Adaptive planner for facilitating the management of tasks in MOOCs

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Abstract—**Massive Open Online Courses (MOOCs) provide open access to a wide variety of learning contents in many different knowledge areas, so that eventually anyone in the world can join these courses and learn, no matter the level of education. However, the majority of participants that currently take advantage of MOOCs already have Higher Education qualifications. Therefore, there is an open challenge in promoting the embracement of MOOCs by those who have not achieved a college degree, in a society that demands more and more up-to-date competences. MyLearningMentor is an early-stage application aimed at facilitating the acquisition of work habits and study skills when learning through MOOCs, so that even people without college degrees can easily address the challenge of successfully completing MOOCs. This paper presents a planning algorithm to suggest students' study time efficiently and dynamically, considering their profiles, study preferences and the MOOCs they signed up. This algorithm is implemented by the adaptive planner, the main component in MyLearningMentor.**

Keywords—MOOCs, planning, mentor, study skills, work habits.

I. INTRODUCTION

MOOCs (Massive Open Online Courses) are a disruptive trend in education, and have positioned as a complement to traditional Higher Education, promoting also lifelong learning [1]. MOOCs have attracted the interest of many teachers and students, as well as most educational institutions and mainstream media [2] in just over two years. MOOCs have generated a growing community that includes educators, researchers and technologists concerned about the challenges that are emerging within this new educational context.

One of the main characteristics of MOOCs is their open nature, which enables anyone with Internet connection to access courses provided by elite universities [1]. This characteristic turns this new way of disseminating knowledge packaged as courses into an opportunity for offering free education and training for all, regardless of their origin and background.

Nevertheless, despite the open nature of MOOCs, recent studies pointed out that most participants completing these courses had already obtained Higher Education degrees [3]. As an example, 76% of the people completing the first five MOOCs delivered at Harvard had a Bachelor's Degree or above [4]. According to this trend, MOOCs will eventually widen the education gap between those with more and less qualifications. This is especially critic in the current job market in which people with lower qualifications are being hit hardest by unemployment.

The higher proportion of participants with college degrees completing MOOCs can be partially explained to the extent that MOOCs demand a high responsibility and self-direction [5], which are skills typically developed by people who have gone into higher education. In contrast, people who left school usually lack work habits and study skills. Particularly, the fact that teachers cannot provide personalized support to students in MOOCs contributes to the need for a higher responsibility and self-direction in order to successfully complete a MOOC.

In this context, the authors are working in the project MyLearningMentor [6], which addresses the design and development of a homonymous application for guiding and advising MOOC participants with less study know-how in the challenge of facing MOOCs. This application aims to scaffold self-direction in MOOCs and improve participants' performance providing personalized planning and feedback for the development of work habits and study skills. This paper focuses in the main component of the project MyLearningMentor, which is the adaptive planner. The adaptive planner suggests users the best times of the week to work in the tasks defined in MOOCs, in an efficient and dynamic way, and taking into account students' profiles, study preferences and availability, and the MOOCs in which students signed up.

The rest of the paper proceeds with Section 2 reviewing the state-of-the-art related to recommender systems and adaptive planners for educational purposes. Then, Section 3 introduces MyLearningMentor enumerating its main requirements and describing its architectural design. Section 4 focuses on the adaptive planner of MyLearningMentor, characterizing tasks and sequences of tasks in MOOCs, and proposing the planning algorithm. Finally, Section 5 presents the conclusions and future work.

II. RELATED WORK

The automated creation of task schedules and activity planning has been studied in a generic form since more than three decades ago [7]. As the topic has matured, research works have specialized in constrained domains. One of the domains of interest has been the design of personal assistants, as proposed by Mitchel et al. [8]. Their work provided an

exploratory study of applying learning machine methods through the development of a calendar manager called Calendar Apprentice (CAP). They demonstrated the feasibility to detect user preferences in regards to schedule meetings. In addition, other studies have described how the analysis of the characteristics and relations of tasks can facilitate the accomplishment of such tasks [9].

With the increasing interest on adaptive learning, educational scenarios have become a case of study for the application of personal assistants. In this context, the tasks to be scheduled are defined as learning activities that a student must follow in a given order; this concept is understood as course sequencing [10]. Brusilovsky and Vassileva described three approaches for the use of course sequencing: 1) using it as the core of a course maintenance system; 2) generating an adaptive courseware for a group of learners; and 3) dynamically generating a courseware that observes and adapts to students' progress.

In another example of automatic course sequencing, Karampiperis and Sampson have proposed the application of ontologies and learning object metadata to recommend a sequence of learning resources to be provided to the learner [11]. In their approach, domain concepts and learning resources are modeled as interconnected networks and combined into a "directed acyclic graph". The learning path is obtained from the application of a shortest-path algorithm towards the domain concept to be acquired.

Adaptive learning researchers have contributed several tools for the personalization of learning environments. Recommender systems (RS), originated within the field of adaptive hypermedia, are among most common solutions in this area. Some RS have focused on the recommendation of learning activities adapted to the student's profile and current context. For instance, Koper [12] proposed the recommendation of appropriate learning paths, or sequences of units-of-learning, by analyzing social interactions. An interesting result of applying this kind of recommendations is the increase of effectiveness in lifelong learning scenarios [13]. As an evolution of this idea, Hummel et al. [14] have proposed the design of a RS to find appropriate learning paths by combining social information, learning profiles and characteristics of the learning activities. For a complete review of context-aware recommender systems in the domain of education, the reader can refer to [15].

Furthermore, several examples of activity recommendations can be found in experiences of ubiquitous learning. Chen et al. [16] presented a combination of a learning website and the use of mobile devices to take advantage of the affordances of each technology. In this case, the activity schedule was defined by the teacher and informed to the students, who had to update their personal schedules if needed. Similarly, Yau and Joy [17] introduced Context-aware and Adaptive Learning Schedule (CALS), a framework to support students in their daily routines. This framework is intended for the development of applications for mobile phones, which increases the characteristics of the student's context. Their approach takes into account learning style and current learning context for the recommendation of appropriate activities. In their proposal, students predefine schedules with predefined types of activity slots, and the adaptation occurs in the specific activity to be performed during that given time. This differs from our approach given that MyLearningMentor is in charge of suggesting a learning activity without an underlying schedule template.

Wang and Wu [18] proposed a recommender of learning resources. The common factor in their approach is the consideration of student feedback in order to measure the effectiveness of the recommendation system and to inform self-adjustments. Student feedback indicating the tasks that were completed for the suggested planning is something that will be incorporated in the case of MyLearningMentor because of its importance to make adjustments and refinements in future planning, as reported in [18].

More recently, Li et al. [19] have explored the use of records of acquired knowledge, denominated ubiquitous learning logs, as a mean to suggest students to perform an action. The recommendations sent to the student can be a reminder to take a quiz, the review of learning resource accessed by other student, or a suggestion to review the concepts learned at a given time. The use of periodic reminders, sent as notifications to students, is something that is also considered for implementation in the case of MyLearningMentor [6].

Our proposal differs from the presented in this section in many aspects, such as the context where the activity planning is done. MOOCs provide a new scenario for the scheduling of activities that will improve the overall learning experience. The importance of coaching and timing has been discussed by Gillet in [20] as some of the dimensions that characterize a continuum between traditional MOOCs and connectivist MOOCs.

III.   MYLEARNINGMENTOR

The requirements of MyLearningMentor stem from the findings obtained after conducting a survey on work habits and study skills to 41 second-year Higher Education students in the Universidad Carlos III de Madrid (Spain) [6]. These requirements are: 1) the application must be distributed as a mobile app since most people have adopted mobile devices in their daily lives; 2) the application must be customizable to different students' profiles since the people that enroll in MOOCs have heterogeneous study preferences and learning outcomes; 3) the application must include an adaptive planner to help people organize the tasks they need to complete in MOOCs; 4) the application must rely on crowdsourced information to get precise information about the tasks that must be completed in each MOOC, their level of difficulty and expected dedication; 5) the application must provide tips and hints to help students, particularly regarding time management, work habits and social learning; 6) the application must serve as a meeting point for MOOC participants with problems and volunteer mentors that want to advise them [6]. From all these requirements, this paper focuses on the third one: **the design of an adaptive planner to help people organize the tasks they need to complete in MOOCs**.

The architecture of MyLearningMentor includes a mobile application in the front-end that communicates with a RESTful API offered in the back-end [6]. The back-end includes three databases that store: 1) users' profiles; 2) data from MOOC (e.g., tasks, dates, and workload); and 3) the feedback to be provided to students as tips and hints. In addition, the back-end includes four services: 1) Account & Profile Management service for managing users' account and profiles; 2) MOOC Directory service for scraping data from MOOCs that is complemented with further information provided by users, following a crowdsourced approach; 3) the Feedback Gathering service for collecting feedback from users regarding the tasks they completed and offering personalized tips and hints, and 4) the Adaptive Planner, which suggests students' study time efficiently and dynamically. From all these services, this paper focuses on the **Adaptive Planner**, which is the most complex service.

IV. ADAPTIVE PLANNER

The adaptive planner is the main component in MyLearningMentor. It provides users a detailed planning of the sequence of tasks to be carried out during the week, indicating the number of tasks, and the best times to complete them, in a personalized manner, and for the MOOCs in which the user signed up. In order to provide a detailed and customized planning, the adaptive planner receives five kinds of input from two different sources: *User information* and *MOOC information* (see Figure 1).

1. **Profile**. Users fill in their profile, which includes two fields: the level of education achieved and the background. Typically those people with lower qualifications need to spend more hours working to complete the tasks, something that the adaptive planner takes into account, as detailed later in this section. In addition, those people participating in MOOCs that are not related to their main background will need some time to catch up on the basic concepts.

2. **Study preferences (and availability)**. Users fill in their study preferences, which include the best time of the day to study (morning, afternoon, evening, night) and the best days of the week to study. In addition, users fill in their availability, indicating their number of available hours per week to study. In this way, the adaptive planner can provide a detailed planning that meets users' availability. In the event that the user has less available hours than the expected weekly workload demanded to complete all the tasks, the

adaptive planner shows a notification that recommends dropping out some of the MOOCs or increasing the available time to study.

3. **List of priorities**. Users arrange the MOOCs they signed up in a list of priorities. In this way, those tasks belonging to MOOCs that are in the top of the list are scheduled with a higher priority.

4. **Tasks completed**. Every week, users indicate the number of tasks that they managed to complete from those suggested by the adaptive planner. In this way, the adaptive planner knows whether the planning was suitable or not and reacts in subsequent weeks.

5. **Sequence of tasks**. Either by scraping the information provided by the MOOCs or relying on crowdsourced information provided by users themselves, the adaptive planner knows the sequence of tasks in each MOOC and uses it to provide a detailed planning. The sequence of tasks includes the number of tasks to be completed per week, the dependencies between tasks, the mandatory nature of each task and the average workload as determined by the MOOC teachers.

The following subsections describe the formal characterization of the sequence of tasks as well as the proposed algorithm.

A. Overview of the MOOCs

Most current MOOCs are structured in modules (sometimes also called lessons or weeks), which include a set of tasks that students should complete in a given order (*sequence of tasks*) to master the concepts taught in the MOOC. These tasks typically include watching videos, completing a series of automatic assignments, completing a series of peer review assignments (including the review of peers' works), and possibly, working on other complementary tasks. The order established by teachers for these tasks defines the *ideal sequence of tasks* for the students.

Some MOOCs offer students the information about all the tasks they have to complete from the very beginning, although many other MOOCs release sets of tasks at predefined moments during the course enactment (e.g., at the beginning of each week). In any case, most MOOCs establish deadlines for some of the tasks, which must be completed on time as a prerequisite for passing the course. Such tasks with deadlines can be classified as *required tasks*. The remaining tasks in the ideal sequence of tasks can be classified as *recommended tasks* since a committed student with enough time will try to cover them all. Finally, there may be other tasks that are not included in the ideal sequence of tasks, but that would be of interest for those students that want to learn in depth about topics related to the course. Such tasks can be classified as *optional tasks*.

However, not every student has the same skills, and even the more committed and skilled ones have time restrictions and priorities. So, the mission of the adaptive planner is to recommend students the best possible planning, without jeopardizing the successful completion of the MOOCs in which users are enrolled, and taking into account users' profiles, time restrictions and priorities.
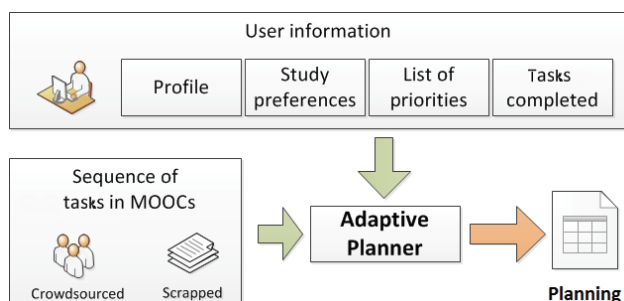

Fig. 1 Input sources and output of the Adaptive Planner

B. Formal characterization of tasks in MOOCs

From a temporal point of view, a MOOC is an ordered and acyclic sequence of tasks (i.e. a MOOC is a particular case of a "directed acyclic graph"). A MOOC task, τ_i, can be characterized as follows:

$$\tau_i = (C_i, \phi_i, D_i, p_i)$$

where C_i is the minimum time needed for completing the task working full-time on it (hereafter, *execution time*); ϕ_i is its *offset* (i.e. the time at which the task is activated in the MOOC taking as reference the start of the course); D_i is its *deadline*; and p_i is its *priority*. We assume that the values of C_i, ϕ_i and D_i can be scraped from the MOOC website or crowdsourced. The value of p_i is set by the student in MyLearningMentor and is the same for all the tasks that belong to the same MOOC.

In MOOCs, tasks are usually gathered in modules, which have precedence relationships. All the tasks within each module are typically made available (or planned by the teaching staff) at the same time. Therefore, in this characterization we consider that all the tasks in the same module have the same value of ϕ_i.

Additionally, as students in MOOCs are very heterogeneous, given a *job* (or task instance), τ_i^s, (i.e. a particular task τ_i within a MOOC for a specific student s), we will use the following notation:

- α^s is the *student profile parameter*. This parameter will take into account the level of education and background of the student as well as the performance in the MOOCs the student signed up (understanding by performance if the student was able to finish the tasks on time). When no information about student's performance is available, the algorithm will only use the level of education and background. Once the student starts interacting with MyLearningMentor, the value of α^s will change according to the performance feedback provided by the student.

- C_i^s is the execution time of the job for the specific profile of the student, where $C_i^s = \alpha^s \cdot C_i$.

- R_i^s is the response time of the student to the task, i.e., the time needed from the activation of the task until its full completion.

Table 1 shows the relationship between the inputs of the adaptive planner and the parameters used for the formal characterization of tasks in MOOCs. As it can be seen, the value of α^s is dynamic, changing as more information about student's performance is known by the algorithm.

The value of the *deadline* D_i for each task τ_i is calculated taking into account the mandatory nature of the task. We assume that in order to pass a MOOC, **a student should complete all the required tasks before the deadline imposed by the teachers**. So, for required tasks, D_i is fixed beforehand and known by the students. The planning suggested to students must always ensure that required tasks are completed before D_i time units from their arrival time ($R_i \le D_i$). Recommended and optional tasks do not usually

	Input Parameters to the algorithm			
	Sequence of tasks in MOOCs	Profile	List of priorities	Assignments completed
C_i	√			
ϕ_i	√			
D_i	√			
p_i			√	
α^s	√	√		√

Table 1 Relationships between the parameters that characterize tasks in MOOCs and the input of the adaptive planner. Study preferences are not used to characterize tasks in MOOCs.

have explicit temporal requirements, although sometimes recommended tasks are expected to be completed before the next required task in the sequence; in such cases, recommended tasks share the deadline of the next required task. However, missing a deadline of a recommended or optional task is not critical, since the student can pass a MOOC without completing non-required tasks. Given a student with enough available time, the planner will suggest him the completion of every single task in a MOOC. However, if there are time restrictions, the planning will apply the priorities set by the student between MOOCs; and within each MOOC required tasks will be prioritized over recommended and optional tasks.

Table 2 classifies the tasks that can be typically found in a MOOC depending on their content. Usually, the only required tasks are assignments (summative automatic assignments and peer-review activities), which have a fixed deadline known by the students. Recommended and optional tasks will implicitly have the deadline of the next required task.

We consider that video tasks (VT) are the only tasks with a fixed execution time (C_i): the length of the video. However, as the concepts in a video can be difficult to understand for a non-skilled student, the execution time of the job for a given

Type of tasks		Mandatory nature	Deadline
Video task (VT)		Recommended	Implicit
Automatic Assignment	Formative (AT-F)	Recommended	Implicit
	Summative (AT-S)	Required	Explicit
Peer-review	Assignment (PAT-A)	Required	Explicit
	Review (PAT-R)	Required	Explicit
Forum task (FT)		Optional	–
Other tasks		?	–

Table 2 Types of tasks in MOOCs, mandatory nature and deadline. Other tasks, apart from those considered here, may be included, indicating their mandatory nature and deadline.
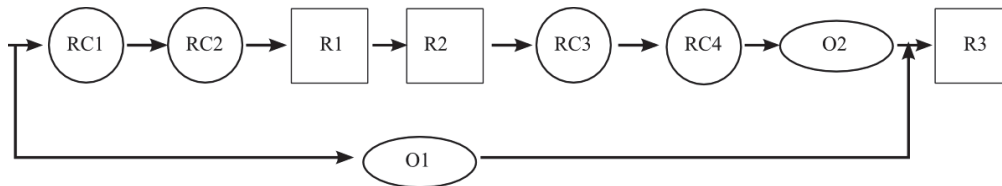
Fig. 2 Example of an ideal sequence of tasks in a MOOC: R (required tasks), RC (recommended tasks), O (optional tasks).

student (C_i^s) will take into account the needed repetitions (or stops and starts to process the contents more carefully) in the α^s parameter. For all the remaining types of tasks presented in Table 2, the algorithm will set an initial C_i using scraped of crowdosurced information. The value of C_i will be modified depending on the profile of the user, and on the feedback from the students that complete the task.

Video tasks also have a special consideration for the algorithm, which always recommends the full completion of a VT; that is, once a VT starts, the adaptive planner will allocate enough time for watching the whole video, including the needed repetitions. The allocated time can also include extra time for optional tasks (e.g. forum tasks), so that the student searches further information related to the video in order to better understand the concepts explained. Therefore, video tasks are considered indivisible for the algorithm and can be linked to optional tasks.

The tasks related to assignments are generally required tasks, with the exception of formative automatic assignments (AT-F). AT-Fs are recommended tasks due to their formative nature (inheriting the deadline of the next required task). Summative automatic assignments (AT-S), peer-review assignments (PAT-A), and the subsequent reviews of peers' work (PAT-R) are normally required tasks and have their own deadlines established by the teaching staff of each particular MOOC.

Finally, teachers may decide to also include optional tasks in the MOOC. Optional tasks do not normally have deadlines and are assumed to be active throughout the MOOC. Reading and making contributions to the forum (FT) is usually considered to be an optional task. The adaptive planner will suggest students to work in optional tasks when there is spare time (available time not used by the student to work on required or recommended tasks). The adaptive planner will also distribute the spare time of students suggesting them to check the forum when trying to complete an assignment. If after completing the required and recommended tasks there is still some available time before the end of the module, the adaptive planner can suggest students to work in other optional tasks established by the teaching staff of a particular MOOC.

C. Formal characterization of sequences of tasks in MOOCs

The *ideal sequence of tasks* was previously defined as the completion of all the tasks in a MOOC strictly following the order established by teachers (Figure 2 shows an *ideal sequence of tasks*). In addition, we define the *recommended sequence of tasks* as the one that the adaptive planner recommends to a student at a given moment. Given a student with enough available time, the *recommended sequence of*

tasks provided by the adaptive planner will be the *ideal sequence of tasks*. We also define the *actual sequence of tasks* as the one that the student was able to complete until a given moment. The recommended sequence of tasks will take into account both the ideal and the actual sequences of tasks, and will evolve with time. The algorithm in the adaptive planner for calculating the recommended sequence of tasks can be executed every time the actual or the ideal sequences of tasks in a MOOC change.

D. Proposed planning algorithm

Given the *ideal sequence of tasks* and the *actual sequence of tasks* in MOOCs, the student's profile and preferences, the proposed planning algorithm will proceed as follows:

1. For each MOOC where the ideal sequence of tasks is available at the time of planning, the algorithm will initially allocate the amount of time required to complete the ideal sequence of tasks weighted by the α^s parameter (to take into account the student's profile). For each MOOC where the ideal sequence of tasks is not available at the time of planning, the algorithm will initially allocate an amount of time equivalent to the overall workload of the MOOC (which teachers typically include in the general information of the course), weighted by the α^s parameter.

2. The MOOCs will be ordered following the list of priorities given by the student. The time initially reserved for each MOOC will be adjusted following the list of priorities.

3. For each MOOC, the algorithm will generate the combination of the remaining required tasks. For example, if the *ideal sequence of tasks* in "MOOC A" is the one shown in Figure 2, and the student has not started the MOOC yet, then the combination of the remaining required tasks will be {R1, R2, R3}. At this point the algorithm will compute if it is possible to guarantee the deadlines of all the required tasks from all the MOOCs, given the remaining available time. If not, it will inform the student of such situation and will ask the student to withdraw some MOOC.

4. With the remaining time, the algorithm will schedule the recommended tasks for each MOOC independently, starting from the MOOC with a higher priority.

5. If there is still available time at the end of the previous step, the algorithm will schedule the optional tasks for each MOOC following the list of priorities, starting always with the forum task.

It is noteworthy that when planning both recommended and optional tasks, the algorithm will explore the *ideal sequence of tasks*, allocating enough time for each task, taking into account the profile of the student (with parameter α^s modifying the time a student needs to complete a task).

This algorithm first ensures the completion of the required tasks and, then, tries to allocate as many recommended tasks as possible, trying to recommend the completion of the MOOCs that are ranked in the top of students' priority list. This design decision is due to our belief (as teachers) that, once ensuring the completion of the required tasks, it is better to deepen in the concepts of a specific course than to acquire a superficial knowledge of multiple courses. However, this allocation policy can change depending on students' goals (e.g. if all the MOOCs a student signed up received the same priority).

Finally, it is important to point out that every time a student marks a task as completed, the algorithm can be executed again in order to offer a more accurate planning to the student: if the student spent more time than expected, the algorithm will reduce the time allocated for recommended or optional tasks; if the student spent less time than expected, the algorithm will allocate more time for recommended or optional tasks.

V. CONCLUSIONS AND FUTURE WORK

This paper has focused on the adaptive planner, which is the main service in MyLearningMentor, an application that addresses the lack of study skills and work habits in many of the students that face the challenge of participating in MOOCs. More specifically, this paper has described the inputs of the adaptive planner and how these inputs serve to characterize the ideal sequence of tasks in a MOOC. In addition, this paper has proposed a planning algorithm that takes into account, the ideal sequence of tasks, as well as the profile, preferences, availability, list of priorities and feedback regarding the tasks completed for each student, in order to provide a recommended sequence of tasks particularized for each student.

Future lines of work include: a) the implementation of the proposed algorithm and its evaluation with data obtained from real MOOCs and different students' profiles; and b) the integration of the adaptive planner in MyLearningMentor. Finally, once MyLearningMentor is fully developed (including all its services) it will be evaluated as a supporting application for students with different profiles that participate in several MOOCs at the same time.

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