Personalizing E-Learning 2.0 Using Recommendations

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Abstract. Recommender systems support users in accessing information available on the Web. This process ensures personalization since recommendations are generated according to user's characteristics. In the educational domain, in the most cases, recommendations refer to learning materials. Besides that, there is a potential for using recommendation techniques in order to personalize other aspects of e-learning context. This paper describes a recommendation model for providing personalization of a collaborative learning process. Well-known recommendation techniques are adapted for online learning environment that consists of an LMS and different Web 2.0 tools. The recommendations are used to support students before and during e-tivities and include four different types of items: optional e-tivities, collaborators, Web 2.0 tools and advice.

Keywords: Recommender System, Recommendation Techniques, E-Learning, Collaborative Learning, TEL, Web 2.0.

1 Introduction

Recommending items that are potentially useful for the target user or that are within the scope of his/her interests can provide the solution for information overload problem [1]. The usefulness of items (utility) is in recommender systems expressed as a numerical value (rating). This value is determined by the user or it can be predicted. The recommendation problem comes down to the prediction of the unknown utility values in order to recommend item or items with the highest utility to the target user. Recommendation techniques vary depending on the prediction method and can be divided into three main groups [1], [2]: collaborative filtering, content-based and knowledge-based techniques. Hybrid recommenders combine these techniques.

Recommender systems are increasingly used in e-learning [2]. Their advantages also enable personalization within the so-called e-learning 2.0 [3]. E-learning 2.0 emphasizes collaborative learning through a variety of e-learning activities (e-tivities) [4] like online discussions [5], mental mapping, WebQuests. E-learning 2.0 is supported with Web 2.0 tools (e.g., Blogger, Flickr, and YouTube) [4]. Thus with the functionalities of a particular learning management system (LMS), which are the same for all users, students in e-learning 2.0 can use the appropriate third-party

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services available on the Web [6]. Since the choice of recommendation technique depends on the domain, it should be conducted in accordance with the particularities of the context [2].

The paper presents original model of using recommendation techniques as a prerequisite for the development of the system that will personalize the e-learning 2.0. The paper is structured as follows. The second chapter gives overview of items, users and recommendation techniques for the given context. The third chapter describes methods for using selected recommendation techniques for recommendation of four different items: e-tivities, collaborators, tools and advice. The fourth chapter presents conclusions and plans for future work.

2 Educational Recommender Systems

Recommendations for education should be distinguished from those for commercial purposes. The aim of educational recommender systems (ERS) is to ensure efficient use of available resources and to support the learning process based on specific learning strategies and pedagogical principles [2]. Domain particularities can be considered in relation to *what* is recommended, *to whom* is recommended and *how* is recommended. Therefore, the identification of potential items, target users and techniques was performed as the initial phase of our recommender system development.

2.1 Items

The process of e-learning can be observed as a sequence of actions (activities) performed by students in response to a task. The recommender system endeavors to intelligently recommend a particular action to the student so the variety of items depends on what kind of actions can be recommended [7]. Existing ERS, overviewed in [2], in most cases recommend teaching materials or courses in general [7]. The remaining related work includes recommendations of actions that support the process of learning programming: programming tasks of varying complexity [8], keywords for tagging learning materials [9] and actions with warnings regarding the most common mistakes [10]. TORMES system [7] represents domain independent approach of recommending different actions in dotLRN LMS.

The characteristic of e-learning 2.0 is collaborative learning through e-tivities that are realized with Web 2.0 tools. Thus, we are developing ERS that will enable personalization in environment that includes LMS and a dozen of Web 2.0 tools. Students use the LMS for studying the lessons, solving the (self)assessment tests, and communicating with teachers and colleagues. They use the Web 2.0 tools for the realization of individual or group-based e-tivities (such as writing learning journal with tool Blogger) [11]. In such context, actions that could be supported with recommendations are selection of collaborators for group e-tivities or a specific tool for its realization. Recommended action can also be the participation in an optional e-tivity, for example to collect extra points for the course. In addition, recommendations may be presented in the form of advice to support students (groups) in the e-tivities realization. Accordingly, the selected items that will be tailored to student's characteristics are [11]: optional e-tivities, collaborators (colleague students), Web 2.0 tools, advice.

The prerequisite for mentioned recommendations is that the teacher allows a certain level of flexibility when planning course activities. This involves enabling students to group themselves, planning e-tivities that can be realized with different tools or optional e-tivities between students (groups) will choose one. An example of activity sequence is shown in Fig.1. After introductory *f2f* class, students study lessons, solve online test for self-assessment and participate in WebQuest e-tivity, using one of the offered tools (Blogger, Wikispaces or Google Drive) and divided in groups. They summarize their WebQuest results in a form of presentation published on SlideShare. These activities are followed by one of the optional activities through which students can repeat the main knowledge concepts by making notes, mind mapping or by bookmarking additional web resources before the final online test.

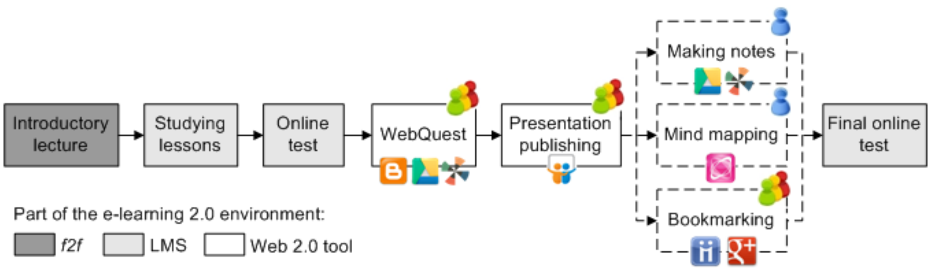

Fig. 1. Example of the course workflow that enables different types of recommendations

2.2 Target Users

The user of an education recommender system is a student. Recommendation process is based on data about his/her previous actions and achievements, and data about students like him/her. Therefore, specific domain requirements are related to the characteristics which will represent students. Unlike commercial recommender systems where recommendations are based on what users like (interests), in ERS items that students like are not always pedagogically most appropriate for them. Thus, it is often necessary to recommend different items to the students with the same interests [2].

Student's characteristics are represented with student model [12]. Besides interests and preferences, these models can include data regarding knowledge level [9], communication level [7], learning styles [9] and affective states [13]. Needed data can be collected explicitly, using feedback from users, or implicitly (automatically) by collecting data about user interaction with the e-learning environment and recommender system. Priority should be given to implicit collection because it does not increase students' cognitive load [1].

Student model for the ERS that we are developing includes learning styles preferences according to the VARK model [14] and preferences of Web 2.0 tools, both collected via questionnaires at the beginning of the course. The model also contains information about the knowledge level identified on the basis of (self)assessments. An important characteristic is also the activity level which is calculated based on automatically collected data about the students' interaction with Web 2.0 tools. It is calculated periodically during the e-tivities (at intervals specified by the teacher) [11]. The mentioned set of data allows generation of the desired recommendations.

In the context of collaborative learning there is also a need for group recommendations which can be generated based on data from group model or aggregation of data about group members from the student model [12]. Group model for our ERS contains data regarding group activity level. Recommendations based on the other characteristics will be generated using appropriate data from the student model.

2.3 Recommendation Techniques

When choosing recommendation techniques for educational domain, it should be considered whether the technique allows personalization based on pedagogical rules, and not only on students' preferences. All techniques, as described below, allow so.

In *collaborative filtering* (CF), items recommended to target user are those preferred by similar students [1]. Similarity between students is calculated based on known preferences. This technique can be used in different learning environments and for recommendations of different items. The filtering can be also done in respect to students' characteristics, which enables the implementation of pedagogical rules (*attribute-based collaborative filtering* method) [2].

Content-based recommendations (CB) predict item's usefulness based on the usefulness of the similar items for the target user. Prediction can be based on known preferences (*case-based*) or, more valuable for e-learning, on student's characteristics (*attribute-based*). The later allows the definition of pedagogical rules as part of a recommended strategy but requires (detailed) items representation [2].

Recommendation can be generated based on series of rules as well. Such *knowledge-based systems* (KB) enable recommendations based on expert's (teacher's) knowledge are can be valuable when there is no sufficient amount of data about the student. When it becomes available, collaborative filtering can be used.

Hybrid recommenders combine mentioned techniques and, according to [2], often provide the most accurate recommendations because they can overcome problems that occur in a particular technique. Between them cold-start problem should be pointed out. It implies that there is not enough information about the user or the items to provide recommendations [1].

3 Recommendations for E-Learning 2.0

This chapter describes our own model of using recommendation techniques in the context of e-learning 2.0, where a set of recommended items includes items insufficiently present in existing educational recommender systems: optional e-tivities, collaborators, Web 2.0 tools, and advice. Table 1 shows the target users and selected recommendation techniques, as well as student's characteristics that will be used in the recommendation process.

Table 1. Target users, user's characteristics and selected recommendation techniques

		Optional e-tivities	*Collaborators*	*Web 2.0 tools*	*Advice*
Target users	Student	+	+	+	+
	Group	+	-	+	+
User's characteristics	Learning style	+	+	+	-
	Tools preferences	+	+	+	-
	Knowledge Level	+	+	-	-
	Activity Level	+	+	-	+
Selected techniques	Collaborative filtering	-	-	+	-
	Content-based	+	+	+	-
	Knowledge-based	-	-	-	+

3.1 Optional e-tivities Recommendations

This type of recommendation will support students and groups in choosing optional e-tivities. The aim is to rank possible e-tivities for the target student (group) taking into account teacher's criteria.

The chosen technique for this task is *content-based recommendations*, more specifically *attribute-based recommendations*. In general, with this technique, characteristics of items recommended to the target user correspond to his/her needs, which is calculated based on the similarity metrics [2]. Therefore, the similarity of characteristics which represents students (groups) and e-tivities will be calculated and will represent usefulness measure. The teacher, according to pedagogical principles, will define a set of characteristics for calculating the similarity. For example, the teacher may decide that the e-tivities will be recommended depending on the combination of knowledge level of a specific lesson and preferences of learning styles. On the other hand, optional e-tivities can be recommended depending on the activity level of preceding e-tivity or preferences for the tools offered for its realization.

This technique allows assigning weights to characteristics used for similarity calculation that enables the teacher to determine to what extent will each characteristics affect the usefulness of e-tivities. Usefulness calculation based on the characteristics from the student model can be made for the first e-tivity, assuming that students solve VARK questionnaire and specify few Web 2.0 tools preferences at the beginning of the course. In other words, the so-called cold-start problem [1] will not occur.

3.2 Collaborators Recommendations

Collaborators recommendations will support students in the selection of collaborators for group-based e-tivities. The aim is to rank the potential collaborators (colleague students) who are, according to the criteria defined by the teacher, the most appropriate for the target student. The same technique as for recommending e-tivities is chosen: *content-based* (*case-based*) *recommendations*. Usefulness of potential collaborator will be determined based on the similarity of his/her characteristics with the characteristics of the target student. The teacher will chose the set of characteristics for calculating similarity between the students. The possibility of assigning weights will in this case as well allow him to determine the extent to which each characteristic will affect the final usefulness value. The chosen technique enables the recommendations according to different grouping methods. In the case that students should form homogeneous groups, the colleagues whose characteristics largely coincide with target student's characteristics will be recommended (most useful are the most similar students). On the other hand, a heterogeneous group forming can be encouraged by recommending colleagues with (mutually) different characteristics.

Assuming that students solve VARK questionnaire and specify few tools preferences at the beginning of the course, cold-start problem for new item will not occur. Therefore, usefulness of potential collaborators based on these characteristics can be calculated for the first e-tivity. A possible problem is the lack of diversity [2] in situations when the same collaborators students are recommended for several e-tivities. Since the recommendation criteria is not necessary the same for all e-tivities within the course, this is not considered as major shortcoming. In addition, student's characteristics change over time, which to some extent also affects diversity.

3.3 Tools Recommendations

The recommendation techniques will be also used to support selection between the Web 2.0 tools. The aim is to rank the tools offered for an e-tivity in accordance to what student (group) prefer. Therefore, the usefulness of each tool for the target student (group) will be determined based on the Web 2.0 tools preferences.

The *hybrid approach* [2] is chosen, taking into account that the number of items (tools) is relatively small and that the number of students will increase before a number of tools. Therefore, the recommender will switch between collaborative filtering and content-based recommendation based on the number of known student preferences. *Collaborative filtering* technique will be used to solve the cold-start problem for a new student (student whose preferences are not known). Similarity between student will be calculated based on the student characteristics (*attribute-based collaborative filtering* method) [2], namely learning styles preferences. Two students will be considered similar if they have similar learning styles preferences according to the VARK model. To solve cold-start problem for the new tool (tool for which there is no known preferences), the *content-based* (*case-based*) *recommendations* will be used. That assumes that target student will like tools that are similar to those he/she prefers (tools similarity will be calculated based on his/her preferences for the other tools) [2].

The list of tools offered for the realization of e-tivity will be presented to students, ranked by usefulness. This does not restrict recommendations to the set of the most popular items, which is a limitation of the collaborative filtering approach. In addition, it allows the student to explore tools that he/she has not used before. The problem of the small number of preferences (*sparse rating problem*) occurs for both selected techniques [2]. In order to overcome this limitation, explicit collection of data regarding tools preferences and collaborative filtering based on the student characteristics is planned.

3.4 Providing Advice

Providing advice will be used to motivate students and groups for active participation during the e-tivities (at the end of the intervals defined by the teacher). The aim is to encourage students in reaching higher activity levels which can potentially contribute to greater success in solving the given task. Recommendations will be presented in the form of advice that will relate to different aspects of active participation such as number of different kinds of contributions (e.g. publication of content, commenting, tagging), continuous participation, encouraging collaborators (group members) to participate, etc.

The chosen technique is *knowledge-based recommendations* [1]. Using selected method, recommended items are associated with the student’s (group’s) needs based on explicitly stated "if...then..." expert rules. Target student's characteristics will be compared the to the teacher expectations, so the rules will contain a number of control parameters. According to that, this kind of recommendations will greatly depend on the pedagogical principles derived from expert's (teacher's) knowledge. Example of advice might be: "*Your activity level for [e-tivity_title] is not satisfying. E-activity lasts till [end_date] so it is highly recommended that you participate to a greater extent.*". It should be noted that the lack of this approach is the complexity of formal representation of the expert knowledge.

4 Preliminary Results, Conclusions and Future Work

Besides learning materials, there are others items in the context of e-learning 2.0 that can be adapted to students’ characteristics. For the presented recommendation model optional e-tivities, collaborators, Web 2.0 tools and advice were pointed out. Student's characteristics that have potential to ensure personalization and overcome possible problems (i.e. cold-start) were identified. Recommendation techniques and methods were selected in accordance with the structure of the e-learning environment and available students’ data. The recommendation model described in this paper was implemented in the prototype of E-Learning Activities Recommender System - ELARS [15]. The system was used for two e-courses at the Department of Informatics, University of Rijeka, Croatia. With the help of the e-learning designer familiar with the model and the system's authoring component, teachers planned the e-tivities and adjusted the recommendation criteria according to the desired pedagogic strategies.

The most interesting findings of the survey performed with students (N=42) are that the system positively influenced on their level of engagement in e-tivities (74%, while 17% was neutral) and their motivation for learning (52%, while 36% was neutral). They were satisfied with received recommendations (50%, while 32% was neutral), find ELARS useful for the context of e-tivities (57,4%, while 30,1% was neutral) and easy to use (87%, while 13% was neutral).

These preliminary results are encouraging for further work on the system's e-tivities authoring component. Since three out of four types of recommendations depend on teacher's knowledge, we aim to develop an user friendly interface which will enable teachers to independently plan e-tivities workflows and adjust the personalization methods. This will be followed by evaluation of system's usefulness and usability from teacher's perspective in order to get insights to possible improvements of the recommendation model and e-tivities authoring component.

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