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On the use of case-based planning for e-learning personalization

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ABSTRACT

In this paper we propose *myPTutor*, a general and effective approach which uses AI planning techniques to create fully tailored learning routes, as sequences of Learning Objects (LOs) that fit the pedagogical and students' requirements.

myPTutor has a potential applicability to support e-learning personalization by producing, and automatically solving, a planning model from (and to) e-learning standards in a vast number of real scenarios, from small to medium/large e-learning communities. Our experiments demonstrate that we can solve scenarios with large courses and a high number of students. Therefore, it is perfectly valid for schools, high schools and universities, especially if they already use *Moodle*, on top of which we have implemented *myPTutor*. It is also of practical significance for repairing unexpected discrepancies (while the students are executing their learning routes) by using a Case-Based Planning adaptation process that reduces the differences between the original and the new route, thus enhancing the learning process.

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1. Introduction

E-learning is the process of providing on-line courses on the Internet for students so that they can study and learn from any place and computing device (personal computer, mobile phone, tablet, etc.) by using electronic media, information, Internet technologies and platforms, such as Learning Management Systems (LMSs). Although e-learning has become an increasingly popular training option, it cannot rely just on the upload of contents to the Internet or the developments of new standards. On the contrary, it needs to offer a feasible, personalized way that facilitates and enhances the students' learning process by combining such contents appropriately.

As proposed in related literature (Caputi & Garrido, 2015; Comi et al., 2015a; Essalmi, Ben Ayed, Jemni, Graf, & Kinshuk, 2015; Garrido & Onaindia, 2013; Garruzzo, Rosaci, & Sarne, 2007b; Kurilovas, Zilinskiene, & Dagiene, 2015; Rosaci & Sarne, 2010), a revolutionary key challenge of the current century is advanced personalized learning to promote adaptivity and fully tailoring of the e-courses. The idea is to use intelligent systems to construct and recommend a personalized learning route of contents that fit the individual requirements of each student, and even the device each student is using at that moment (Garruzzo, Rosaci, & Sarne, 2007a; Rosaci & Sarne, 2010).

As a motivating example, let us assume two students with different background (initial knowledge) and learning outcomes, interested in the same course. Obviously, under a fully personalized perspective, the LOs and their sequence cannot be the same for both students. A different subset of LOs can be combined in different ways according to the learning style, current knowledge and learning goals of each student. For instance, one student will need a shorter route than the other, or a particular type of contents, different to the other's. Also, although in some scenarios the LOs could be the same, the learning route to be planned will have to be different according to the specific needs. Therefore, we require some kind of planning to select the best sequence of LOs, and in the best order.

More precisely, rather than having a predefined flow of contents the student has to follow in a course, which may be too teacher-oriented and somewhat frustrating for the student, we want to have an individualized sequence of contents that is generated and accommodated to what the student needs, thus being 100% student-oriented. Achieving such a high level of individualization is not a straightforward enterprise as it requires: i) the combination of pedagogical theories (Brusilovsky & Vassileva, 2003), and ii) to take into account the causal relationships among the tasks to be done in the course (Caputi & Garrido, 2015; Garrido, Morales, & Serina, 2012). For instance, a given task has some

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prerequisites to be held before it can be initiated (e.g. when some previous knowledge has to be acquired), which means some orderings among tasks may be arbitrary but others are compulsory and, therefore, enforced in any individual route.

The construction of personalized routes requires an intelligent decision-making procedure to recommend the most adequate content for each student in every step of his/her learning process. Unfortunately, e-learning content selection is difficult. It depends on many variables, involving learning contents, their (semantic) ontology, their degree of difficulty, the time required, how long the course lasts, the available time each student has, the student's preferences and learning styles, the resources that are available, the devices to be used, and also the level of cooperation and peer-to-peer (P2P) group formation among tutors and students (Messina, Pappalardo, Rosaci, & Corrado, 2013). As we will discuss in the related work section, many techniques can be applied here and, particularly, AI planning is very valuable not only to recommend contents that fit the students' needs, but also to find the right order in which such contents need to be sequenced (Brusilovsky & Vassileva, 2003; Caputi & Garrido, 2015; Castillo et al., 2010; Garrido & Onaindia, 2010; 2013; Ullrich & Melis, 2009). After all, planning can be seen as an intelligent reasoning process to select the right contents and to place them as an ordered route of executable tasks to reach certain goals subject to several constraints.

In this paper we present an approach, named *myPTutor*, which takes as an input an e-learning model described in a standard e-learning language and produces a PDDL (*Planning Domain Definition Language*) model as an output. In particular, it applies standard AI planning and CBP (*Case Base Planning*) techniques to the generation and sequencing of e-learning routes, which are fully tailored to the students' profiles and necessities. Our main contributions address the following topics:

- Knowledge representation, in which we analyze and extract metadata information from learning contents encoded in e-learning standards, and produce an automated compilation of standard PDDL domain+problem files. This PDDL representation allows us to use any PDDL-compliant planner, thus making our model planner (i.e. solver) independent.
- Learning route personalization, not only in terms of contents but also in terms of their sequencing. In planning terminology this means a plan, generated by a case-based planner or any other planner.
- Content and rules datasource, as a CBP repository for planning domain+file compilations that contains students' learning information to be reused in the future. This has some resemblance to a collaborative recommendation technique, which reuses some recommendations that appear the most similar to similar students. In *myPTutor*, the stored compilations are successively analyzed by our case-based planner (Serina, 2010), which retrieves the best element that fits the current requirements and only adapts it if necessary (Fox, Gerevini, Long, & Serina, 2006).
- Learning designs development. Particularly, we provide a simple translation of the resulting sequence learning contents (plans) into another standard representation, namely learning design (IMS, 2008), that provides a usable manifest for standard online learning platforms, thus closing the e-learning cycle.
- Extension of *Moodle*, a well-known and widely used LMS. We have implemented a full vision that encompasses all the previous aspects on top of *Moodle*, as a flexible way to make curriculum authoring easier. All in all, our contribution shows a practical significance to help tutors and teachers choose the most suitable learning route and semi-automatically adapt it in accordance with the students' goals and individual features.

The remaining part of the paper is structured as follows. Section 2 explores some related work and how planning technology can be useful in e-learning. Section 3 describes the problem and introduces the role of planning for learning routes personalization. In Section 4 we present our general approach in detail, describing its structure, main elements, the e-learning-to-planning compilation and the CBP techniques we use. In Section 5 we explain our current implementation and how it is integrated on top of *Moodle*. A thorough evaluation with a large collection of experimental results is provided in Section 6. In Section 7 we discuss the lessons learnt, and the strong and weak features of our planning approach within an e-learning setting. Finally, in Section 8 we present the conclusions and the future work.

2. Related work and how planning can help

2.1. Related work

There are many aspects within e-learning in literature, which are beyond the scope of this paper. But in general, e-learning and course personalization has been traditionally addressed from a double perspective: student's modeling and adaptive+dynamic courseware composition.

On the one hand, student's modeling can be defined as the process of gathering relevant information to infer the current cognitive state of the student and to represent it to be accessible and useful in e-learning (Chrysafiadi & Virvou, 2013). There are many approaches to construct a student's model. For example, the overlay model that represents the student's knowledge level in Gaudioso, Montero, and Hernandez-del Olmo (2012); statistical, data mining and machine learning techniques to understand and improve the performance of the student's learning process (Campagni, Merlini, Sprugnoli, & Verri, 2015; Natek & Zwilling, 2014; Pena-Ayala, 2014); cognitive theories to explain human behavior (Alepis & Virvou, 2011); fuzzy logic modeling techniques and Bayesian networks to deal with the uncertainty of students' diagnosing (Jeremic, Jovanovic, & Gasevic, 2012); and ontologies to reuse students' models (Clemente, Ramirez, & de Antonio, 2011; Comi et al., 2015b). These approaches can be used on its own or be combined, thus building a hybrid model to personalize contents according to the students' needs and available resources (Kyriacou, 2008). Although our work could effectively adopt these modeling techniques, we do not explicitly focus on students' modeling. We have limited our analysis to the students' information necessary for automatically creating an AI planning representation. We follow the approach described in Baldiris et al. (2007), based on Felder's classification (Felder & Silverman, 1988) and SCORM (2004), which allows us to enrich the standard IMS-LIP representation (IMS, 2008) and improve students' personalization.

On the other hand, the idea with course composition is to recommend and personalize contents to students to ensure they complete all the activities that an instructor deems important. Moreover, an interesting issue is to assist students while navigating throughout the contents, and to monitor their progress and interaction in order to dynamically adapt the contents to their specific requirements.

From the point of view of personalizing e-learning contents, many techniques have been applied, such as neuronal networks, adjacency matrices, constraint programming models, soft computing methods, integer programming, machine learning, multi-agent approaches, swarm intelligence models and recommendation techniques (Anaya, Luque, & García-Saiz, 2013; Brusilovsky & Vassileva, 2003; Comi et al., 2015a; de Oliveira, Ciarelli, & Oliveira, 2013; Essalmi et al., 2015; Garrido, Onaindia, & Sapena, 2008; Idris, Yusof, & Saad, 2009; Kurilovas, Zilinskiene, & Dagiene, 2014; 2015; Martinez, Magoulas, Chen, & Macredie, 2004; Rosaci & Sarne, 2010). They all have in common the interest in simulating human

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