An Approach to Design the Student Interaction Based on the Recommendation of e-Learning Objects

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ABSTRACT
In the last years, the adoption of recommender systems for improving user interaction has increased in e-learning applications. In the educational area, the recommendation of relevant and interesting content can attract the student's attention, motivating her/him during the learning-teaching process. It is very important, thus, to know learner preferences to suggest suitable contents to the students. The goal of this work is to present an approach to design the student interaction based on the recommendation of e-learning content, determining a more suitable relationship between learning objects and learning profiles. In our proposal, the learning profile is split into categories to attend different student preferences during the teaching-learning process: perception, presentation-format and participation. Our recommendation uses these categories to filter out the most suitable learning objects organized according to the IEEE LOM standard. We present a prototype architecture named e-LORS, over which we perform demonstrative experiments.

Categories and Subject Descriptors
H.1.2 [**User/Machine Systems**]: Human Factor, Human Processing Information.

General Terms
Management, Human Factors

Keywords
Recommendation systems, learning objects, LOM standard, learning profile, learning model, Felder-Silverman Learning Style Model

1. INTRODUCTION

The recommendation of e-learning content has been adopted as a solution to satisfy student preferences during the teaching-learning process. A number of ongoing researches focus on a variety of aspects of user-oriented elements, one of the main such efforts is the adoption of recommendation mechanisms. The adoption of recommendation mechanisms to support the design of the student interaction may improve her/his experience in e-learning environments.

The recommendation process occurs through the investigation of the user's preferences. Based on information obtained from her/his explicit and implicit learning practices, it is possible to identify her/his needs within the context in which she/he interacts [19]. The elements and traits of the student behaviour delineate her/his profile and highlight the features that characterize her/him, such as: personal and social preferences, learning profile, and subject knowledge level.

By means of interviews – as was done in this work, or during monitored interaction, the students produce evidences about their *learning styles*, which are stored as implicit information into data objects named *learner profiles*. Learner profiles are one of the most important components of recommendation systems, providing relevant data about usage preferences [20].

The dynamic linkage between contents and student learning profiles may enhance the adequacy of the *learning objects* that will be offered to the students [20][21]. The observation of learning styles provides users with different teaching strategies, meeting the student's individual needs. In this sense, it is important to highlight that the student learning style should be observed through different dimensions achieving diverse aspects of her/his preferences, such as media format and participation in group activities.

The use of metadata standards adds value to learning systems in the task of handling learning objects, improving their reuse and retrieval [22]. Learning objects are specified by fields that describe their general data (e.g., title, description, keywords), technical details (e.g., media format, size, software and hardware requirements), learning features (e.g., concrete and abstract approaches, visual and verbal elements), and other relevant metadata [24].

This work presents an approach to design the student interaction based on the dynamic recommendation of e-learning objects. To do so we consider the *theme* of learning and the student learning profile. In our systematization, the learning profiles are described by a set of *preference categories* that describe the student learning preferences. A relationship between the learning profiles and the learning objects is drawn upon the linkage of the preference categories to the metadata fields of the learning objects. The approach was validated in a regular college course on Computer Engineering Data Structures. The course is part of the graduation curriculum from Brazilian university *Faculdade de Engenharia de Sorocaba* (FACENS).

The remainder of this work is structured as follows: section 2 explores related works and concepts; section 3 presents the recommendation approach proposed here; section 4 reports the validation experiments; and section 5 discusses some conclusions and outlines future works.

2. RELATED WORKS AND CONCEPTS

We review research relative to four important aspects of our work: related systems, recommendation strategies, learning profiles and learning objects.

2.1 Related Systems

In the literature, there are many e-learning proposals that work with learning profiles. Following, we present the ones that are more related to our work.

Milošević et al. [1] proposed the adoption of a learning style that allows the system to build learning workplaces, bounding learning content and learning styles through the SCORM (Sharable Content Object Reference Model) [21]. Although this propose adopts a standard to support the concept specification, it does not consider the learning profile according to elements of categorization.

The Personalized Learning Policy [2] presents a flexible approach to organize the learning activities through a set of rules and procedures, adjusting the adaptive mechanism during the e-learning process. The authors argue that the student profile will be composed of student observable features by establishing and linking the rules to events that occur during the learning experience. The proposal does not deal with the dynamic binding between the contents and the learning style characteristics.

Romero *et. al.* [3] present a component to personalize the user interaction based on data mining algorithms that evaluate the student log data in order to suggest content links. The proposed component was integrated to the AHA! project, an e-learning environment that follows adaptive hypermedia concepts to provide contents to the students. The recommendation contents are restricted, as they are based on links subscribed to the course.

2.2 Recommendation Strategies

Recommender systems focus on suggesting information and services to users based on their preferences, comparing them to specific referential characteristics. The recommendation process enriches the user interaction process, as her/his communication interface will be designed with elements that correspond to her/his interests. Hence, the information and the services available in the interface will satisfy the user needs according to usage context [4]. In general, the recommendation process is accomplished by the following recommendation approaches: collaborative filtering, content-based filtering, rule-based filtering, or hybrid combinations of these techniques [4] [5] [8].

The most disseminated approach is collaborative filtering, which provides personal recommendation on a group-based fashion, adjusting to sets of people with similar preferences and interests [3] [5].

Content-based retrieval techniques implement the nearest-neighbor model. The content-based approach concerns the content rather than the users. To do so, it learns about the most relevant contents based on the features derived from the objects that the user has accessed [6][7][8]. Metadata and ontology may be used as a solution to sort out semantic terms in relevant documents or objects during the filtering [9].

Bilgic and Mooney [7] proposed an extension of the content-based classifier method; the authors use the Keyword Style Explanation approach, which explains to the user how the system achieves the suggestions.

Decision rules, in rule-based filtering, may be manually or automatically designed by those who have a strong correlation with a domain area, as e-business for instance. The techniques allow the rule's designer to heavily control the adaptation process [10].

Brusilovsky [11] emphasizes that recommendation techniques have influenced the design of techniques and systems for web navigation. According to the author, the recommendation process influences the choices for what is to be offered to the user, determining a dynamic communication design. In the educational context, recommendation acts not only on the motivational aspect of students but, also, on the development of certain abilities in specific learning scopes.

2.3 Learning Profiles

One main need in teaching activities is to identify the outstanding characteristics that define the learning preferences of the students. Then, in order to satisfy a given learning style, the teacher must use strategies that will meet the needs of different learning perspectives. The same is expected from content recommendation systems, what can be done through the use of learning profiles that, implicitly, contain learning style information [15].

Each individual fits into a specific learning style, what makes her/him adopt attitudes and behaviors that are repeated in different moments and situations [14]. During interaction, the student receives stimuli from an environment and her/his actions produce evidences about her/his learning profile. Alternatively, the student learning profile can be identified via questionnaires that capture learning styles according to well-defined models [20].

There are several models used in the characterization of learning profiles, each of which is suitable for a different learning scope. Although there are many learning style models, Felder and Brent [14] highlight five of them: the Myers-Briggs Type Indicator – MBTI, Kolb's Experiential Learning Model, the Hermann Brain Dominance Instrument (HBDI), the Honey-Mumford's Learning Styles Questionnaire (LSQ), and the Felder-Silverman Model.

Among the possibilities of leaning style modeling, the Felder-Silverman model was chosen to be used in this work. This is due to the fact that it has the strongest emphasis on the relationship of learning styles and teaching strategies. Felder and Silverman [15] remember that the application of this model is especially suitable for Engineering Education. This is an important fact because engineering refers to applied science, just as computer science, which is our application domain.

2.4 Learning Objects

One of the goals of teaching-learning environments is to offer educational material, usually called learning objects (LOs). In this context, LOs must be selected so as to correspond to the students' preferences [23]. Within the scope of e-learning, the aim is to create contents in digital formats that can be reused for different learning objectives, or even employed in the construction of other learning objects [16].

Table 1. Description of LOM categories

LOM Category	LOM Field	Characterization
General	Identifier, Type, Title, Language, Description and Keywords.	General description of the learning object.
Technical	Media Format (video type, sound), Size, Physical location, Requirements (object use: software version, for example).	Technical features description.
Educational	Interactive type (active, expositive).	Educational functions and pedagogical characteristics object description.
	Learning Resource Type (exercise, simulation, and questionnaire).	

One of the ways to organize learning objects so that they can be used and reused systematically is through the use of descriptive metadata, that is, a set of attributes that describes learning objects. The LOM (Learning Object Metadata) standard [13] of the Institute of Electrical and Electronics Engineers (IEEE) is the most commonly metadata specification used for e-learning. The LOM standard has a structure that describes learning objects through descriptor categories. Each category has a specific purpose, such as describing general attributes of objects, and educational objectives. Table 1 shows the LOM categories adopted in this work.

3. E-LEARNING OBJECT RECOMMENDATION

Recommender systems, with educational focus, follow the ratings that the students confer on learning strategies, or on learning contents. These systems track such ratings by structured profile delineation questionnaires, or by monitoring the explicit and implicit actions of the students over the system. These data are then analyzed in order to automatically suggest the content during the learning process. The user tracking process may occur in many ways, for example, by applying explicit questions for the students [3] or by observing the selected pages in a specific moment.

Here we use the Soloman and Felder questionnaire [12] to mold the learning style for e-LORS – e-Learning Object Recommendation System. System e-LORS employs the fundamentals of content selection to suggest learning objects considering two aspects: learning-teaching theme and student learning profile. In e-LORS, the learning objects are organized according to the LOM standard, and the learning profile is split into categories of preferences based on the Felder and Silverman model.

3.1 Preference Categories of the Learning Profile

The Felder and Silverman model describes the student learning style by four different behavior dimensions: orientation, perception, presentation format, and student participation. In the model, these features are related to specific learning styles and teaching methods, factors that are used to support the student learning preferences [15].

In another work, Zaina and Bressan [17] relegate Felder/Silverman's orientation dimension, proposing an alternative approach that splits the student learning profile into three categories: perception, presentation format and student participation. Along the text, this altered model is referred to as *Preference Categories*; its goal is to detect clusters of preferences that reflect different data perspectives caught during the tracking of learning styles. Each category, as shown in Table 2, has a teaching-method correspondence that defines the matching with the students' learning styles, as predicted in the Felder/Silverman proposal.

Table 2. Preference categories of the learning profile

Preference Categories	Features	Learning Styles	Teaching Methods
Perception	The focus is in the best way through which the student can obtain information: contents, exercise types, for instance.	Sensing	Concrete
		Intuitive	Abstract
Presentation Format	It is related to the input. Content preferences chosen by the student such as media types.	Visual	Visual
		Auditory	Verbal
Student Participation	It represents the student preferences for the activities participation or observation.	Active	Active
		Reflective	Passive

The *Preference Categories* concern different dimensions of the student learning behavior in e-learning environments. The *Perception* category reports the type of information that the student prefers to interact with. The *Presentation Format* category describes the preference channel to input information. In turn, the *Student Participation* category reflects her/his preferences to process the information, participating in activities or reflecting about the subject.

The *Preference Categories* of a given student can be identified with the application of the online questionnaire provided by Soloman and Felder [12].

3.2 System e-LORS Content Recommendation

System e-LORS has a flexible specification that allows a variety of e-learning systems to adopt it. The system uses the student learning profile (Preference Categories) in order to recommend the appropriate learning objects. It works by confronting and handling a given content theme of interest to a given student request. Figure 1 presents an overview of the e-LORS architecture.

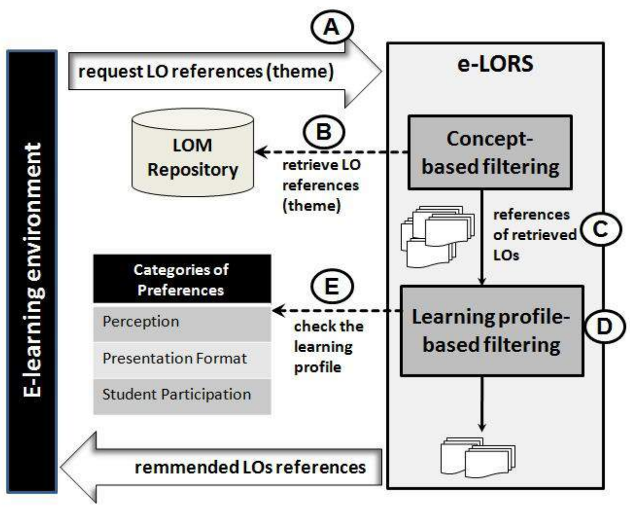

Figure 1. The e-LORS architecture.

In the first step (A), e-LORS starts the recommendation process by receiving the *theme* parameter. This parameter describes the topic of interest according to the metadata defined by the LOM standard. The *theme* is used to determine which LOs are to be considered for matching the learners' profiles.

In step B, as soon as e-LORS receives the requisition for a recommendation process, it starts the theme-based filtering searching the LO references in the LOM-based repository (LOMR – LOM Repository). According to the *theme*, defined from one or many words that are passed as parameters to the system, the filtering is performed. Then, the system seeks (*searchLO*) for learning objects that match the *theme* parameter according to the fields of *title*, *description* and *keywords*, which belong to the LOM's General Category. The method returns a set of LO identification references (LOSet) that fit the *theme*. In Figure 1, the passage of the LOSet refers to step C, as formally defined in equation (1) and in predicate (2):

$$\text{searchLO: LOMR} \rightarrow \text{LOSet} \quad (1)$$

$$\text{LOSet} = \{\ \text{LO: LO} \in \text{LOMR AND} \quad (2)$$

$$\text{LO}_{\text{category}} = \text{General AND } \mathit{theme} \text{ IN } \text{LO}_{\text{LOMFields[i]}}\},$$

$$\text{where i} = \{\mathit{Title, Description, Keywords}\}$$

After the concept-based filtering, e-LORS begins the next filtering based on the criterion of *learning profile* – step D – performing it only over the first outcome of references (LOSet) achieved in the previous step.

The student Preference Categories reported in the learning profiles are compared to the Interactive and Learning Resources found in the Educational LOM standard category (Table 1), being restricted only to the LOSet instead of the entire LOMR. Table 3 presents the binding between the fields of the LOM standard (describing the learning content – Table 1) and the students' Preference Categories (Felder-Silverman – Table 2).

As shown in Table 3, for example, when the Preference Category of a student is *Perception* and her/his profile is *Sensing* the correspondent teaching method is *Concrete*. According to Felder and Silverman, this teaching-learning style corresponds to *Active* learning objects in the *Interactivity* field of the *Educational* LOM category.

Table 3. Link between the LOM fields and the preferences categories

LOM – Educational Field	Educational Field Values	Teaching-Learning correspondence	Preference Category
Interactivity	Active	Concrete-Sensing	Perception
	Expositive	Abstract-Intuitive	
Learning Resource Type	Figure, Video, Film, and others	Visual-Visual	Presentation-Format
	Text, Sound, and others	Verbal-Auditory	
	Practical Exercise, Experiment, and others	Active-Active	Student Participation
	Questionnaire and Readings	Passive-Reflective	

In the last step, system e-LORS selects the LOs from the LOSet and match them to the students learning profiles, step E in Figure 1, resulting in the new subset (LOSubset) as formally defined in equation (3) and predicate (4):

$$\text{searchLOLearningP: LOSet} \rightarrow \text{LOSubset} \quad (3)$$

$$\text{LOSubset} = \{\ \text{LO: LO} \in \text{LOSet AND} \quad (4)$$

$$\text{LO}_{\text{category}} = \text{Educational AND}$$

$$\text{PreferenceCategory[j]} \ni \text{Learner Model AND}$$

$$\text{PreferenceCategory[j]} \equiv \text{LO}_{\text{LOMFields}}\text{[i]}\}, \text{ where:}$$

$$\text{j} = \{\text{Perception, Presentation-Format, Participation}\} \text{ and}$$

$$\text{i} = \{\text{Interactivity, Learning Resource}\}$$

Finally, e-LORS recommends a set of LOs, each of which recognized by an *Identifier* field (LOM General category) used to retrieve content files from the LOM repository. The final result set, then, may be used to build the learning workplace that satisfies the student's preferences.

4. SYSTEM e-LORS VALIDATION

We have implemented a prototype of e-LORS that was used in a regular college course on Computer Engineering Data Structures with 50 students. The course is part of the graduation curriculum from Brazilian university *Faculdade de Engenharia de Sorocaba* (FACENS). No specific course management system was used as Moodle [18], but an ad hoc institutional system integrated to e-LORS. This system was used as a supplement to traditional lectures.

Led by the outcomes produced by the questionnaire of Soloman e Felder [12] answered by the 50 students, the preferences of the students were identified and the values of Preference Categories were updated in the student learning profile objects of our system. The questionnaire reflects the student learning style in different dimensions according to Felder and Silverman Learning Style Model.

4.1 Preparing Learning Objects

In order to test our system, we have catalogued several learning objects for the topics on Data Structures, what allowed us to attend different learning styles during the experience. A crew of professors and assistants were designated to create the LOs at the same time that they were catalogued for further use by e-LORS.

The professors were responsible for planning the LOs so that they would carry metadata in accordance to the LOM standard. This way, the LOs would fit both the concept-based (theme), and the learning profile-based filtering modules of e-LORS. The assistants helped up in the task and raised a LOM-based repository over which the whole system would work. For the Data Structures course, the crew of professors and assistants catalogued 80 learning objects – corresponding to 6 lessons. Some examples of the objects that were catalogued are: demonstration simulations, interactive simulations, explaining texts, figures, exercises, illustrations and case studies.

4.2 e-LORS in Action

Initially, the recommendation process receives the theme parameters, that is, a topic of interest for a specific lecture.

As an example, following we report an illustrative operation in which the theme *binary tree* is passed to the system as the topic of interest of a student with a learning profile with values *sensing*, *visual* and *active* corresponding to categories *perception*, *format presentation*, and *student participation*. Shortly, e-LORS defines a two-fold course of action:

- *Concept-based filtering:* seeks and selects in the LOM General category for all the occurrences likewise "b*inary tree"*. Ten different learning object identifiers are returned and sent as a list of objects to the next step;
- *Profile learning-based filtering:* from the list of objects in the *concept-based filtering*, e-LORS picks up the objects matching preferences *sensing*, *visual* and *active*, which correspond to the Preference Categories of a given student. The system identifies a simulation, a video-lecture, a chat session about de theme and a discussion topic in a forum. This content will be used for designing the communication interface.

System e-LORS returns the list of recommended learning objects and the process is concretized with the building of the student workplace with the recommended objects. Other learning objects are made available through a link to other materials, allowing the students to have their own choices as illustrated in Figure 2.

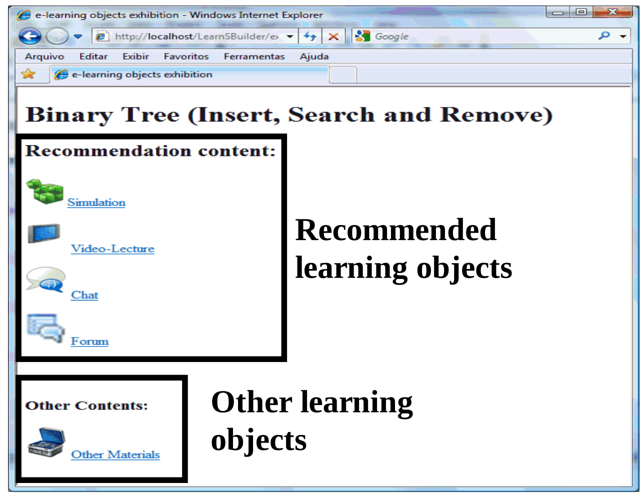

Figure 2. Example of a student workplace with a set of recommended learning objects

4.3 User Satisfaction Evaluation

The final step of the experiment was the evaluation of the students' perception of the system. To do so, an evaluation form was posed for the students who had to indicate their satisfaction with the recommended learning objects. In the form, the answers were standardized in a 1 to 4 score scale; 1 for totally non-satisfied and 4 for completely satisfied.

The students reported that the workplaces achieved with the use of e-LORS were, in fact, more adequate than what would be achieved with casual browsing. For the Data *Structures* course, the students summed up 76% of complete (score 4) or almost complete satisfaction (score 3).

5. CONCLUSIONS

In this work, we have defined a methodology that links learning objects and learning profiles for automatic content recommendation. To do so, we have used the Felder-Silverman Learning Style Model along with the IEEE LOM standard, a combination that, extending former works, can suitably relate learner profiles and learning objects, automatically, in different fields of learning, and consistently reflecting the intrinsic style of the students.

We use a multiple-criteria-filtering methodology that, through modules with different responsibilities, selects the learning objects according to two criteria: concept (theme), and profile (style). Our work has put together an ensemble of well-established methodologies in an innovative system; a system capable of a versatile recommendation of learning objects, structured and reproducible according to well-defined conventions. Our approach supports the dynamical design of communication interfaces, reflecting important aspects of the users' personalities.

There are further developments to be achieved. One of them is to extend the proposal to consider technological aspects of the learning context as, for example, mobile devices. Another future work is to consider the semantic interpretation of learning objects, learning styles and contextual information.

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