State-of-the-Art on Recommender Systems for E-Learning

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Recommender systems (RSs) are increasingly recognized as intelligent software for predicting users' opinions on specific items. Various RSs have been developed in different domains, such as e-commerce, e-government, e-resource services, e-business, e-library, e-tourism, and e-learning, to make excellent user recommendations. In e-learning technology, RSs are designed to support and improve the learning practices of a student or an organization.

recommender systems similarity metrics recommendation goal e-learning

1. Introduction

We form opinions about things we do not care for, like, or dislike daily. It happens more often in our daily life; for instance, we may decide to go to school in the morning, play soccer in the afternoon, and watch an action movie at night. Similarly, when trying to purchase an item from a store, one can decide to purchase a snack, an item from the dairy section, a book, or a beverage. However, making the right decision is one of the challenges people face in their daily activities. Thus, there is a need for an intelligent system to help predict user preferences for new items. Recommender systems (RSs) emerged to deal with this problem to help users find what is genuinely relevant to their needs [1]. Such systems have intelligently changed how we find articles, information, and even how we see others. RSs' main function is to predict user interest by relating the user's history, information, profile, and queries used, searched, created, and expressed [2]. Recently, learning has drastically shifted from a traditional classroom to an e-learning environment [3]. In technology-enhanced learning, RSs are used to find and suggest suitable learning objects to the learner, and a learning object (e.g., a problem) has several categories that indicate topics or fields [4]. RSs are generally essential in education and any activity involving accessing and sharing resources among people or communities. It uses different users' and items' characteristics, such as their interests, educational backgrounds, levels of expertise, geographical locations, and so on, to propose sequences or novel resources that might interest users [5]. However, when providing recommendations for e-learning contexts, the system should consider the users' interests and learning goals [6].

2. Recommender Systems for E-Learning

E-learning is a way of learning, in which a learner can study online from anywhere, which can be self-paced with available learning resources. E-learning is one of the fastest learning methods in recent years due to the rapid growth in technology development [7]. Learners can now search for desired educational information, products, and services via computers and mobile devices [8]. The number of educational resources continues to grow, making it increasingly difficult for traditional search engines to meet requirements related to online searches for information about educational products and services during the learning process [9].

Problems of information overload create difficulties for people to discover items or make the right decision on a particular item that can satisfy their needs. The same issues arose when learners tried to find suitable learning materials. RSs are intelligent systems that can solve problems of information overload by using various techniques to find and recommend valuable items to users. They are subclasses of information filtering systems aimed at predicting preferences or ratings that a learner would provide to learning items and creating lists of relevant items for recommendations, ranked according to their various degrees of relevancy to the items required. RSs for learning cover almost all fields of technology-enhanced learning, such as mobile learning, formal learning, informal learning, and traditional and modern ways of learning. Various definitions have been suggested for RSs in general. In learning, RSs for learning have similarly retained almost all their definitions. The only distinction is that the term “items” used in this context strictly refers to a learner (or sometimes to both learners and students). RSs have become one of the main tools for personalized content filtering in the educational domain [9]. As indicated by H. Drachsler et al. in [10] and G. McCalla in [11], RSs for learning aim to support learners by providing valuable learning materials. In addition to what RSs do in other application domains, such as e-commerce, to recommend products to customers, RSs for learning also support various user tasks such as recommending learning peers, lessons and lectures, self-assessment materials, etc.

2.1. Related Works

Research in RSs for e-learning is continuously growing, with an effort by authors to summarize and map different aspects of this field.

Drachsler et al. in [10] presented a state-of-the-art review on technology-enhanced learning RSs. This study considered 82 papers published between 2000 to 2014 and provided a comprehensive overview of the area. The authors introduced parameters for evaluating technology-enhanced learning RSs and analyzed different recommendation techniques and sources of information. Khanal et al. [12] presented a systematic review of machine learning-based RSs for e-learning. The authors developed a taxonomy that accounts for components required to develop effective RSs. The study focused on four traditional recommendation techniques: collaborative filtering, content-based, knowledge-based, and hybrid approaches. The authors’ analysis was based on machine learning algorithms and the method of evaluating the RSs. They also addressed challenges regarding input and output characterization. They summarized the overall findings with an observation that machine learning techniques, algorithms, datasets, evaluation, valuation, and output are necessary components in Rs for e-learning.

Zhang et al. [13] presented a survey on RSs for e-learning. The authors reviewed and analyzed the research on e-learning RSs, identified the traditional recommendation techniques used in e-learning, and identified new research directions. They also proposed a framework with three major components: a user interface, a database server, and a recommendation engine. This paper highlighted how recommendation techniques could support learners in universities and life-long learners to gain skills to stay competitive. It aimed to provide guidance for researchers and practitioners in developing e-learning RSs. Urdaneta-Ponte et al. [1] conducted a review on RSs for education. The authors surveyed 98 articles to analyze the work undertaken in RSs that support educational practices to acquire information related to the type of education and areas dealt with, the developmental approach used, and the elements recommended.

Rivera et al. [14] presented a systematic mapping to investigate the use of RSs in education. The authors extensively reviewed 44 research papers to extract and classify relevant data to obtain valuable insights about the uses, approaches, and challenges addressed by RSs. Salazar et al. [15] conducted a systematic review of affective RSs in the learning environment. The authors presented a macro-analysis, identifying the primary authors and research trends. They also summarized different aspects of RSs, such as the techniques used in affectivity analysis, the source of data collection, and the state of the art of influence of emotions in the educational field.

2.2. Methods of Evaluating Recommender Systems for Learning

Frameworks have been suggested for evaluating the system, the usefulness of recommendations given to users, and evaluating whether users are delighted with the services the system offers. Mojisola et al. [16] have surveyed various methods for evaluating RSs for learning. The main aim of evaluating RSs is broadly categorized into three parts. First is measuring the performance of the systems, which entails the performance of algorithms used or the system’s general performance from a technical point of view. The second is measuring the impact on learning to evaluate if the learning performance of the user has improved after using the system for a considerable period. Third is user-centric evaluation, which measures users’ contentment and satisfaction with the system. The first evaluation category can be achieved offline using a dataset containing interactions between users and similar systems to evaluate the effectiveness of the recommendation algorithm or the entire system. The impact of the system on learning can be measured scientifically from the users’ perspectives to determine the level of learning improvements and how the system influences their studies. Finally, real-life testing allows users to use the system over a long period to measure their satisfaction. One way to achieve this is through interviewing users either by face-to-face interaction or via the distribution of questionnaires.

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