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CONTEXT-AWARE ADAPTIVE SYSTEM FOR M-LEARNING PERSONALIZATION

Fayrouz Soualah Alila

LE2I, UMR CNRS 6306, University of Bourgogne, Dijon, France

fayrouz.soualah-alila@checksem.fr

CrossKnowledge, 4 Port aux Vins avenue, 92150 Suresnes, Paris, France

fayrouz.soualah-alila@crossknowledge.com

Christophe Nicolle

LE2I, UMR CNRS 6306, University of Bourgogne, Dijon, France

christophe.nicolle@checksem.fr

Florence Mendes

LE2I, UMR CNRS 6306, University of Bourgogne, Dijon, France

florence.mendes@checksem.fr

Abstract. *Context-aware mobile learning is becoming important because of the dynamic and continually changing learning settings in learner's mobile environment, giving rise to many different learning contexts that are difficult to apprehend. To provide personalization of learning content, we aim to develop a recommender system based on semantic modeling of learning contents and learning context. This modeling is complemented by a behavioral part made up of rules and metaheuristics used to optimize the combination of pieces of learning contents according to learner's context. All these elements form a new approach to mobile learning.*

Keywords: Context-awareness, recommendation, semantic web, m-learning, metaheuristics.

JEL classification: Education and research institutions, Industry studies: services.

1. Introduction

As mobile technologies have become pervasive, many researchers [1] [2] have questioned whether they can enhance learning experiences. So the learning domain started to make use of these new technologies to deliver and support a new approach of electronic learning (e-learning), called mobile learning. It could be argued that mobile learning, also called m-learning, is an approach to e-learning that simply utilizes mobile devices, yet it can also be viewed as a quite different learning experience [3]. So far, the learning environment was either defined by an educational setting (work, trainer, etc.), or imposed by the educational content (the learner must then arrange this environment to receive training). The objective of m-learning is a society with access to knowledge and learning for everyone, everywhere and at any time [4]. However, the dynamic and continual changing learner's settings in a mobile environment and the diversity of learner's characteristics as well as mobile devices and networks, give rise to many different learning contexts and therefore requires personalization for different cases. The educational activities and the provided infrastructure have to be automatically configured according to the learner needs, interests and objectives. Multiple sources of information would be used to adapt learning contents to every situation and condition. To achieve this objective, it is necessary to improve current e-learning systems with new technologies for representing, modeling, indexing and adapting learning contents in a mobile context.

This paper presents a general architecture for context-aware adaptive system for mobile learning that aims to offer a new approach for designing and recommending learning contents

as part of industrial training. Hence, we propose a m-learning system made up of two levels: a semantic level and a behavioral level (figure 1).

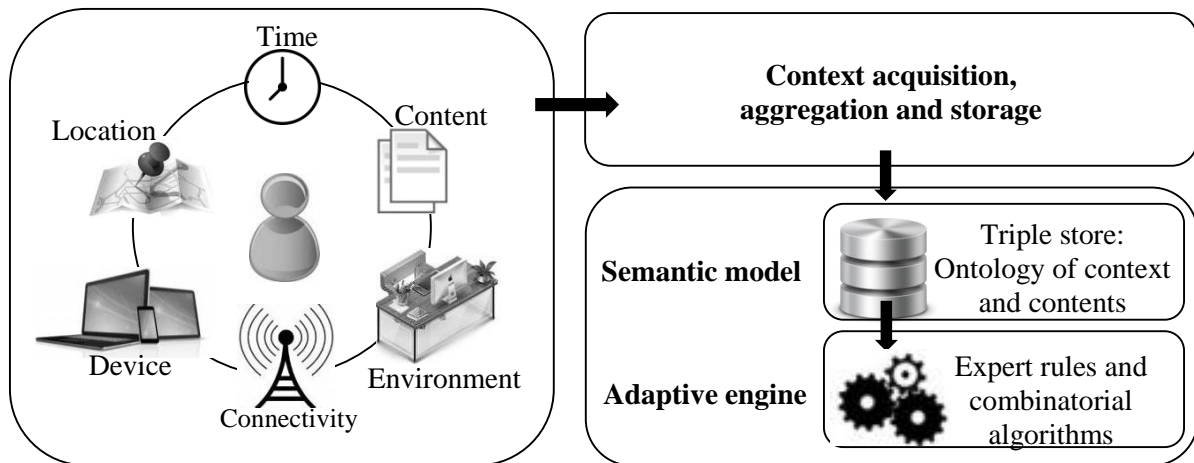


Figure 1. Context-aware adaptive m-learning system architecture

The semantic level aims to express semantic input data characteristics, namely learning contents and mobile context (what, how, when, where, via which device, etc.). It is described in section 2. Then section 3 focuses on the behavioral level, which corresponds to the adaptation engine designed to overcome the problem of information overload. The behavioral level contains best learner practices, transformed in a set of logical rules and algorithms of combinatorial optimization. The last section concludes this paper.

2. Semantic learner's mobile contextual model

The adaptation engine of the system acquires input data and produces the adaptation results. Part of the input data into the adaptation engine is closely related to the context description and learning content modeling.

Context is defined as “any information that can be used to characterize the situation of an entity participating in the interaction between a user and a system” [5]. Different types of information about a user can simultaneously be relevant to a given adaptation decision [6]. In the case of m-learning, location, time, identity and the mobile technology used to learn are the primary context types for characterizing the situation of a particular learner in a mobile LMS (Learning Management System) [7]. In [8], an ontology-based context model considered time, place, environment, and learner profile and device capacity. Personalization in mobile LMSs refers to the process of enabling the system to fit its behavior to the pedagogical needs (learning goals, knowledge, interests, etc.), the personal characteristics (learning styles and different prior knowledge, etc.) and the particular circumstances (current location, movements in the environment, environment properties, etc.) of the learner [9]. Furthermore, context can be information about devices (smartphone, tablet, connectivity, etc.) and time (time of day, day of week, holidays, etc.) since this may change the way learner interact with any device they may be using. We model mobile context according to five dimensions: learner profile dimension, temporal dimension, spatial dimension, device dimension and learning content dimension (see [10] for a detailed description).

In e-learning, resources are designed and developed by different organizations and trainers, usually constituting semantically autonomous and heterogeneous data sources. Therefore, interoperability between these resources is complex. To build an approach of quality, international standards are developing in educational technologies. One standard largely used is the IEEE-LTSC LOM (Learning Object Metadata) standard. Learning contents are

described by metadata about Learning Objects (LOs) repository. A LO is defined by the IEEE as “any entity, digital or non-digital, which can be used, re-used, referenced during technology supported learning”. Learning object attributes such as LO identifier, described concept, estimated learning time, LO relationship to other LOs, multimedia nature of embedded content, semantic density of the content, are described traditionally in the LOM schema [11].

Context-aware applications need acceptable context modeling and reasoning techniques. Modeling context knowledge is an important task to support the delivery of the right contents at each moment, to adapt and to personalize contents, and to anticipate the results. There are several methods for modeling context: key-value models [12], markup schema models like XML [13], UML graphical models [14], ontology-based context model [15]. Ontologies are a very promising instrument for modeling contextual information due to their high and formal expressiveness and the possibilities for applying ontology reasoning techniques. The use of ontologies enables also a standard-based LO metadata modeling. With a semantic modeling based on ontologies, experts could express semantic characteristics of LOs by using a common and interoperable model. This transfer of knowledge from experts to the computer enables our system to perform more intelligent reasoning, combined with expert’s rules and combinatorial metaheuristics, according to changing constraints.

Our ontology is defined using the OWL (Web Ontology Language) standard, so enabling interoperability at the semantic level if required, and is called *contextual m-learning ontology*. Once the ontological model is achieved, we integrated data using Talend Data Integration tools. Then, we used the OWLIM Sesame middleware as a triple store, to store the corresponding ontology. OWLIM includes inference engine and a semantic query engine. The mobile context-aware ontology is stored in the triple store and is connected to the learning repository.

The system uses a set of ontological expert rules to achieve personalized context-aware learning by integrating knowledge embedded in the ontology. The output of the reasoning process is the extraction of metadata that will allow discovery and adaptation of LOs. That’s the role of the behavioral model described in the next section.

3. Adaptive model

Adaptive systems have become very popular since 1990s to allow users to access to personalized information [16]. In m-learning, training courses have witnessed high dropout rates as learners become increasingly dissatisfied with courses that do not engage them [17]. Such high dropout rates and lack of learner satisfaction are due to the “one size fits all” approach that most current learning course developments follow [18], delivering the same static learning experience to all learners. In addition, the nonlinearity of learners’ progress in their training procedure needs them to build their knowledge by creating connections between different ideas, which can cause a problem of being lost in hyperspace. Adaptive educational solutions have been used as possible approaches to address this dissatisfaction by attempting to personalize the learning experience.

When connected to our system, a learner profiling is achieved by automatic collection of data based on use interactions and its device capabilities. The profile is also refined by information provided by system administrators as well as by the user itself. Mobile devices send spatio-temporal information and the learner can specify some constraints of the environment. From this profile and learner context, logical rules run through the global m-learning ontology to identify and extract relevant LOs. Certifying training is subject to various expert rules. They define how to select and combine the different items setting up the training. 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 part modules are independent, while some modules need other modules as a precondition. 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".

Using the Semantic Web Rules Language (SWRL), rules are written, so that a reasoned tool can infer LOs that will be offered to a given learner. We distinguish two categories of rules: precedence rules and contextual rules. Precedence rules are used to define the possible positioning of a LO relative to others (see for example rules 1 and 2).

```
Learning_Object (LO1) ^ Learning_Object (LO2)
-> has_next (LO1, LO2)
```

Rule 1: LO1 must be learned before the LO2

```
Learning_Object (LO6) ^ Type ("quiz") ^ has_lo_type (LO6, "quiz")
-> has_next (LO6, ?x) ^ Type ("conclusion") ^ has_lo_type (?x, "conclusion")
```

Rule 2: When a LO is a quiz it should be followed by a concluding LO

Contextual rules describe how the system should act according to a particular context (see rules 3 and 4).

```
Learner (?x) ^ has_location (?x, ?y) ^ has_location_properties (?y, "dynamic_user") ^ Learning_Object (?z) ^ has_format (?z, ?f) ^ swrlb:contains (?f, "audio")
-> has_access (?x, ?z) ^ p (?z, 10)
```

Rule 3: Access to audio LOs for dynamic learner (running, walking, etc.)

```
Learner (?x) ^ has_device (?x, ?y) ^ has_device_connectivity (?y, "wifi") ^ Learning_Object (?z) ^ has_lo_type (?z, "videocast")
-> has_access (?x, ?z) ^ p (?z, 10)
```

Rule 4: Access to LOs on streaming when the learner is connected (wifi, 3G, etc.)

To each LO is associated a weight LOW . It reflects the importance of the knowledge presented in the course unit according to a context. For example, in the rule 3, LOW is equal to 10. The more important the learning object is, the larger the value of LOW is. We propose to weight the LOs with values belonging to the interval $[0,10]$. If a LO_i is of high importance then $LOW_i = 10$, if a LO_i is of medium importance then $LOW_i = 5$, if a LO_i is of low importance then $LOW_i = 1$, and finally if a LO_i is of insignificant importance then $LOW_i = 0$. Each LO_i is also described by a duration d_i and affected to a particular device $device_i$:

$$LO_i = \langle LOW_i, d_i, device_i \rangle, i \in [1, |LO|]$$

The logic behind rules reasoning is that the learner should be able to choose whether he would like to have access only to those LOs according to his context following predefined rules. These rules are defined by experts in the learning domain. As these experts do not necessarily know how to write SWRL rules, we developed a rule generator to easily manipulate m-learning ontology concepts and generate automatically SWRL rules.

The adaptive m-learning system offers an optimized panel of LOs matching to the current context of the learner. This optimization should reduce the duration of the training and maximize learner satisfaction. If the context changes during the learning, the system can immediately switch a LO by another, adapting the learning through constraints evolution.

If each LO was accessible on every learning device, it would be easy to choose at any time the best support for training according to the learner's context. Actual cases that we studied showed us, on the contrary, a great heterogeneity of LOs available on devices. Training has different structure and different duration, depending on the device used. This forbids changing learning devices while training without risking redundancy of some LOs. From this, a combinatorial optimization problem can be identified. It corresponds to a multimodal

shortest path problem, which is a variant of the well-known shortest path problem [19]. This problem cannot be resolved by an exact method, because of the exponential growth in complexity depending on the size of the problem. We use a heuristic method to achieve a solution in a reasonable time.

By using a greedy algorithm, we construct a first solution by starting from a given LO, then, at each step the algorithm moves along the edges of the precedence graph. At each step, we check the LO's list, accessible in a particular context and on a particular device, and we choose among the edges, that do not lead to LOs that it has already visited. The LO selected in the next step should, either, maximize learner satisfaction, or minimize learning time, or both. Algorithm stops when a LO of the particular device Target has been reached.

Then we define the following function to evaluate the global relevance of the solution:

$$R = X \cdot \underset{i=1}{\overset{|LO|}{\text{minimise}}} \sum d_i x_i + Y \cdot \underset{i=1}{\overset{|LO|}{\text{maximise}}} \sum LOw_i x_i$$

where $X, Y \in 0,1$

and $x_i = 1$ *if* lo_i *is selected in the solution else* $x_i = 0$

Equation 1. Relevance function

The next step is to ameliorate the first solution obtained by the greedy algorithm. For this purpose, we are currently implementing some standard metaheuristics, such as simulated annealing and randomized variable neighborhood search.

Conclusions

In this paper, we presented an adaptive m-learning system that takes into account constraints associated to mobile context, making use of learning practices already deployed in e-learning and adopting them in m-learning. Our approach is built around an ontology defining learning contents and supporting context-awareness. The use of this ontology facilitates context acquisition and enables a standard-based LO metadata annotation. The adaptive system afterwards uses a set of ontological rules and metaheuristics to achieve personalized context-aware LOs by exploiting knowledge embedded in the ontology.

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