Recommender system for combination of learning elements in mobile environment

RECOMMENDER SYSTEM FOR COMBINATION OF LEARNING ELEMENTS IN MOBILE ENVIRONMENT

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ABSTRACT

This paper presents an ongoing research about the development of a new recommender system dedicated to m-learning. This system is an extension of content based recommender system proposals. It's made of three levels architecture: 1/ a domain model describing the knowledge of teaching, 2/ a user model defining learner's profile and learning's context, 3/ an adaptation model containing rules and metaheuristics, which aims at combining learning modules.
Our system takes into account the spatio-temporal context of the learners, the evolution of learner's profile and the dynamic adaptation of modules during the learning process in a mobile environment. The result of the recommendation is one of the best combinations of pieces of training according to mobility constraints of learners and of the know-how of teachers.

KEYWORDS

Recommender system, m-learning, ontology, metaheuristics, spatiotemporal context, learner's profile.

1. INTRODUCTION

Due to the rapid growth of information technology and communications, the learning methods are evolving. Now, the great challenge of e-learning companies is to bridge the gap between the static e-learning and the mobile learning (or m-learning).

The m-learning features are numerous but can be focused on these three mains: flexibility, accessibility and informality. The flexibility is the ability of the system to access freely the learning training without constraints in time and space. The accessibility is the ability of the system to find any piece of information about the learning training independently from the initial organization of this learning. The informality is the ability of the system to develop a process of learning beyond the original path of learning defined by the teacher. The development of a system respecting these features is a difficult task.
(Quinn, 2000) considers that m-learning refers to all learning using smart phones. (Geddes, 2004) presents m-learning as "the acquisition of all knowledge and skill using mobile technologies, regardless of place or time, causing a change in behavior." In this definition, three main elements are important: the association of knowledge and skill, the definition of a spatio-temporal context of learning and the change in the behavior of learners.

According to this observation, this paper presents an ongoing research about the development of a new recommender system dedicated to m-learning. This system is an extension of content based recommender system proposals. It's made of a static part representing both knowledge of the teachers and profile and context of learners, and a behavioral part containing rules and metaheuristics, which aim at combining learning modules. Our system takes into account the spatio-temporal context of learners, the evolution of learner's profile and the dynamic adaptation of modules during the learning process in a mobile environment.

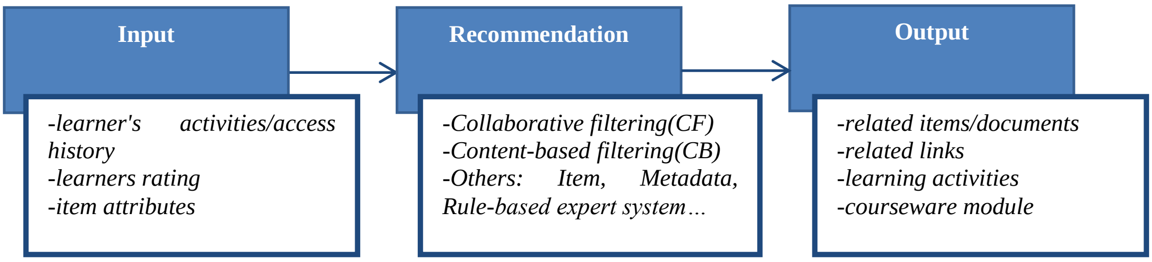
The rest of this paper is articulated in three parts. The first part presents a background of the recommender system domain. The second part presents our proposal and more specifically our architecture. The third part focuses on the combinatory problems of m-learning domains, and the last part concludes this paper.

2. RECOMMENDER SYSTEM BACKGROUND

Recommender systems are based on adaptive hypermedia systems (AH) developed during the end of the 90's. E-learning was considered as the first application of adaptive hypermedia systems. In the e-learning domain, most of the existing proposals are based on a set of layers (Cristea & de Mooij, 2003) which are closed to the AH architectures. A consensus of proposals described a basic set of three layers made of the domain model, the user model and the adaptation model. The domain model describes knowledge of the domain. The user model represents all the information characterizing the user. It is used by algorithms contained in the adaptation model in order to extract, transform and combine information from the domain model. Derived from adaptive hypermedia systems, the architecture of the recommender systems is closed to these set of layers.

A recommender system can provide personalized recommendations into a specific space of knowledge. Derived from the work of (Khairil Imra & Nor Aniz, 2009), figure 1 summarizes the various strategies of recommendation in the e-learning domain. The two main types of recommender systems are collaborative filtering or content-based filtering (Adomavicius & Tuzhilin, 2005), (Lousame & Sanchez, 2009).

Figure 1. E-learning recommendation strategies



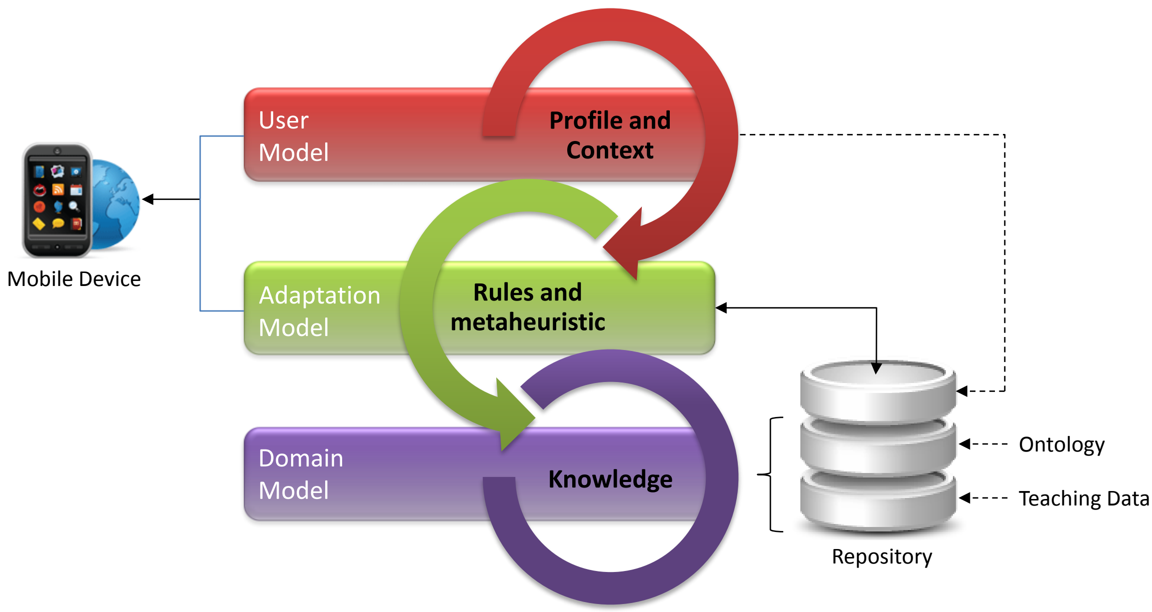
On the one hand, recommendations by collaborative filtering are calculated on how users use the system. The system recommends pieces of training, called items, which have been already selected by other users in the past. This system is limited to e-learning applications. To be build, the recommendation depends on other users. This system requires a period before being efficient.
On the other hand, content-based recommender system analyses the resources or descriptions of these resources to determine which resources are likely to be useful or interesting for a given user. These systems are attractive in the e-learning domain because the recommendation can start directly after system's deployment. Anyway, it needs an initial time of parameterization. These systems require an indexation of resources and a definition of relationships between system's resources. These processes of indexing and binding on resources are generally driven by ontology (Stojanovic & al, 2001). Ontology is an abstract representation of knowledge independent from physical implementation of resources (Gruber, 1991). Nevertheless, in a mobile environment, the main gap is the modeling of the context of learning. This context may be defined by spatio-temporal constraints (where and when) but also, by personal or environmental constraints such as "the weather", "into a plane", "at home with children", "the heterogeneity of skill levels of the learners", etc. These last constraints require a semantic modeling of user's profile. Moreover, in m-learning, the teacher ability to build specific teaching is hindered by the complexity of different learning's circumstances in mobility.

We argue that m-learning systems are content-based recommender systems, which need to be improved to take into account the learning context and the learner profile. This will be done by improving the user model with semantic modeling of learner profile and learning context, and with the improvement of the adaption mechanisms. This will be done by a dynamic process combining pieces of training course according to profiles and contexts of learning.

3. APPROACH

This section describes our approach and mainly the architecture of our system. This architecture is articulated in three main parts: domain model, adaptation model and user model.
The model domain contains the semantic description of knowledge describing learning modules. This description is structured as an ontology dedicated to m-learning. This OWL ontology contains the semantic description of each piece of training according to the teaching description. The concepts and links in this ontology are defined according to learning goals of teachers and answers to constraints of mobility (for example: switch the teaching output flow from audio to text if the learner can't hear the speech). In our system, we use the Sesame middleware as a triple-store, to store the corresponding ontology. This part is connected to the learning repository containing the physical data of learning module. This repository could be standard relational databases. The user model contains the definition of profiles and definition of the possible contexts. These two elements are modeled into an ontology store in Sesame.
The adaptation model contains both rules and metaheuristics. Rules model the skill of the teacher and metaheuristics resolve the combination problem of items, according to the constraints described in the context (for example, geolocalisation of the learner) and the profile information of the learner.

Figure 2. M-learning recommender system architecture



When a learner uses our system, he has to define its profile or load an existing one. This profile is completed by context information send by the mobile device and completed by the user (the mobile send spatio-temporal information, and the user can specify some constraints of the environment). From this profile and user constraints, logical rules run through the ontology to identify and extract pertinent pieces of training course. Next, metaheuristics are used to find the best combination of these elements according to profile and context. Finally, a proposal of course (made of a combination of elements) is sent to the learner through the mobile device. If the context changes during the learning, the system can directly switch an element by another, adapting the learning with the new constraints.

This approach is derived from the TourismKM project (Picot-Clémente, 2011), which aims to develop a recommender system dedicated to the combination of tourism offers. The TourismKM project defines a metaheuristic specifically adapted to the optimization problem in the tourism domain. In our approach, we have to define the optimization problem of m-learning, which consists on the building of a training by combining items, according to constraints defined in the profile and the context part of our system. A description of the metaheuristic used in our approach is presented in the next section.

4. M-LEARNING AND METAHEURISTICS

Validate training independently from the heterogeneity of the learner (profile and context) is the major goal of an m-learning's recommender system.

The validation of training is subject to various business rules. They define how the different items constituting the training must be selected and combined. Each item of training is defined by a subject, a context of use (mode, duration), a type (lectures, exercises, practical work) and precedence constraints that define the possible positioning of the item relative to others. For example, some training's component modules can be followed by an entirely independent way, while some modules require other modules as a prerequisite. Similarly, for each new concept to learn, it will be more suitable to have taken over an item of type "course" before selecting an item of type "exercise."

The platform of m-learning proposes an optimized panel of training items corresponding to the current profile of the learner. This optimization bridges the gap between the learner and the teaching. It reduces the cost and the duration of the training. Furthermore, it maximizes the gain skills and makes the teaching relevant to the training material.

For this, an evolutionary scheduling of items and an evaluation of the benefits of different proposals is needed. From this, a combinatorial optimization problem can be identified. This problem can be reduced to a multi-objective difficult scheduling problem. Such problems cannot be resolved by an exact method, because of the exponential growth in complexity depending on the size of the problem; we propose to use an approximation solution method of metaheuristic type, which will ensure the achievement of a solution in a reasonable time. The metaheuristics used must be adapted to take advantage of rules described in static layer of the system. We, therefore, wish to link the semantic modeling techniques in the offer of training and user profile with powerful algorithms derived from combinatorial optimization, to provide a recommendation system that maximizes the availability of m-learning.

CONCLUSION

In this paper, we present a recommender system applied to the field of m-learning. The idea is to combine technologies of Semantic Web, adaptive hypermedia systems and combinatorial optimization algorithms to help users to access easily to learning modules on their mobiles. This system is made of a static part representing both the knowledge of teachers and the profile and context of the learners, and a behavioral part containing rules and metaheuristics. Our approach allows the teacher to represent his how-know using rules and ontology. Next, in a mobility environment, it allows to take into account the constraints of the environment and the constraints of the user with the definition of profiles and contexts. Finally, the metaheuristic part of our proposal makes it possible a dynamic combination of pieces of training according to these constraints. This specific architecture gives to our system flexibility, accessibility and informality features.

This work is partially supported by the CrossKnowledge Company. We are working on the modeling of the ontology, and the connection of the existing training courses contained in the databases of the company. In parallel, we are studying the impact of this approach on user behaviors in learning context.

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