Recommender Systems for an Enhanced Mobile e-Learning

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Abstract. In the last years we have been witnesses of the increasing use of on-line educational systems known as e-learning. Every year there are more teaching centers, both public and private ones, which provide their students with web-based access to Learning Management Systems (LMS). Also, it is important to mention platforms for Massive Open Online Courses (MOOC) which are a type of on-line educational system recently developed according to the design and participation akin to the presential courses at most prestigious universities. These systems provide to all kind of students with didactic resources as well as activities. In another hand the Adaptive and Intelligence Web-based Educational Systems (AIWBES) are made in order to solve the problem of to automate the adaptation of the system to the user features and needs. One more recent alternative is implementing Recommender Systems, which might offer their users customized suggestions to find activities and educational content. Such systems filter user information, for instance, preferences known by a user community for forecasting preferences for the new user, this approach is known as collaborative Filtering. With this proposal we are trying to model and represent the domain knowledge about the learner and learning resources discovering the learners' learning patterns.

Keywords: Recommender Systems · e-Learning · Mobile computing

1 Introduction

One of the problems that exists around the use of Learning Management Systems is that it is necessary to personalize them. This type of problem requires a restructuring of how the teacher has designed the subject, and access to the tools, to support the subject in order of to know which design is better adapted to the characteristics and interests of the learners/students. Then is necessary to ask: How can the use of Learning Management Systems is improved to make them easier to use and learn? How can this interaction is made more effective and satisfactory?

This work has been funded by Universidad de Córdoba (Colombia).

C. Stephanidis (Ed.): HCII 2019, LNCS 11786, pp. 357–365, 2019.
https://doi.org/10.1007/978-3-030-30033-3_28

This paper reflects the ongoing endeavor toward response, in some way, the prior questions. Our approach involves five steps: (1) creating knowledge representation about the learner and learning resources, (2) computing user's similarity based on the frequent pattern mining of learner's actions, (3) generating the recommendation through association rules, and (4) displaying the recommendations into a mobile application taking in account the research challenges (mobile technology).

The remainder article is outlined as follows: in Sect. 2 we discuss the literature review about the application of Recommender Systems in the e-learning context. In Sect. 3 we present the contribution of our work. Finally, Sect. 4 concludes the article and presents our ongoing work.

2 Related Work

In e-learning, Recommender Systems (RS) assist users or learners to discover worthy learning objects which fulfill their needs. To this end, RS aim at providing users with no obvious suggestions about learning objects which, hopefully, might help them to understand the topic of interest. The main recommendation approaches are as follows (Burke 2007; Ricci et al. 2010): (1) content-based RS, (2) collaborative filtering, (3) demographic, (4) knowledge-based RS, (5) community-based RS, and (6) hybrid RS. From previous techniques, the most common adopted in the e-learning domain are content-based RS, collaborative filtering, knowledge-based RS, and hybrid techniques.

In *Content-based RS*, both the history of users taste and content features are used to compute the recommendation to the active user. In the e-learning context, the content is composed of a learning objects collection, each one with its features.

Systems based on *collaborative filtering* suggest to the active user the content which has been preferred to other similar users in the past. In the original approach, the content is not taken into account to compute recommendations (Schafer et al. 2007), whereas matrix factorization has been adopted to infer latent factors which describe the content and the history of users preferences as well (Koren et al. 2009). When the system starts working, most of the users' preferences are unknown, therefore either content-based RS or collaborative filtering based RS tend to fail at suggesting content, this is known as the *cold-start problem*.

On the other hand, *knowledge-based* RS tend to overcome the cold-start problem because recommendations are computed according to specific domain knowledge, and how content features match users' needs and preferences. The knowledge may be represented and encoded either as constraints or cases. The drawback of knowledge-based systems is these RS lack learning components, so knowledge-based systems might be outperformed by other approaches (e.g., collaborative filtering), e.g., where RS use logs of the interaction between users and computers, thus, knowledge-based RS cannot adapt to changes in the domain, such as users who have improved their skills and need new content.

In order to tackle the cold-start and adaptation problem, RS are designed with a combination of several techniques (e.g., collaborative filtering and knowledge based-RS), this kind of systems is named hybrid RS. In the e-learning context, the resulting endeavor has produced hybrid RS. Besides, the e-learning domain poses specific challenges such as learning style (e.g., auditory, kinaesthetic, reader, competency, and visual), both users' preferences and skills are always changing.

In prior research, some hybrid RS for the e-learning domain are based on collaborative approaches besides other ones. Collaborative filtering is combined with other methods such as:

1. Web log mining approach, where the occurrence order between learning objects is used for mining sequential patterns (Li et al. 2011).
2. Modeling attributes of learning objects in a recommendation framework (Salehi and Kmalabadi 2012).
3. Knowledge and content-based approaches, where content features are obtained from the metadata of learning objects, while the knowledge is gathered from users' profile, personal information, interactivity, level, language, preference, learning style, and usage history (Palanca et al. 2018). In another approach, the knowledge is modeled as an ontology, so ratings are predicted for the active user based on the ontology, then collaborative filtering is applied for recommending the top k learning objects, furthermore, the resulting suggestion is computed through a sequential pattern algorithm (Tarus et al. 2017).
4. Collaborative tagging for creating a set of tags, known as folksonomies, which describe learning objects (Klasnja-Milicevic et al. 2018).

Moreover, in the e-learning domain, other research approaches combine content-based with other techniques as follows:

1. Self-organization of the content (i.e., learning objects). Every object is simulated as a smart agent, where these agents interact with one another aiming to improve the adaptability and diversity of the content-based recommendations (Wan and Niu 2018).
2. Personalizing the learning process by matching the compatibility level of the content to the user's learning style as well as the content complexity level and the user's knowledge level. With this approach, researchers aimed at improving the users' performance during evaluations and their satisfaction as well (Christudas et al. 2018).

Besides the above-mentioned kinds of recommendation approaches, data mining algorithms such as K-means and Apriori association rules have also been adopted for designing RS in the e-learning context (Aher and Lobo 2012). Moreover, information retrieval has been combined with knowledge-based systems for suggesting and guiding users in the e-learning environment (Gulzar et al. 2018).

Related to user model for recommendations, the research of Chung et al. (2007) has the objective of to propose a framework for recommender systems applications with a focus on supporting personal decision making. The system named VCR - virtual community recommender - Lee et al. (2007) recommends optimal virtual communities for an active user by case-based reasoning (CBR) using behavioral factors suggested in the technology acceptance model (TAM) and its extended models. In addition, it refines its recommendation results by considering the user's needs type at the point of usage. The study of Weng and Chang (2008) utilizes ontology to construct user profiles and makes use of user profile ontology as the basis to reason about the interests of users. Furthermore, this study takes advantage of the spreading activation model to search for other influential users in the community network environment, making a study on their interests in order to provide recommendation on related information The paper of de Gemmis et al. (2010) provides a general (and interesting) overview of the approaches to learning preference models in the context of recommender systems. The work of Polydoropoulou and Lambrou (2012), presents an innovative methodology for the development of a training advisor for e-learning environments. We consider e-learning personalization issues and present an e-learning recommender framework based on discrete choice models and Bayesian theory.

In the context of e-Learning, we can cite some works that adopt recommender systems for personalization of pedagogical content. The work of Baloian et al. (2004) proposes a methodology for characterizing multimedia learning material based on the use of collaborative techniques in order to define a vector of characteristics for a certain document. This vector will reflect the opinion the people who have seen this document before and will evolve as new people express their opinion about the document. Drachsler et al. (2010) is a hybrid recommender system, so-called ReMashe, that takes advantage of the tag and rating data of the combined Web 2.0 sources. The users of ReMashed are able to rate the emerging data of all users in the system. Bobadilla et al. (2009) observed that learners' prior knowledge have a considerable effect on recommendation quality, for this reason he suggested to students a set of tests and introduced the results in recommendation calculation. Durao and Dolog (2010) used similarity between tags defined by learners to provide personalized recommendations. Anjorin et al. (2011) designed a conceptual architecture of a personalized recommender system considering the CROKODIL e-Learning scenario and incorporating collaborative semantic tagging to rank e-Learning resources. A hybrid architecture that combines enhanced case-based recommending with (collaborative) feedback from users to recommend open courseware and educational resources presented in Vladoiu et al. (2013).

Lichtnow et al. (2011) created an approach for collaborative recommendation of learning materials to students in an e-Learning environment considering learning materials properties, students' profile and the context. Addressing more user/learner-centric Technology-Enhanced Learning streams, recommendations seem to be a powerful tool for this solution (Mödritscher 2010). In accordance with Benhamdi et al. (2017): "Personal Learning Environments, information are filtered based on significant context limits thanks to personalized recommendations (Anandakumar et al. 2014; Salehi et al. 2014; Wilson et al. 2007), giving learners the opportunity to take the best of an environment where shared content differed in quality, target audience, subject matter, and is constantly expanded, annotated, and repurposed (Downes 2010)".

Among the above-mentioned approaches, so far there is not enough information to determine which one provides users with the best recommendations. This is because either some of these approaches have been evaluated through user-driven tests with different experimental settings, or no evaluation has been conducted over the other approaches in the state-of-the-art. Besides, in mentioned prior research, authors have not published a public data set to evaluate their contributions in an off-line fashion and reproduce their results. As a consequence, set up an off-line test for comparing all previous approaches is not possible. Furthermore, traditional performance metrics (e.g., precision, recall, F1, etc.) used to evaluate RS do not measure to which extent the RS contribute at improving the users' experience to learn new knowledge or acquire abilities through e-learning environments. For instance, a particular learning object about the multi-layer Perceptron topic might be liked by the user, but it does not mean that the object actually helps the user to understand how the multi-layer Perceptron works.

3 Recommendation Approach

The adopted approach is carried out in two steps as follows:

1. Creating the user neighborhood by mining the use log (see Fig. 1).
2. Computing the recommendation by finding rules which explain how users' actions are associated with one another in the active user neighborhood.

With neighborhood creation we aim at mining use logs to determine aspects such as personalizing the application to a group of users or a single one, regarding

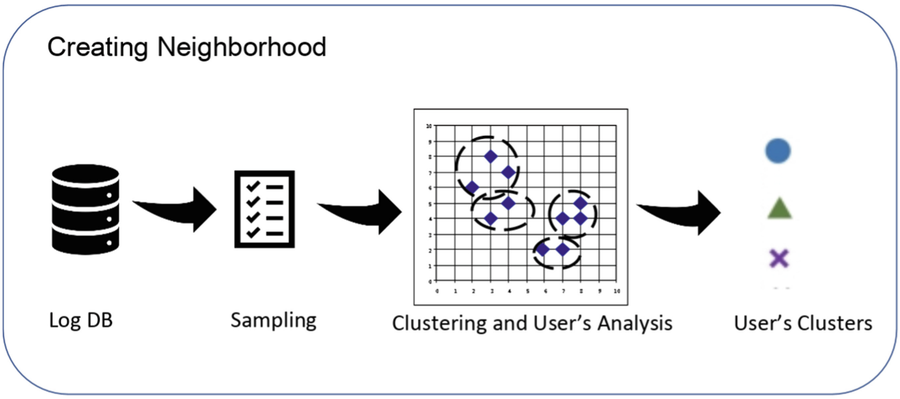

Fig. 1. Steps for computing recommendations

the analysis of advantages and drawbacks, which allows easier and friendlier access to the portal tools.

For use mining and users profile analysis, there are available various candidate techniques, e.g., association rules, sequence patterns and classification, statistics analysis, and clustering. A wider explanation about these techniques is provided as follows:

– Given a database, the association rules technique find causality-based relations between items through conditional probabilities (Agrawal et al. 1996). For instance, an association rule of the form $a \implies b$ means the antecedent a implies the consequent b. In the e-learning context, the item a might be an action such as downloading a content, which implies the item b, that might be the action of solving an exam.
– In sequence patterns, the goal is finding patterns in a set of items, where items are related to each other, according to their chronological order (Han et al. 2007).
– Statistics analysis involve both descriptive techniques (i.e., mean, mode, variance, standard deviation, etc.) and statistical inference (i.e., regression).
– By clustering items, we aim at finding those users who follow similar behavior pattern when they access the system. K-means is a representative clustering technique (Gersho and Gray 1991).

In our context, at Universidad de Córdoba there is a server-based e-learning platform named Campus Virtual, which is a customized version of Moddle. Campus Virtual stores actions carried out by the users in a log. So far, students have no been classified by an expert in the domain, therefore, we adopt clustering of students, with data of access and use frequency (e.g., Quiz view, course view, resource view, etc.). The clustering is performed by taking into account similar actions carried out among students during their learning process.

Currently, the student database and the Campus Virtual data, in particular, the uses logs, are the data sources to model user profiles and features which involve the more often actions carried out by users, in order to estimate serendipitous and novel recommendations.

Once the clusters are computed through K-means algorithm (Gersho and Gray 1991), the recommendation to the active user is computed based on the users' profile who make up their cluster. Thus, the Apriori algorithm (Agrawal et al. 1996) is applied for finding associations rules between the common actions carried out among similar users who belong to the cluster rather than discovering association rules through the whole uses log, which is more costly in terms of computation.

The recommender system suggests actions to the active user, which, hopefully, might improve the learning experience by complementing the current action the active user is either performing or has done previously.

Although Aher and Lobo (2012) adopt the same algorithms (i.e., Apriori and K-means), we apply association rules and clustering on user actions rather than user ratings which represent user tastes. We assume the rating might not represent to what extent the content actually helps the user.

Furthermore, through this approach we avoid dealing with missing values which is a common issue in both collaborative filtering and content-based recommendation, and the one proposed by Aher and Lobo (2012).

4 Conclusions and Ongoing Work

In this work we propose a hybrid recommendation approach based on K-mean and Apriori algorithm to be implemented in the e-learning platform known as Campus Virtual at Universidad de Córdoba. To this end, we have taken into account the problem that e-Learning environments consider that all learners are similar in their preferences and abilities, hence, we have proposed the integration of personalizing tools, focusing on the integration of new recommendation approach in learning scenarios.

By integrating the recommender system into the e-learning platform, our goal is enhancing the personalizing procedure and improving learning quality, while students attain the control of their learning process across different tools and services.

So far we are implementing the recommender systems and setting the evaluation environment to conduct user-driven tests in our approach. Moreover, we will compare its effectiveness to other well-known approaches such as content-based systems and collaborative filtering, the main goal of these experiments is to evaluate the impact of learner's properties on the quality of recommendations and learning processes.

Finally, there are other challenges to be considered for further work, for instance, customizing the content according to the mobile features, and active user skills. The other challenge is providing users with suggestion according to their changing needs and tastes.

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