SyncRec: A Synchronized Online Learning Recommendation System

Yixuan Zhang, Wenkang Zhang, Linqi Liu, Xuxue Sun(✉), Hao Zeng(✉), Weijuan Zhao, Youbing Zhao, and Weifan Chen

Communication University of Zhejiang, Hangzhou 310018, China
{sunxuxue,hao.zeng}@cuz.edu.cn

Abstract. With the rapid development of digitalization and big data technology, numerous online learning materials have become available for self-regulated online learning. However, there is still a lack of a practical recommendation platform that can achieve synchronization between massive online learning materials and multiple users at different stages. To fill the gaps, we present a synchronized online learning recommendation system (SyncRec). The multi-source heterogeneous information fusion module integrates online learning materials from different digital platforms. The dynamic knowledge status tracing module tracks the real-time knowledge status and learning progress of online learners via dynamic mapping to a set of knowledge trees. Furthermore, the personalized recommendation module achieves adaptive recommendation of digital learning materials for each self-regulated online learner based on current knowledge status and learning needs as well as preferences. The demonstrated system helps improve learning outcomes and user experiences. An illustration video could be found here (https://github.com/Edith-xuan/video/blob/main/demo.mp4).

Keywords: Multi-source Heterogeneous Information Fusion · Knowledge Status Tracing · Synchronized Recommendation · Online Learning

1 Introduction

1.1 Background

Online learning platforms have gained increasing attention in the past decade due to the rich multimodal learning materials, such as the MOOC platform [1]. However, existing platforms in real practice are not feasible for self-regulated online learners at different learning stages due to issues of confusion and information overload in the e-learning process. Moreover, learning outcomes may vary among different users, which also presents challenges [2]. There is a need for a practical system that can synchronize the real-time knowledge status of online learners at different stages with massive heterogeneous digital learning materials, and further provide adaptive recommendations for online learning. Such a system can reduce the cognitive overload of self-regulated online learners and improve both the learning outcomes as well as the learning experiences.

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1.2 Literature Review

Existing literature addresses the topic of online learning recommendations from different perspectives. In some studies, online learning content is recommended at the group level, such as the multilayer bucket recommendation method for similar online learners [3], and the clustering strategy-based method for the recommendation of similar learning content [4]. Others focus on individual-level online learning recommendations, such as personalized recommendations based on learner preferences [5], and reinforcement learning-based dynamic recommendations [6]. Moreover, some used a hybrid method with collaborative filtering and association rules for online learning recommendation [7]. However, there are few practical online learning recommendation systems that can effectively synchronize massive online learning materials with real-time user knowledge status, as well as user needs and preferences.

To fill the above gaps, we propose a new online learning recommendation system that effectively synchronizes heterogeneous online learning materials with varying user knowledge status and personal needs as well as preferences.

2 Methodology

With fused online learning materials and traced user knowledge status, the system achieves adaptive online learning recommendations, as shown in Fig. 1.

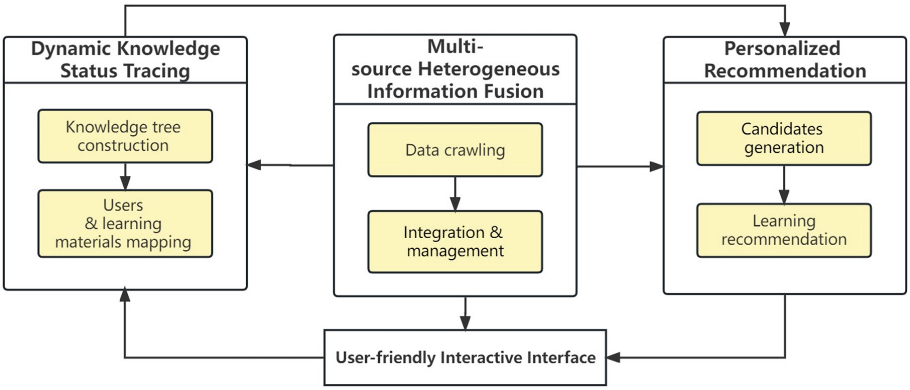

Fig. 1. Framework illustration of SynRec system

2.1 Multi-source Heterogeneous Information Fusion

We utilize the Selenium and Python toolkit with robust anti-scraping capability to facilitate information retrieval from online courses and videos over three digital platforms (e.g., MOOC, NetEase Cloud Classroom, and Bilibili). Online learning materials vary significantly among different platforms. In order to address the consistency issue, the developed system fuses and integrates multi-source information. To improve overall performance, the Supabase hosting platform [8] is used for data storage due to its self-hosting feature and database scalability, as well as support for frequent requests.

2.2 Dynamic Knowledge Status Tracing

In order to achieve dynamic tracking of the status of user knowledge, we use chapters from online courses or sequences of e-learning videos as tree nodes. The developed system utilizes a knowledge graph to capture the dependency between knowledge points and further provides query functionality. We employ the Neo4j graph database [9] to create and store the knowledge tree. When a user selects a learning plan, the learning process starts at the root node of the corresponding knowledge tree. The system keeps track of changes in user knowledge through interactive interfaces. After accomplishing the learning on a specific tree node based on recommended online resources, the user can alter the knowledge status via interactive self-assessment and automatically enroll into the next stage.

2.3 Personalized Recommendation

Based on the above modules, we further synchronize the fused massive online learning materials with the tracked real-time user knowledge status, as illustrated in Fig. 2. We use course/video tags from the fusion module and user knowledge status from the tracing module to generate candidates via automatic matching. Since the deep learning-based recommendation method could effectively discover the underlying patterns [10], we further employ a hybrid recommendation

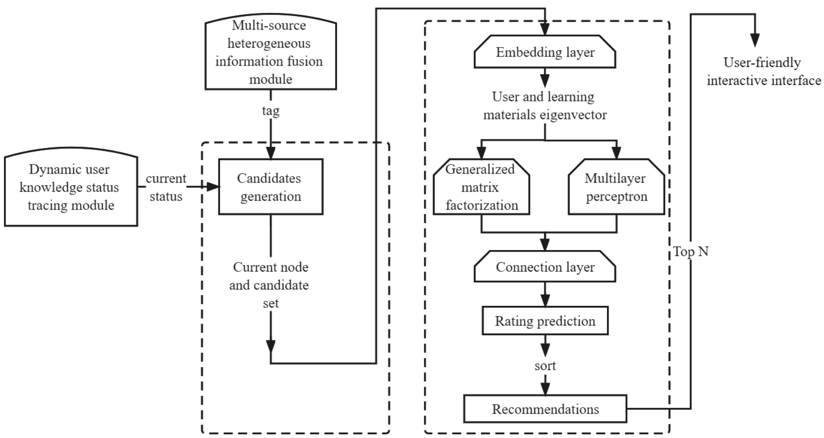

Fig. 2. Personalized adaptive recommendation

method with traditional matrix factorization and multilayer perceptron (MLP), which is capable of extracting both low-dimensional and high-dimensional features simultaneously. Unlike existing methods, the system generates embedding vectors based on multiple features, including the user ID, the status of user knowledge, the online learning material ID, and the ratings. The generalized matrix factorization (GMF) layer can learn the interactions between users and online learning materials. The MLP layer can retain the effective components in the high-dimensional sparse features and transform others into low-dimensional representations. Nonlinearity is further learned by concatenating multiple fully connected layers. Finally, the results of the GMF layer and the MLP layer are combined to generate a predicted rating for recommendations.

3 Application Scenarios

In this demo, information is collected from more than 16000 digital learning materials and further integrated into the Supabase platform, as shown in Fig. 3(a). We use course category, number of learners, and teacher information from MOOC and NetEase platforms to represent the information about tags, video publishers, and viewer counts respectively. To further illustrate the tracking of knowledge status, we use a triplet list that stores the dependency of the nodes to build a knowledge tree for each learning topic, as shown in Fig. 3(b). When a user sets up a learning goal via an interactive interface, the system automatically maps the knowledge status to the root node of the corresponding knowledge tree. When the user finishes the learning process of the current node, the system dynamically alters the user knowledge status via a self-assessment method. Moreover, to improve the fidelity of the recommendations, the system synchronizes the status of user knowledge with massive learning materials and displays the recommendations via a user-friendly interface, as shown in Fig. 4.

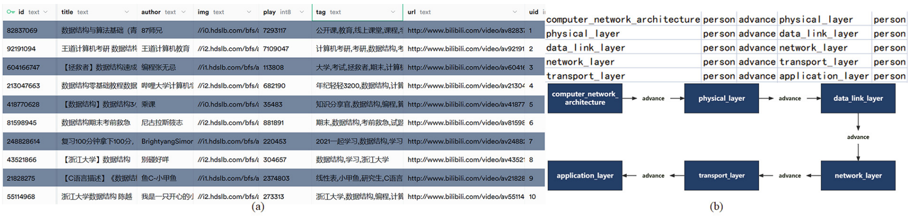

Fig. 3. (a) multi-source information integration, (b) knowledge tree

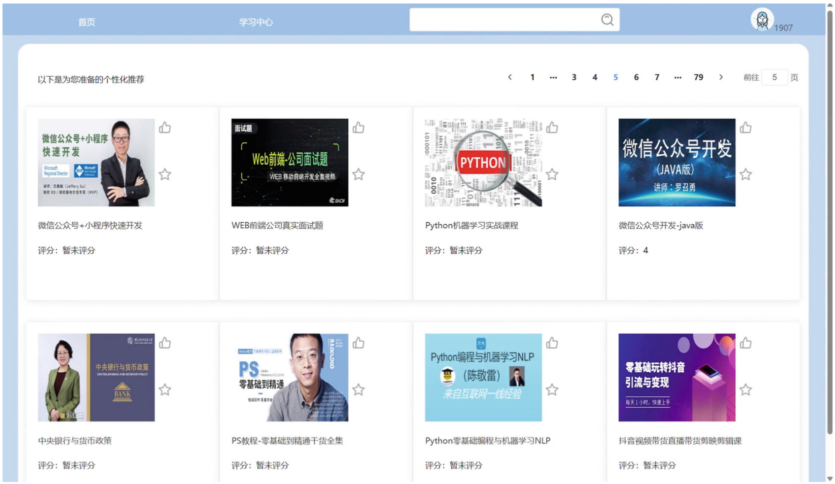

Fig. 4. Recommendation results

4 Conclusion

The proposed system synchronizes the dynamically evolving knowledge status with heterogeneous multi-source online learning materials. The synchronization mechanism enables effective recommendation of learning materials for multiple online learners at different stages. The proposed system with a user-friendly interface addresses the issues of confusion and cognitive overload during the self-regulated online learning process and improves learning outcomes as well as user experiences.

In future work, more interactive functionalities can be introduced to explicitly and implicitly retrieve online learner behaviors. The data could then be augmented with more online resources and user characteristics to improve modeling fidelity. In addition, comprehensive assessments, such as quizzes and tests, can be incorporated to improve the rationality of the tracing of knowledge status.

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