

4.3 Learning resource recommendation

On the basis of the results of learning resource similarity, AROLS can make predictions by computing the interest $P(x, i_m | c_k)$ of a learner x in cluster c_k on an item i_m,

$$P(x, i_m | c_k) = \sum_{i_n \in S(x) \bigcap S(i_m, L)} \text{sim}(i_m, i_n | c_k) \tag{6}$$

where $S(x)$ is the set browsed by x and $S(i_m, K)$ represents the top L of the most similar learning resource to i_m.

Subsequently, AROLS generates a recommendation set of variable size by identifying candidate learning resources with high tendency. The tendency describes how likely a learner tends to click a learning resource. We define the tendency that a learner x of cluster c_k choose i_m as

$$T(x, i_m | c_k) = P(x, i_m | c_k) \times \sum_{I_j \in F(x)} \text{conf}(I_j \to \{i_m\} | c_k) \tag{7}$$

where $P(x, i_m | c_k)$ is the interest that learner x of cluster c_k has on item i_m and $F(x)$ is the set of frequent item sets generated by the browsing history of learner x.

To adjust the size of recommendation set dynamically, we define the tendency threshold as

$$T_{\text{threshold}}(x, L | c_k) = \mu \times \frac{1}{N} \sum_{i \in R_{\text{CF}}(x, L)} T(x, i | c_k) \tag{8}$$

where $R_{\text{CF}}(x, L)$ is the top L recommendation sets generated by item-based CF and μ is a user-defined parameter. The enhanced method only recommends items whose tendency is equal or more than the tendency threshold.

The application of recommendation algorithm on reduced dataset clusters simplifies the computation and concentrates on extracting patterns from learners with similar learning style. By using association rules with high confidence to filter the results of item-based CF, the enhanced method focuses not only on the personal preferences but also the item-item relationship derived from the learner cluster. The improvement in precision is remarkable because rather than offering a set of N items, the enhanced method dynamically recommends items without fixing the size of the recommendation set.

5 Evaluation

5.1 Data preparation

Open University Learning Analytics Dataset (OULAD)[32] is a recently released open-source dataset, which contains the information about 22 modules, 32 593 learners, their assessment results, and logs (10 655 280 records) of their interactions with the Virtual Learning Environment (VLE). In this paper, we focus on VLE data, which show learner preferences in choosing learning materials as the author of OULAD has classified the sites into 20 different activity types. These types partially correspond to the online learning style features.

The data preparation process comprises four steps:

(1) Data cleaning: We select more reliable and valuable data by extracting the 19 263 learners whose average assessment results are equal to or more than 60.

(2) Data aggregation: For each learner, we analyze his VLE data and count the number of clicks on different activity types. The result is a table where each row represents a learner, and each column represents his preference level for that activity type. We consider the combination of activity types as features of the aggregated data. For instance, the number of clicks on the discussion forum can be used to represent the communication feature. Unfortunately, the OULAD does not provide the content of each page in detail so there is a lack of activity types that correspond to sensing and intuitive features. However, our experiments show that six features are sufficient to yield a satisfying cluster result.

(3) Outlier removal: Given that the preferences are described by numerical discrete numbers and the chosen metric for K-means clustering is Euclidean, a large abnormal number may cause great bias to the clustering result. To avoid this issue, we remove records where at least one of the features has more than 10 standard deviations.

(4) Feature selection: Feature selection is one of the most important procedures in data mining as it rejects the redundant information and improves the results' accuracy. We apply ANalysis Of VAriance (ANOVA) to select appropriate features with high variance that have strong effects on the clustering process.

5.2 Learner clustering

Learners are clustered based on the preprocessed result, which is a table representing each learner with eight online learning style features. Choosing the number of clusters (k) is the most crucial part of the K-means clustering process, which is also the most difficult part as the data are not labeled. Whether the chosen k is appropriate for our case should be evaluated by the performance of the model generated afterward. The Silhouette Coefficient (SC)[33] is a good example of such an evaluation. The SC score is bounded between -1 for incorrect clustering and $+1$ for highly dense clustering. We also use the Calinski-Harabaz (CH) index[34], where a high CH score relates to a model with well-defined clusters.

We apply the K-means algorithm on the dataset of 19 002 learners with their six learning style features. Figure 1 shows the variation in the SC and CH scores along with the number of clusters k. The peak of SC score is 0.29 when $k = 6$, and the peak of CH score is 5853 when $k = 5$. However, as the CH score drops down 7% at $k = 6$ and SC only falls 3% at $k = 5$, we believe that $k = 5$ yields the best clustering result on average.

To better understand our dataset and the clustering result, we apply dimensionality reduction and show the result in Fig. 2. Some overlap is observed between

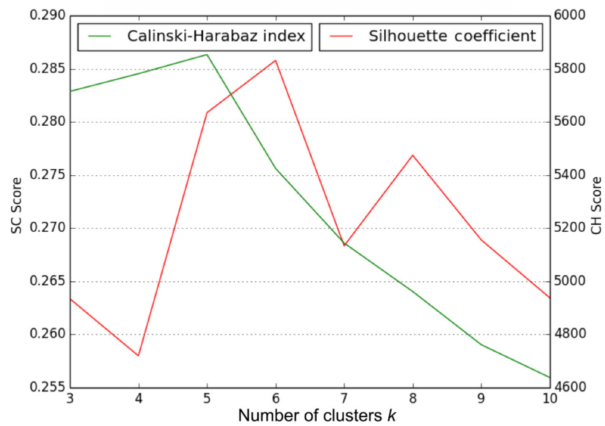

Fig. 1 Variation of SC and CH score along with the number of clusters k.

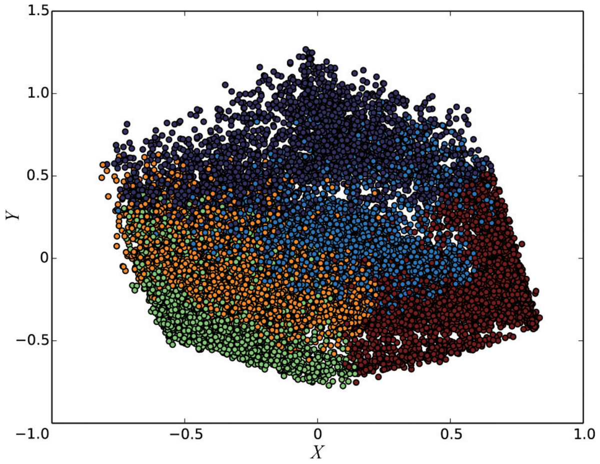

Fig. 2 Visualization of clustering result.

clusters caused by the projection into low-dimensional space. As the figure shows, K-means is a distance-based clustering algorithm. Learners are uniformly clustered into five clusters to guarantee that each cluster has a certain amount of behavioral data to be mined.

5.3 Evaluation metric

Three experiments are considered to compare the recommendation performance: the item-based CF (ItemCF), item-based CF on clusters (Clustering + ItemCF), and enhanced method (AROLS). We employ the precision and recall metrics, which are widely used in RSs to evaluate the quality of recommendations[35]. Precision is the fraction of correctly recommended items in the recommended items, and recall is the fraction of correctly recommended items in the test set. Although these measures are simple to compute and intuitively appealing, they may cause conflicts because increasing the size of the recommendation set improves recall but reduces precision[36]. The F1 score[37], which can be interpreted as a weighted average of precision and recall, reaches its best value at 1 and worst value at 0. Specifically, the relative contributions of precision and recall to the F1 score are equal,

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{9}$$

5.4 Recommendations and analysis

We evaluate the performances of AROLS based on top N recommendation, where the support threshold is 0.2, the confidence threshold is 0.95, and the tendency threshold $\mu = 0.7$. Figure 3 shows the precision, recall, and F1 score of three recommendation methods. The results show that learner clustering based on learning styles (Clustering + ItemCF and AROLS) is useful for

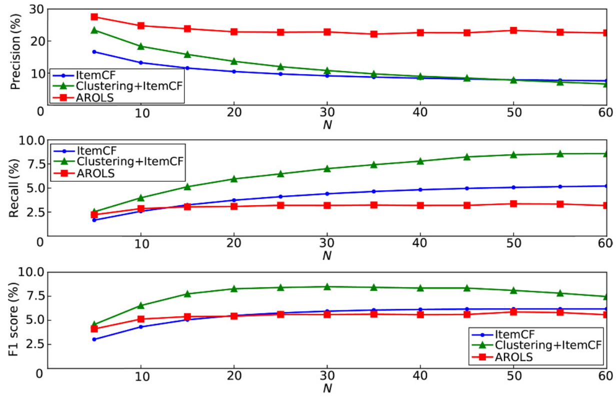

Fig. 3 Recommendation evaluation for three methods.

improved recommendations. Meanwhile, AROLS has a better precision score than traditional item-based CF, and its performance is fairly stable because it limits the length of the recommendation list.

However, having both good precision and recall is somehow incompatible. Compromise has to be made in choosing the right method. We believe that precision is much more important than recall in this case as learning is an evolutionary process. For example, recommending a resource of Chapter 5 to increase recall is useless if the learner is still working on Chapter 2. Therefore, we add the tendency threshold in AROLS to remove low tendency items.

Figure 4 shows the performance of AROLS as the tendency threshold varies based on Top 10 recommendation. The filters with high tendency threshold can filter more items than those with low tendency threshold. Precision increases more slowly when $\mu > 0.7$, whereas the drop of recall and F1 score accelerates at that interval. Thus $\mu \approx 0.5$ is a better choice in this case.

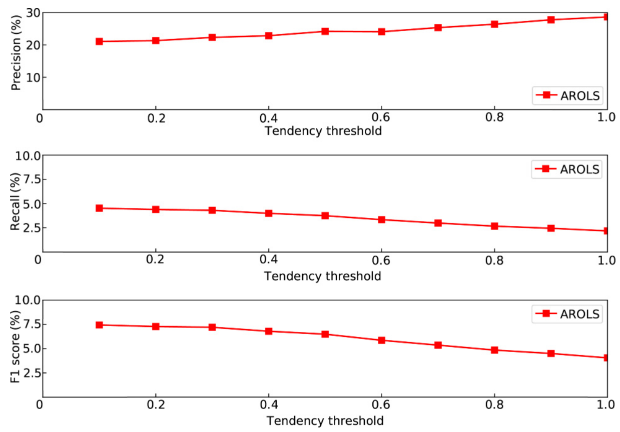

Fig. 4 Recommendation evaluation for different tendency threshold.

6 Conclusion

This study introduces a new online learning style model that represents online learners through eight features. This model does not only describe online learners' individual traits, but it also provides explanations for their behaviors and helps cluster learners in our new adaptive learning resource recommendation method named AROLS. This method focuses on mining the behavioral patterns of similar learners (i.e., learners of closer online learning style). AROLS first divides the learners into several groups by the clustering algorithm. It then applies item-based CF and the Apriori algorithm on data of clustered learners to compute item-item similarity and association rules. Finally, AROLS generates a recommendation set of variable size to make the most precise prediction for learners' current needs. Experiments show that AROLS achieves the best recommendation precision among the three methods. Our experiments prove the value of integrating online learning styles in learning resource recommendations.

In our future work, we will attempt to deploy our enhanced method on a real-world online learning system with an identification mechanism of the online learning style. Given that the proposed method only uses behavioral data, the learning resources' contents are necessary for more effective personalization service.

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