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Assembling Learning Objects for Personalized Learning. An AI Planning Perspective

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Abstract

The aim of educational systems is to assemble learning objects on a set of topics tailored to the goals and individual students' styles. Given the amount of available learning objects, the challenge of e-learning is to select the proper objects, define their relationships, and adapt their sequencing (i.e. course composition) to the specific needs, objectives and background of the student. This paper describes the general requirements for this course adaptation, the full potential of applying planning techniques on the construction of personalized e-learning routes, and how to accommodate the temporal and resource constraints to make the course applicable in a real scenario.

1 Introduction

Internet offers many opportunities for promoting student learning: one can find terabytes of resources available as learning object (LO) repositories for course assembling, customization and content packaging [1, 2, 3]. Despite this amount of data, institutions engaged in educational processes have traditionally opted for developing their own non-standard solutions. The resulting incompatibility of LOs format, along with the tendency of regarding LOs in isolation, leads to a lack of reusability and interoperability.

For effective interoperability, a LO must be a stand-alone, modular entity that incorporates its learning context (semantic relationships) in its own metadata. Metadata labeling is a key issue for semantic annotation, encoding, exchanging and reusing LOs, as it offers a successful way to catalogue and navigate its content, context, usage and structure [4, 2, 5, 3, 6]. This is valid for adaptive courseware generation, where the goal is to ensure a student completes the required activities, and dynamic courseware generation, where the goal is to assist students in navigating a complex hypermedia space. Metadata labeling is also crucial for dealing with a correct task adaptation in terms of educational aspects like the difficulty of using the LO and how it affects the learning process [7, 8, 9]. Intuitively, the ultimate goal is to create a personalized course, a student-centered solution in which the gathering of activities and their sequencing is tailored to the specific needs, objectives and background of each student.

This personalization perspective has been addressed by using different techniques, such as adjacency matrices, integer programming models, neural networks and intelligent planning techniques [10, 11, 12, 9]. Particularly, AI planning techniques have been successfully applied to the construction of adapted courses as a means to bring the right content to the right person [10, 12]. However, designing a course usually requires to deal with aspects such as group interaction, collaboration and sharing of some particular (and perhaps costly) resources. Thus, it is not only about bringing the right content to the right person, but also at the right time and with the right resources, a missing aspect in traditional e-learning.

We explore here the potential of metadata enrichment and the promising avenue of planning technology as a step to conduct e-learning investigation towards the development of (re)usable interoperable LOs, and push forward the agenda for innovative instructional engineering methods and joint tools.

2 Content and context adaptation: a motivating example

Let us assume two students, John and Rebecca, interested in a Java programming course organized in seven modules according to the tutorial available in `www.merlot.org/merlot/viewMaterial.htm?id=88853` (see Figure 1). John is at his first year of B.S. in Computing Science and is interested in programming. Rebecca is a self-taught programmer with experience in OOP and C++, and wants the Java certificate.

As shown in Figure 1-top, there are different routes to achieve the learners' goals. If we focus on the LOs of the module *Learning the Java Language* (Figure 1-bottom), the number of routes is even higher. John will require most of the LOs here, whereas Rebecca will need just a few to learn the main features of Java, excluding the OOP-related LOs thanks to her background. This is content adaptation; students are given different sequences of LOs according to their profile, knowledge and interests. On the other hand, imagine the *An example* LO requires the use of a computer —Rebecca has a laptop but John has no computer, so he needs to go to a lab. Picture now that the *Generics* LO is a lecture that requires in-person attendance on Tuesday 1-3p.m. and the classroom max capacity is 20 people. This is context adaptation; considering the real-world (time, resource consumption and synchronization of group activities) constraints to schedule the route, or perhaps avoiding some LOs if another route is feasible. Thus, adaptation implies provision for dynamic learning content, an adaptive behavior to promote the quality of learning, and a flexible process that

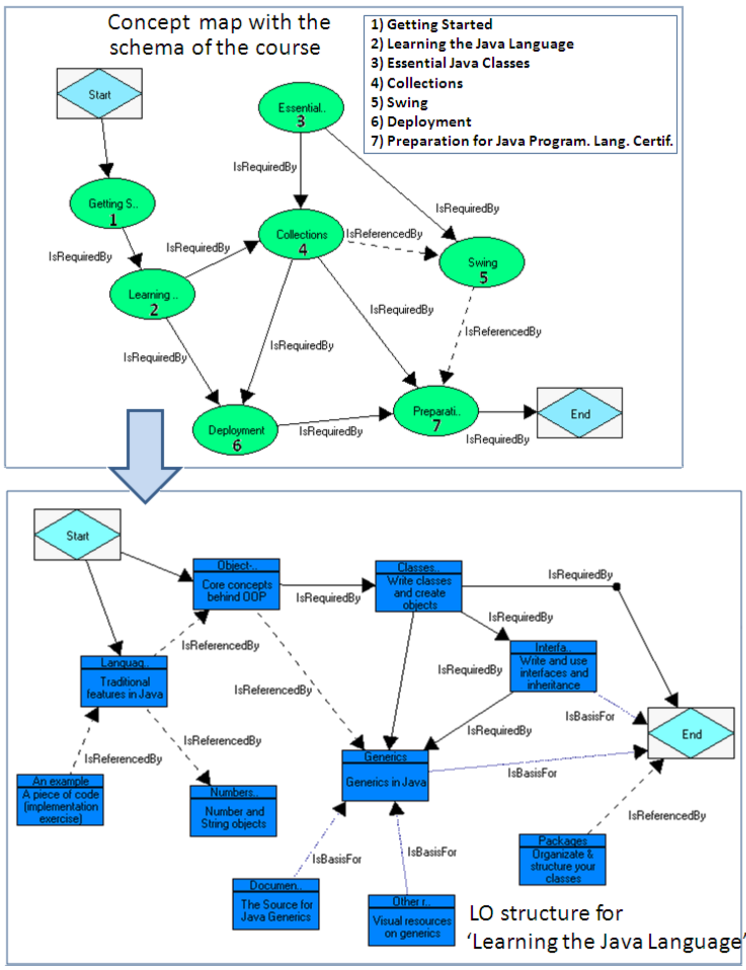

Figure 1: A Java basic course organized as a 7-module conceptual map (top) and the detailed structure for module 2, *Learning the Java Language*, (bottom).

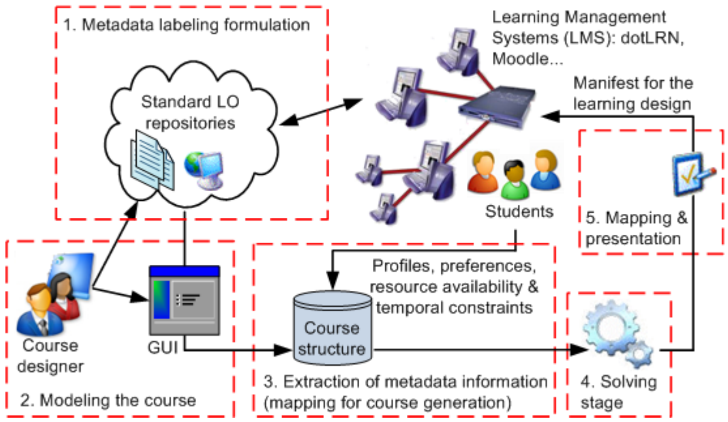

Figure 2: 5-step schema for personalized learning.

allows students to adjust their schedules to the resources of the course.

3 Requirements for supporting adaptation

Adaptation involves several technological issues, as depicted in Figure 2: use of common LO repositories and modeling tools, algorithms for students' information acquisition, application of solving techniques, and visualization of learning designs on Learning Management Systems (LMSs). The role of course designers is to model a course by reusing or defining new LOs. The relationship of students with the system is established when setting their profiles and preferences as well as during the navigation through their personalized learning designs. One route per student is generated (in an offline mode) before using the LMS, so the student's learning behavior does not require any particular change — technological aspects are transparent to students. This personalized learning encompasses five essential requirements, which are presented below.

3.1 Metadata labeling formulation

Metadata labeling is specified by the LOs creators usually in an XML standard format, such as IEEE-LTSC LOM (Learning Object Metadata [4]). The purpose is to offer a unified way to label LOs to be (re)used as interoperable units (see Figure 3). There exist many useful entries for pedagogical theories, including the general descriptors, but only three aspects address personalization:

1. The platform requirements for the LOs. The technical definition of a requirement is rather vague, e.g. *Unix operating system*, but in other cases it is precisely regarded as a resource, i.e. an entity of limited availability required by the LO.

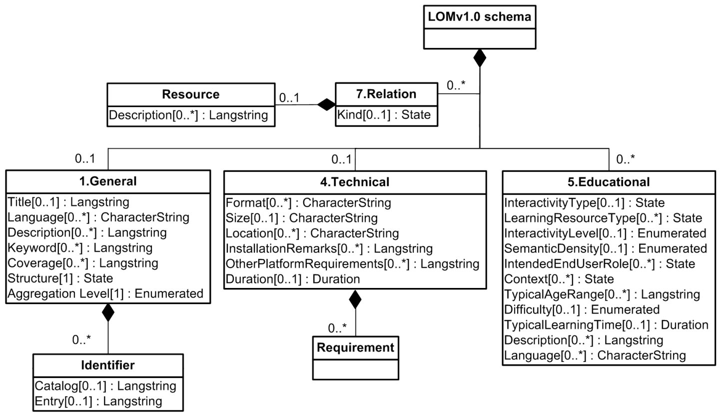

Figure 3: Simplified view (4 out of the 9 main elements) of the LOM base schema (`http://en.wikipedia.org/wiki/Learning_object_metadata`). Image used under the terms of the GNU Free Documentation License.

2. The information about the student's learning style (profile) and its suitability to the LO in terms of educational difficulty and typical learning time.

3. Relationships as content dependencies among LOs. They comprise the hierarchical structures (*IsPartOf*, used for LOs aggregation), and three types of orderings to represent causal dependencies: *Requires*, *IsBasedOn* and *References*, as conjunctive, disjunctive and recommended preconditions, respectively. The two first relations represent hard preconditions, but the third one denotes a soft precondition that may involve a kind of incentive or learning reward.

This information is sufficient in most situations, but more details are necessary for real scenarios. For instance, how many resources are available, at what time, with which cost and capacity? This is important because a limited resource might not be available for all the students simultaneously. Also, when a LO is adequate for a profile, does this mean that it is inadequate for other profiles? And the same happens with the soft preconditions: how to measure the incentive value when a recommendation holds? These are challenging questions that require expertise to be answered. Consequently, this metadata specification, sound from a pedagogical perspective, needs some further extensions.

3.2 Modeling the course

Creating personalized courses is a hard task because LOs in themselves are insufficient for significant instruction. Hence, offering an incremental and friendly way to link LOs using pedagogical and instructional design theories is highly appreciated [13]. A course, initially designed with the same LOs for all students (see Figure 1), can be later enriched by including collections of tailored LOs suitable to particular profiles. For instance, according to Felder's learning style classification [7], a lecture is very recommendable for verbal students but not for visual ones, and just the opposite holds for a diagram. This incremental process allows the designer to extend the metadata records of LOs, thus improving their adaptation capabilities. However, there exist some limitations. First, not all LOs are fully compatible and can be assembled with others freely. Second, LOs can only be combined under certain conditions and dealing with coherent metadata information is crucial; 'LO1 *Requires* LO2' and 'LO2 *Requires* LO1' would entail a contradiction —though this is automatically detected and avoided during the modeling. Third, the course designer needs some experience with LOs of a given domain to accomplish a high degree of personalization.

3.3 Extraction of metadata information

The mapping for course generation is a translation process that extracts the LOs metadata information and automatically builds the course structure through the causal dependencies between LOs and their adaptation aspects. Note that there is not a unique mapping, as it depends on the techniques used in the solving stage, e.g. a set of formulas for mathematical models, an action-based formulation for planning or a constraint satisfaction problem for constraint programming. The underlying idea in any mapping is to process the LOs of the course and include the information on the students (background, profile, learning goals and temporal+resource constraints) to create the course structure that will be used as an input for the particular solver.

3.4 Solving stage

The result of the solving stage, regardless the used technique, is a tailored learning design: a sequence of LOs that suits each student's preferences and necessities. From a pedagogical perspective, a tailored design is simply a collection of LOs, but the temporal and resource constraints need to be contemplated in a real scenario. Thus, some LOs may be associated to a time stamp and to a particular resource —e.g. a LO that requires the use of a shared microscope, only available when the lab is open.

3.5 Mapping for presentation

This step is another translation process to transform the calculated learning design into a standard language (manifest) used by LMSs. Although current LMSs support different languages, such as IMS-LD for dotLRN or Moodle templates, the compilation algorithm is quite general. For each student, the process generates one or more documents that include: i) the learning goals; ii) the prerequisites and previous knowledge; iii) the roles; iv) the activity structure, which represents the LOs and their orderings; and v) the resources required by the LOs. After uploading these documents on an LMS, the student progressively navigates through the contents, avoiding being exposed to all the LOs of the course.

4 Achieving full adaptation via planning techniques

From an AI planning perspective, we can exploit the previous general adaptation requirements even further. The idea is to adapt profiles to LOs, thus generating extremely flexible learning designs, by extending the modeling, metadata extraction and planning techniques (steps 2, 3 and 4 of Figure 2).

4.1 Modeling (and extending) the course for planning

We revisit the Java course and the two students introduced in section 2 to explain the potential of planning for modeling adaptation (see Figure 4). Note the two LOs of Figure 4-bottom. LO1 (*An example*) requires students with Programming skill={High, Medium}, whereas LO2 (*Documentation*) is adequate only for Felder's verbal learners. A flexible adaptation for profile-dependent scores or grades is also possible. In the case of LO1, if the student's programming skill is high, (s)he will get the max value (100%) of the competence level or score, but if the skill is medium this value is reduced to 70%. This means that a more skillful student, such as Rebecca, will get a better outcome from this LO than a medium one, such as John.

Moving beyond, a higher level of adaptation can be modeled, as shown in LO3 (*Classes and objects*) of Figure 4-top. Given two levels for OOP previous knowledge, namely high and low (Rebecca's and John's, respectively), LO3 is valid for any type of student, but if the student's OOP previous knowledge is high, the prerequisite for this LO is lower than if it were low. Additionally, the outcome of LO3 is higher when the student's profile is high and smaller if the profile is low. This means that when using LO3, a more OOP-experienced student such as Rebecca will require less effort than John. After doing this LO, a student with more OOP-experience will become more competent in Java classes than a novel student who has just started with OOP. Analogously, we can model temporal and resource constraints for context adaptation like, for instance, that LO1 requires a computer, or that LO3 needs to be done in a collaboration group, which entails synchronization constraints among the students (and other constraints to arrange/attend a seminar).

4.2 Extraction of metadata information for planning & scheduling

This stage analyses the students' information and iterates all over the LOs to generate one PDDL (standard Planning Domain Definition Language) action per LO and student, as detailed in the mapping of Table 1. This compilation is

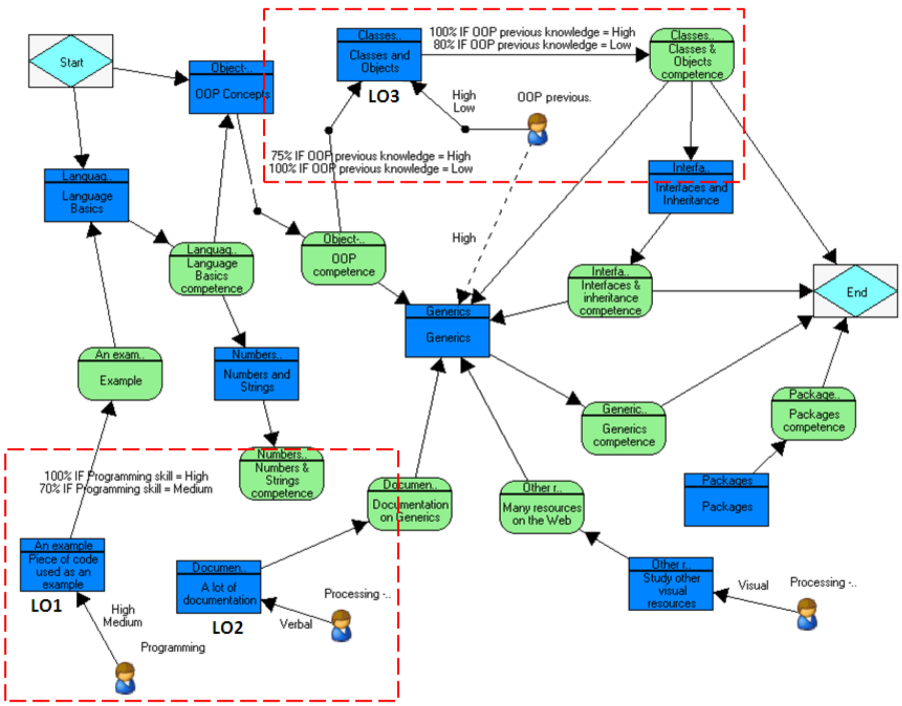

Figure 4: Exploiting planning for adaptation of profiles to LOs, requirements and outcomes.

very efficient, as each action comprises four entries automatically extracted from the values of the LO metadata: i) name, with the LO name; ii) duration, with the LO learning time; iii) conditions, based on the profile's dependencies plus the relations defined in its metadata; and iv) effects, based on the learning outcomes. This process also validates and matches preconditions and effects, thus detecting incorrect LO metadata and discarding unfeasible actions. The PDDL action for LO3 of Figure 4 adapted to Rebecca ('OOP previous knowledge=High' profile) is:

```
(:durative-action LO3_Classes_and_Objects_Rebecca
   :duration (= ?duration 50)
   :condition (and ;; LO3 not done yet and OOP competence requirement
                (at start (= (LO3_Classes_and_Objects_Rebecca_done) 0))
                (at start (>= (OOP_Competence_Rebecca) 75)))
   :effect (and ;; LO3 now done and competence outcome
             (at end (increase (LO3_Classes_and_Objects_Rebecca_done) 1)
             (at end (increase (Classes_and_Objects_Competence_Rebecca) 100)))))
```

Numeric values represent different competence levels and are useful to model adaptation, costs or learning rewards, which allows us to deal with multi-objective metrics.

The scheduling mapping is even simpler. Students' and LOs' constraints are directly mapped to a Constraint Satisfaction Problem (see Table 1). Variables represent the start time of each action (LO) and restrictions represent the dependency relations and temporal+resource constraints (see [10] for more details). For instance, assuming that Rebecca and John perform LO3 in a collaborative group, the CSP asserts the following constraint: `(LO3_Classes_and_Objects_Rebecca = LO3_Classes_and_Objects_John)`. If LO3 needs a seminar that opens from 1-3p.m (780-900 if time is measured in minutes), the constraint is: `((LO3_Classes_and_Objects_Rebecca` $\geq$ `780)` $\wedge$ `(LO3_Classes_and_Objects_Rebecca + 50` $\leq$ `900))`, assuming 50 as the LO3 duration, which also restricts John's LO3 due to the previous equality. Note that this information is still uncommon in standard LOs and requires some extensions when designing the course, which can be easily modeled from a planning perspective [13].

4.3 Solving stage

Mapping the e-learning problem to a standard PDDL+CSP model facilitates the use of independent solvers and to abstract out the e-learning features from the planning and scheduling details. A whole description of planning and scheduling technology is out of scope here, but more information about the solver we have implemented is given in [10]. In short, the planner decides *which* are the best LOs, whereas the scheduler deals with plans for students sharing temporal and resource constraints, thus deciding *when* and *how* to use such LOs.

Planning mapping

LO metadata item →	PDDL action entry per student
`general/title`	`action-name`
`educational/typicallearningtime`	`:duration` for temporal planning

dependency relations:
type of relation:
switch (`relation/kind`)
case (*Requires*): conjunctive (and)
case (*IsBasedOn*): disjunctive (or)
the LO: `relation/resource/entry`
	`:condition`
	`(and (at start (= (action-name_done) 0))`, and
	if and-precondition: `(and ...`
	else-if or-precondition: `(or ...`
	for each `entry`:
	`(at start (>= (action-`*competence*`)` *val*`))`
	... other optional preconditions for profile adaptation taken from `educational` item)

model that the action has been done, and increase the competence value, and increase a reward/utility (if any) due to:
profile adaptation:
`educational/learningresourcetype`
additional adaptation:
if `relation/kind` is *References*
	`:effect`
	`(and (at end (= (action-name_done) 1))`, and
	`(at end (increase (action-`*competence*`)` *val*`))`
	`(at end (increase (reward_student)` *val_LRT*`))`
	`(at end (increase (reward_student)` *val_Ref*`))`
	... other optional rewards and/or costs)

Scheduling mapping

LO information →	Formulation in the CSP model (vars. & restricts.)
time stamp for the LO	variable `action-name` $\in [0, \infty)$, which represents the start time of the LO
ordering relations: `relation/kind` and others `relation/resource/entry`	`action-name`+duration(`action-name`)$\leq$ `action-name_`*entry*
temporal synchronization (collaboration) of LO among students `s1, s2`... `s`$_n$	`action-name_s1=action-name_s2=...=action-name_s`$_n$
capacity constraint for resource $R_i \in$ `technical/otherplatformrequirements`	capacity(R_i) $\leq \sum$ use(`action-name_s`$_j$, R_i), forall `action-name_s`$_j$ that requires resource R_i

Table 1: Planning & scheduling technical mapping for course generation. From LO metadata (Figure 3) to PDDL planning and CSP-based scheduling.

5 Evaluation and discussion

We evaluate our approach from two perspectives: i) a quantitative perspective that measures the system response, and ii) a qualitative perspective that measures the benefits and effort for course designers and students.

A quantitative evaluation

We have tested our approach in four AI courses (short, short-medium, medium-long and long, with approximately 10, 20, 40 and 80 LOs, respectively) from a repository of 172 LOs for different learning styles. We aim at the quality of the plans and the scalability of the system, considering only planning and planning+scheduling (synchronization and resource consumption constraints, randomly generated, on LOs). We have conducted two experiments in our solver, fully described in [10], to: i) minimize makespan (shortest plan), and ii) maximize the students' learning reward based on the LOs that best fit them. We have defined problems with 1, 2, 4, 8. . . 256 fictitious students with different profiles, and run the experiments on a 2.33GHz Intel Core 2 Duo CPU with 3.23GB of RAM.

Figure 5 shows the results. Obviously, the maximization problem involves longer plans, which degrades performance. Processing the scheduling constraints (`+SC`) has also an expectable negative impact in performance, thus solving problems with fewer students (mainly in longer courses). This is a general issue due to the complexity of CSP solvers. Particularly, our embedded scheduler handles up to 1500-2000 variables for the LOs in a reasonable time, but more than this exhausts the allocated time. The main conclusion is that scheduling reduces the scalability approximately in one order of magnitude. However, the performance is still reasonable and allows us to manage scheduling constraints in groups of 10-20 students even for long courses.

A qualitative evaluation

Adopting this personalization approach is challenging and its horizon is still unclear [3]. First, adapting LOs to learning styles requires a change of mind in the conventional way of teaching. Second, some lecturers show reluctant to this way of proceeding due to the start-up pedagogical effort to redesign LOs and courses to fit different profiles. Third, assembling LOs for fully-adapted instructional courses requires experience and training. Finally, adopting this approach entails a handicap for IT illiterate lecturers. But, as long as self-learning and IT approaches are more demanded, the application of planning technology eases the incremental construction of tailored courses [13]. This promotes the exploitation of planning techniques to the level desired by the course designer and reduces the need of background in planning.

We designed a questionnaire (Table 2) about a long AI course to assess the lecturers' opinion on the course contents and on the adaptation to the students' profile. The questionnaire was filled in by 10 lecturers who regularly teach AI to

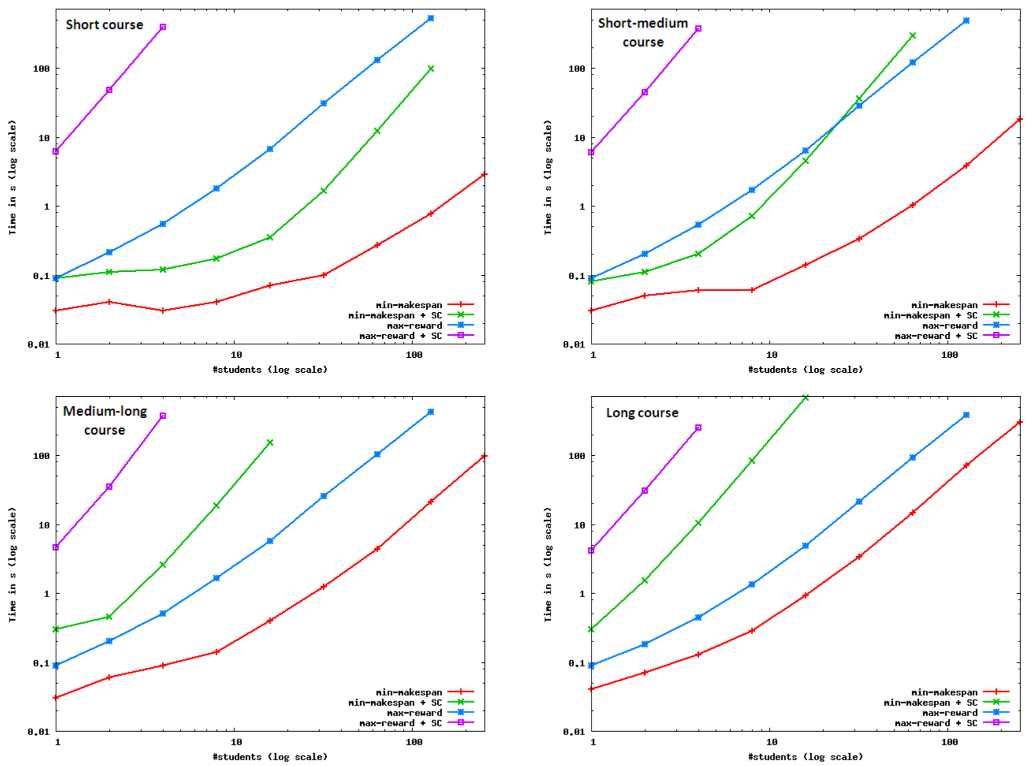

Figure 5: Experimental results for two different metrics and two options, planning and planning+scheduling constraints (+SC). All tests were censored after 360s.

	Very little	Little	Neutral	Much	Very much
Q1				3	7
Q2	2	5	3		
Q3		2	3	4	1
Q4			2	2	6
Q5	2	3	3	2	
Q6	4	5	1		
Q7			2	6	2
Q8			3	5	2
Q9				4	6
Q10				2	8
Q11	4	4	2		
Q12				3	7

Q1. Is the sequence of LOs consistent with the objectives of the course?
Q2. Is the size (number of LOs) of the course appropriate?
Q3. Is the duration of the course appropriate?
Q4. Do you think the learning route and contents are adapted to the student's profile?
Q5. How much experience do you need to deal with these LOs?
Q6. How much planning background is necessary?
Q7. Do you consider this approach useful?
Q8. Would you recommend this approach to other lecturers?
Q9. Do you find e-learning as a positive and motivating experience versus traditional teaching?
Q10. To which extent did the course fit your needs and constraints?
Q11. Would you suggest some changes in the course structure?
Q12. Would you recommend this approach to other students?

Table 2: Questionnaire for a qualitative evaluation of an AI course. First block evaluates the course contents and structure; second block shows the lecturers' opinion on using the LOs; and third block gathers the students' opinion on using this course.

graduate students. We also gathered the opinions of 10 students for this course. Generally speaking, lecturers identify the mainstream of the learning designs with their own experience in giving the course, and very much agree with the lesson plans (sequencing of LOs) for specific topics. However, they miss a higher pedagogical organization of the LOs in the form of advice or recommendations to students. While they generally agree with the course composition and causal dependencies among LOs, they feel that the overall structure of the course is left too open for students.

As for students, the experience was highly positive. They found the provided LOs a very helpful resource to catch up with the background required for the course, grasp the key ideas as well as an ideal mechanism for self-assessment [1]. Students' motivation also stems from the easiness to sign up for the course. No previous training or change of mind is required, they just have to classify themselves in one or more learning styles (see `www.engr.ncsu.edu/learningstyles/ilsweb.html`), define their background, preferences, learning outcomes and, optionally, their temporal+resource constraints. The most outstanding result among students is the degree of satisfaction with the self-organizing activities of the course. This allows students to create a schedule to follow up the course while their personal and temporal restrictions still meet.

In general, we can affirm that students seem more enthusiastic about e-learning than lecturers. From our experience, the use of planning technology has proved to be very successful to promote adaptation. But it is important to note that the success of this approach cannot be directly assessed through the students' grades because using a fully-adapted route does not necessarily mean a better score. However, it brings along a need in students to study effectively and to attempt fast completion of their studies, a higher motivation for using LOs that fit their preferences and learning styles.

6 Conclusions

Traditional learning makes students adapt to course syllabuses and directives of the academic center. In e-learning it is the other way around: everything is about content adaptation and flexibility for students. The use of planning and scheduling techniques allows us to bridge the gap between the e-learning necessities and the generation of learning designs, together with the accommodation of temporal+resource constraints and multi-criteria optimization metrics. This has issued a challenge to a successful integration with standard tools for on-line learning.

The lesson learned is that planning technology is highly appreciated by students but less popular amongst lecturers, who are somewhat reluctant to give up their traditional role of *course planners*. But reality shows that in the context of Web libraries, it becomes difficult for a lecturer to create fully personalized plans for students that meet their personal constraints too. Anyway, a positive reading shows that both students and lecturers agree on the flexible application of planning techniques to provide the right content to the right person at the right time.

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