The Memory Map Model used for Personalization in Intelligent Learning Environments

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Abstract. The knowledge representation model called The Memory Map [1] was used to represent the expert and student modules of college courses. The students and expert modules were compared and the differences were used to personalize the sequence of learning activities for each student. The personalization scheme is designed to detect secondary knowledge gaps (concepts required to understand more complex concepts), and to estimate the correct time and place where a learning activity should be introduced. An implementation of the model was used in to represent a course to see what impact the personalization had on the students. The model was also used to represent the expert domain of an Intelligent Tutoring System.

Keywords. Knowledge representation, competences, skills, learning.

1 Introduction

Artificial Intelligence and Cognitive Science have played an important role enhancing traditional learning environments to turn them into Intelligent Learning Environments (ILE). Examples of these applications can be found in the works of knowledge representation [1], cognitive tutors [2], learning companions [3], emotion detection [4], and question generation [5], among others. ILEs in general show strong tendencies towards personalization; the sequence of learning activities in the learning flow is a central part of the instructional design process [6] and it is one of the most common types of personalization. This personalization of learning sequence means the selection of the content and the way it should be provided in a way that fulfills the need of each particular student. This is important due to the differences in learning between different students when exposed to same learning experience as a result of the differences in learning rate, different previous knowledge and the differences in abilities and competences that each student has. Indeed, cognitive tutors also referred to as Intelligent Tutoring Systems (ITS), address this phenomenon by using a scheme of one on one tutoring proposed by Benjamin Bloom [7]. Sequence adaptation involves adding or subtracting learning activities, as well as changing the order in which they are presented in the original sequence of learning activities [8]. Learning environments should present opportunities for students to learn the knowledge they have missed in previous stages of their learning process. This can be done by personalizing their learning sequences to include those concepts missed or forgotten from the previous stages that are necessary to comprehend the current more advanced content at a pace that is in accordance to the student learning rhythm.

To achieve this kind of personalization a deep understanding of the learner's knowledge is required; the Memory Map (MM) model is designed to represent knowledge with flexible depth in a simple and complete way. This computational model focuses on the understanding of the organization of knowledge, and shows how the student's concepts are linked together with skills; therefore, instructional decisions can be made to improve the students learning process. The following sections describe the way in which the model was used for course personalization. In section 2 the knowledge representation model is presented, in section 3 sequencing of learning objectives is integrated to the model, in section 4 personalization of the learning sequences is explained, in section 5 the application of the model is shown and in section 6 conclusions and future work are presented.

2 Knowledge Representation

The definition of concepts in the MM [1] and the way their behavior are described, are influenced by the ideas of Vygotsky's constructivism [9], Fodor's Language of Thought Hypothesis [10] and Hobbes' Representational Theory of the Mind [11]. Concepts in the MM are defined as dynamic computable units which are composed of other concepts in combination with a specific kind of association function which may be seen as attributes for a given context; similar approaches can be found in the works of [12] The MM combines symbolic representation of semantic networks with a distributed local representation approach found in neural networks [13], i.e. non symbolic systems. This definition of concept and its implications in the model implementation enables the representation of several learning domains. We define a context as the integration of one or more domains; each concept has a set of attributes with relevance that changes depending on the context from which the concept is accessed, i.e., some attributes are more relevant in a particular context than others.

Each subject or academic course can be seen as a context integrated by several domains, for example a course in advanced web programming would be the combination of the knowledge domains: web, programming, servers, PHP, Perl, JavaScrip and HTML, among others. Several contexts can coexist within a single MM, this is a MM with many different domains, this is treated as a student cognitive profile because it represents a natural reflection of the students' knowledge, i.e., the brain is not a rigid structure divided by separate domains it is an intertwined associative network which can activate different connections depending on the context [14]. The adaptation of a learning sequence begins when the MM is first used to represent the concepts and associations that a group of students is expected to learn during the course. This is called the course-MM and would be equivalent to the expert domain inside the expert module of cognitive agent architecture; a small extract of a modeled course is presented in Figure 1.

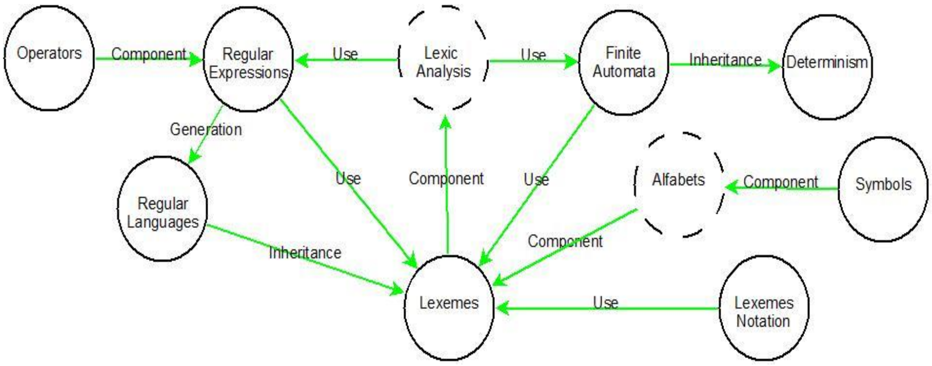

Fig. 1. A graphical representation of a segment of the Theory of Computation course the Memory Map**.**

3 Associative Learning Path

Once the knowledge of the domain is represented in the course-MM, a sequence layer is added. In this sequence layer the associations are numbered and treated as learning objectives. The numbers in the sequence layer create an order for the learning activities; this ordered sequence is the course Association Learning Path (ALP). The types of sequences that can be created in the ALP are based on Botturi's Educational Environment Modeling Language E2ML patterns [15], E2ML is a descriptive and rigorous language for modeling learning objects.

Associations in the MM can be used to describe sub-concepts or attributes of concepts, therefore they are more specific and that is the main reason for using them as the learning objectives. Each association, i.e., each learning objective in the ALP corresponds to a Learning Object LO or to a group of LOs related to that specific attribute or attributes of the concept, in some cases the whole concept which implies all the associations of the concept. In [1], an association is equivalent to learning objectives and learning objectives can be achieved through any of their associated LO.

Sequence modeling is traditionally systems such as IMS-Learning Design [16] are centered in activities, more flexible and precise ALPs can be designed through the conceptual approach for the focus is the development of the concept the activities used to achieve it are the means not ends, however, context independent and modular LOs become more difficult to design when pursuing a pure conceptual approach. An example of the sequence layer of the course MM is shown in Figure 2 through the red numbers, where the first learning objective of the lexical analysis is to understand the use of lexemes and their notation, the sequence structure of the ALP represented through EML notation is presented in Figure 3.

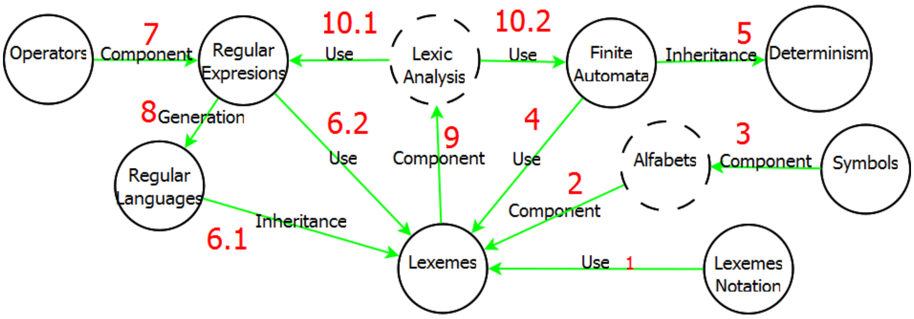

Fig. 2. The numbers indicate the order of the ALP in the Memory Map, this is the order in which learning activities are to be presented to students by default.

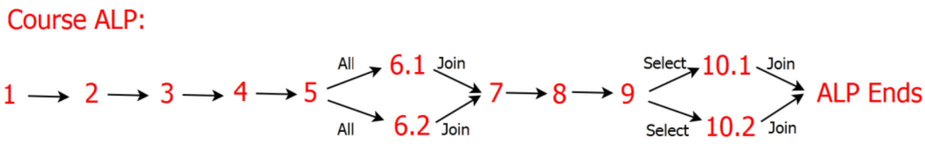

Fig. 3. A graphic representation of the ALP in EML, the type of operation: All, Join, Select or sequence is specified in the association.

4 Learning Path Personalization

An overly Model approach is used for personalization [17], the student model subset for that context (student MM) is a subset of the expert model (course MM) in that context, i.e., the subset of knowledge of the student for domain A, must be a subset of the knowledge for the course knowledge for that same domain. The Stud-MM and the Exp-MM subsets of that context are compared to determine the presence or absence of concepts and associations in the Stud-MM. Taking this into account a Stud-ALP is created for each student, this new Stud-ALP is a personalized version of the course course-ALP. The personalized ALP will integrate recursively all the extra associations and concept a student is missing and remove those concepts and associations which she/he already knows in order to satisfy the course ALP. A general example of the process will is as follows:

1. Figure 1 shows the Exp-MM with a single domain: "lexical analysis", since there is only that domain then the Exp-Domain is the entire Exp-MM.
2. Figure 2 and 3 show the Exp-Domain with the general sequence for the course-ALP, since the student knows the majority of the content there is no inclusion of new concepts or associations.
3. The personalized ALP is created simply by deleting the associations already known by the user from the Sequence in figure 3, giving as a result the ALP that is presented on figure 4.

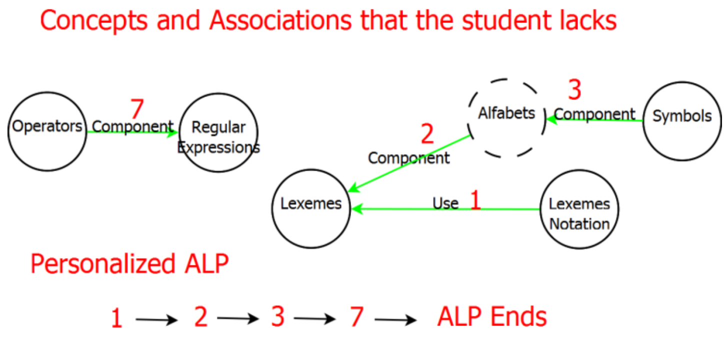

Fig. 4. The personalized ALP of a student that knows most of the concepts from figure 1.

In a different scenario where a Stud-Domain had concepts and associations missing that are required to understand the concepts of the Exp-Domain, the concepts would be included in the paths as is shown in figure 5. This previous knowledge must be specified in the Exp-Domain as such, but it is not included in the course ALP, it will only show up in the personalized ALP of students who lack the previous concepts. Basic operations performed on a course ALP include: Simple Inclusion, Deep/Recursive inclusion, Deletion, Modification. In practice basic ALP personalization is achieved through an iterative process, where student knowledge is periodically measured through evaluations mapped to particular learning objectives, the results of these evaluations are used to modify the students MM. If the students do not yet have a MM then an initial diagnostic evaluation is required, before the learning period starts. The learning sequence personalization could be carried out in real time if evaluation tools for knowledge and skills in real time were available, however since this is not the case, evaluations are carried out at specific stages through the duration of the course.

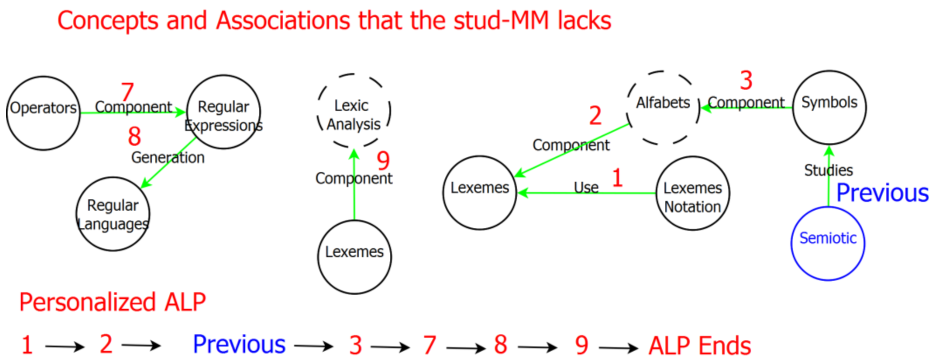

Fig. 5. The personalized ALP of a student who knows some concepts but lacks previous knowledge required to fulfill the ALP.

5 Application

The model has been implemented in a XML Schema (xsd), which describes the model's rules for the composition, and in a set of algorithms to represent model operations; the schema is then mounted to object structure in Java using JAXb. The inference algorithms for knowledge extraction use customized Iterative Depth Search First IDSF with filters. Further reading on the structure of the model and knowledge extraction can be found in [1].

To test the application of the model, the MM was used to model three different kinds of courses: Theory of Computation T.C. a partial course, Artificial Intelligence A.I. a complete course, and Searching Algorithms S.A. for an ITS. The main objective was to see what could be represented and if the model could be used to generate the personalization, the effect of such a personalization will be studied in future work.

In the first two courses (T.C. and A.I.), teachers modeled their course-MMs, the curricula objectives and the course syllabus (the thematic content) were used as a starting point to establish the MM first concepts and associations, i.e., learning objectives. These objectives were refined to match specific Learning Objects. LO were extracted from official repositories such as Merlot and Temoa. At the end of the course students answered a survey regarding their experience of the personalization of the course, performance of the students was also measured to establish correlations among personalization with the MM and performance. Both T.C. and A.I. were tested with groups of 30 students each, the groups were divided into two groups, one with personalized learning courses and one without it. They were not informed to which group they belonged in order to avoid any bias. Through the duration of the course, students were provided with complementary LOs according to what each stud-ALP suggested. The stud-ALP indicated what LO to select, as well as the moment in which to present the activity, this was done by coordinating the dates of course milestones such as weekly labs and evaluations of key concepts, with the sequence dictated by the stud-ALP. In the T. C. course the default ALP was an initial sequence of 27 associations, students who had a perfect score in the diagnostic evaluation remained with the default ALP, it should be noted that this case happened only once, which corroborates that most students come with faulty previous knowledge and misconceptions.

Students lacking previous knowledge had their ALP personalized, the average personalized ALP sequence was 33 associations and there was one student who's personalized ALP had more than 40 associations. The modeling of the A.I. course ALP had 74 associations; the average of personalized ALP was 86 associations.

The ITS follows the tradition Nwanna architecture [18] and uses the MM, not to personalize ALPs, but to build entirely new ones by reacting to the student's performance, this was done by using a reacting agent which would respond each time a student answered a quiz and depending on the performance of the quiz the LP would be regenerated and would allow the student to access new content that was related to those concepts he understood better. Each student's order and difficulty in activities were dynamically assigned as the agent would determine it using as criteria association density, student goals, and tutoring approach.

In the three cases MM was successfully used to model the expert domain and student domain: for partial domains of knowledge, complete domains of knowledge and as the Expert Model for an ITS system.

The domains were different in their granularity, in their size, and one of them was used for different means. This evidence we conclude that the MM is a flexible model that can be used both for ILE as well as for ITS.

6 Conclusions and Future Work

A knowledge representation model was used to create a sequence personalization system. The system was tested with two groups of 30 students each. The MM was successfully used for the representation of both student modeling and expert modeling in both domains and was also used to develop an ITS. Though the experiments were meant to test the applicability of the MM in learning environments, they also pave the road for future work regarding the actual impact in student performance, this is due to the nature of the research, only long term measurements can provide evidence that the personalization of ALPs have a positive impact on the overall learning process.

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