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MyLearningMentor: A Mobile App to Support Learners Participating in MOOCs

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Abstract: MOOCs have brought a revolution to education. However, their impact is mainly benefiting people with Higher Education degrees. The lack of support and personalized advice in MOOCs is causing that many of the learners that have not developed work habits and self-learning skills give them up at the first obstacle, and do not see MOOCs as an alternative for their education and training. MyLearningMentor (MLM) is a mobile application that addresses the lack of support and personalized advice for learners in MOOCs. This paper presents the architecture of MLM and practical examples of use. The architecture of MLM is designed to provide MOOC participants with a personalized planning that facilitates them following up the MOOCs they enroll. This planning is adapted to learners' profiles, preferences, priorities and previous performance (measured in time devoted to each task). The architecture of MLM is also designed to provide tips and hints aimed at helping learners develop work habits and study skills, and eventually become self-learners.

Keywords: MOOCs, planning, mentoring, study skills, work habits
Categories: K.3.1, K.3.2

1 Introduction

The advent of MOOCs (Massive Open Online Courses) has been followed by a revolution in traditional educational structures [O'Connor 2014]. Many universities and institutions across the globe are now including MOOCs in their catalogues. The affordances that stem from MOOCs are being used to enrich traditional courses under terms like "flipped classroom" [Bergmann and Sams, 2012] or "SPOC" (Small

Private Online Course) [Fox, 2013]. Much of the MOOC success can be attributed to initiatives such as edX (http://edx.org), Coursera (http://coursera.org) or MiríadaX (http://miriadax.net), which provide platforms for the deployment of MOOCs, as well as educational support to teachers and universities taking part of these initiatives.

The open nature of MOOCs is usually described as an opportunity for people with different origins, ages, classes, incomes and backgrounds to access high-quality education provided by a variety of institutions, including elite Universities [Yuan and Powell, 2013]. Some people have claimed that this "democratization" of education will bring positive effects in the reduction of the educational gap between those who can easily access Higher Education programs and those who cannot [Jaggars, 2014]. Nevertheless, the first studies that have been published based upon real data suggest quite the contrary: most learners enrolling and getting certificates in MOOCs have some previous academic degree [Honeychurch and Draper, 2013] [Nesterko et al., 2014]. As an example, a recent paper from the University of Pennsylvania reports 83% of learners in MOOCs with post-secondary degrees and 44% with education beyond bachelor's degrees [Emanuel, 2013] [Christensen et al., 2013]. Similar conclusions were extracted from the first MIT and Harvard MOOCs where, for instance, an average of 76% of the people getting a certificate in the first five Harvard MOOCs already had a Bachelor's Degree or above [Ho et al., 2014].

The lower percentages of people without previous qualifications taking and completing MOOCs can be attributed to the need for certain competencies and skills that MOOCs demand to learners [Laplante, 2013]. Examples of these competencies and skills are high responsibility, self-guided learning, or time management [Kay, 2013]. Hew and Cheung [Hew and Cheung, 2014] provide insights on this claim, concluding that the failure to understand the course contents and the lack of appropriate support are two of the main reasons behind most drop outs in MOOCs. There is thus a challenge in providing "personalized" support to learners when facing MOOCs ("personalized" is preferred to "customized" when referred to education and learning [Freund and Piotrowski, 2003]). This personalized support is especially encouraged in the case of learners without previous qualifications, who are the most vulnerable ones due to their lack of the abovementioned competences and skills. This support should help people without previous qualifications follow up and complete MOOCs, as well as develop and acquire these competencies and skills. In this way, drop outs derived from failure to understand course contents and from the lack of support when needing help would eventually decrease.

MyLearningMentor (MLM) is a mobile application designed to address the lack of support and personalized advice for learners in MOOCs. MLM provides recommended planning and advice adapted to MOOC learners' 4Ps: Profile, Preferences, Priorities and previous Performance (measured as the time devoted to complete previous tasks) [Alario-Hoyos et al., 2014] [Gutiérrez-Rojas et al., 2014a]. MLM aims to promote self-directed learning, as well as the development of the competences and skills demanded by MOOCs. Although anyone could use MLM, it is designed for people with less study know-how, who are the ones with more difficulties and higher drop-out rates in MOOCs. The design and implementation of MLM has followed an incremental process. After capturing the requirements, a first functional architecture was drafted. A set of mockups from the user interface showing the expected functionality were also sketched, and can be consulted in [Gutiérrez-Rojas et al., 2014a], for those that want to build a mental model of MLM at this point.

The remainder of this paper is divided into five sections. Section 2 describes the works related to mobile context-aware recommender systems and adaptive learning planners which are the basis for MLM. Section 3 introduces MLM, including the requirements analysis, design and current implementation. Section 4 illustrates the use of MLM with practical examples. Section 5 presents a discussion on MLM. Finally, the conclusions of the paper are drawn in Section 6.

2 Mobile context-aware recommender systems and adaptive learning planners

MLM is built upon research in two main fields (Figure 1). First, mobile context-aware recommender systems provide information about what aspects of the context should be considered to provide planning and advice to learners in MLM. Second, research in adaptive learning planners serves to define how the planner should be designed.

2.1 Mobile context-aware recommender systems

The advances on mobile learning and context-aware technologies in the last decade have been seized as an opportunity to provide context-aware recommender systems [Adomavicius and Tuzhilin, 2011] [Lonsdale et al., 2004]. These systems take the knowledge acquired in the field of recommender systems in Technology Enhanced Learning, the research in mobile learning, ubiquitous learning and learning analytics [Long and Siemens, 2011], and the developments related to mobile personal learning environments [García-Peñalvo and Conde, 2014] [García-Peñalvo et al., 2011] to provide content-driven recommendations based on contextual information.

Context-aware recommender systems rely primarily on the notion of context. However, recommender systems should also take into account the human dimensions since end users are human beings who have different and changing intentions, perceptions, motivations and daily habits [Bellotti and Edwards, 2001] [Freed et al., 2014]. Moreover, human beings establish conversation and relationships of trust with peers who are also part of the context [Buckingham Shum and Ferguson, 2012].

In the particular area of mobile learning, "context" has been defined in an abstract way, as an artifact that is continuously created by people interacting with other people in their surroundings (establishing the aforementioned conversation and relationships of trust) and using everyday tools [Sharples et al., 2005]. When implementing a

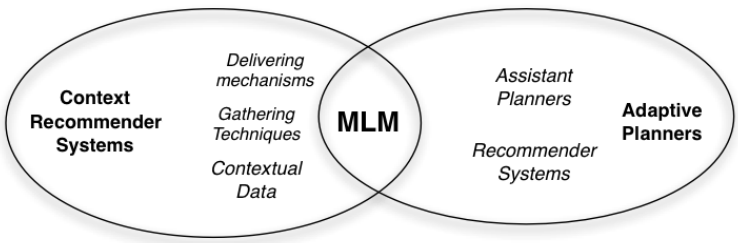

Figure 1: Research domains supporting MLM.

system (such as MLM), context should be specified and defined to fit users' needs [Yujie and Licai, 2010]. Specifically, three issues of the context should be defined: (1) what contextual information is relevant to provide learners with scaffolding for advancing on their aims, (2) how contextual information is gathered, and (3) what mechanisms are implemented to deliver this content to the user. These three issues are also the base of learning analytics, defined as the measurement, collection and reporting of relevant information about learning and the environment where learning occurs [Siemens and Baker, 2012].

Regarding *what contextual information is relevant*, a recent study by Verbert et al. [Verbert et al., 2012] provides an extensive review of context-aware recommender systems and analyzes the context features that are considered in them. The results are summarized into a framework with 8 dimensions, which are consistent with the works on learning analytics [Siemens and Baker, 2012] and social learning analytics [Buckingham Shum and Ferguson, 2012]: (1) computing context, which comprises the software, hardware and network technologies used to retrieve information about the device; (2) location context, which helps to identify where the user is located; (3) time context, such as timestamp data or time intervals; (4) activity context, which includes tracking explicit user interactions to capture information in the context (e.g., scanning a QR code or an RFID tag); (5) physical conditions, which includes data from the environment; (6) resource context, which collects information from learning resources; (7) user context, which includes information about user profile (such as past performance or topics of interest), and (8) social relation context, which includes data related to social connections within a group structure (such as relative performance and progress).

Regarding *how contextual information is gathered*, the literature shows several prototypes that gather and manage contextual information in different ways for filtering a particular content to the user [Lonsdale, et al., 2004] [Adomavicious and Tuzhilin, 2005] [Verbert et al., 2013]. Literature reviews identify three mechanisms to collect contextual information [Adomavicius and Tuzhilin, 2005] [Verbert et al., 2012]: (1) explicit, which relies on manual input from users; (2) implicit, when the information is automatically captured from the environment through different sensors (embedded or not into users' devices); and (3) by inference, in which the contextual information is inferred by analyzing users' interactions with the system or by combining different data. Once the contextual data has been captured, there are two main paradigms that define how to use this information as a filtering parameter for providing recommendations: (1) the context-driven querying and search paradigm, which utilizes the contextual information to filter from a particular corpus of resources, and (2) the contextual preference elicitation and estimation paradigm, which is based on models and learning networks that use contextual data to make the system learn about user preferences [Verbert et al., 2012].

Regarding *what mechanisms are implemented to deliver this content to the user*, recent literature provides some insights about the impact of notifications on mobile devices (one of the most common ways to deliver information to the user). Given the overabundance of information that people are exposed daily, one of the key aspects in the design of mobile and pervasive systems consists on capturing user attention [Ferscha et al., 2014]; alerts or notifications are one of the most common mechanisms for this purpose. Some studies analyze the right moments to issue notifications and propose predictive models to find these moments [Ferscha et al., 2014] [Gallacher et al., 2013]. Poppinga et al. [Poppinga et al., 2014] report some mechanisms to improve the receptivity of the user, such as scheduling interruptions, using proper content, or including notifications during “downtimes”. A recent study suggests that using reminders that include quizzes or reviews on a particular learning resource, and that are based on learners’ records of acquired knowledge (logs of users’ performance), supports students to advance on the course [Li et al., 2013].

MLM is built upon the results of these research studies. First, MLM context definition will include learners’ 4Ps (Profile, Preferences, Priorities and previous Performance), as well as information about MOOCs. This fits with 4 of the dimensions proposed by Verbert et al. and with the definitions of context regarding environment, human aspects and social aspects [Bellotti and Edwards, 2001]: (1) **time context**, considering the availability of the learner and the best times to work according to his preferences; (2) **resource context**, considering the information about MOOCs and how tasks are organized; (3) **user context**, considering the human dimension of the context (intentions, perceptions, motivations and daily habits) by taking into account user’s profile, priorities and previous performance; and (4) **social context**, considering other users’ performances to enrich the planning and advice provided by MLM. Second, MLM will use both explicit and inference mechanisms to collect contextual information. On the one hand, the user will explicitly provide data to define, for instance, his preferences and priorities. On the other hand, inferential mechanisms will collect data to better understand users’ needs and improve the recommendations and planning. All this data will be processed using a context-driven querying and search paradigm, filtering from the corpuses of MOOCs and tips and hints to help users advance on the course. Finally, MLM discards at this time the use of notifications to avoid overwhelming learners. Users will proactively decide when to ask for personalized planning and advice to MLM.

2.2 Adaptive learning planners

Adaptivity is a common term in computer science that refers to the capacity of a system (adaptive system) to adjust itself to new conditions and changes [Cristea and De Bra, 2002]. This term should not be mistaken for adaptability, which refers to the capacity of a system (adaptable system) to be tailored by the user, altering for instance its content or functionality [Cristea and De Bra, 2002]. From now on we will only focus on adaptivity and adaptive systems as a prelude to the introduction of MLM, which is an application designed to be adaptive (but not necessarily adaptable).

Research on personal assistants is a mature domain that explores mechanisms to facilitate the accomplishments of tasks through the automated creation of *planners*, using tools and mechanisms from the artificial intelligence field [Mitchell et al., 1994] [Eder et al., 2003]. In the last decade, researchers in the Technology Enhanced Learning community have been exploring how to take advantage of these personal assistants to support students’ progress by defining sequences of learning activities and tasks. Brusilovsky and Vassileva [Brusilovsky and Vassileva, 2003] described three approaches for applying course sequencing in educational contexts: (1) using it as the core of a course maintenance system; (2) for generating an adaptive courseware for a group of learners; and (3) for dynamically generating a courseware that observes and adapts to students’ progress. Karampiperis and Sampson [Karampiperis and

Sampson, 2004] proposed applying ontologies and learning object metadata to recommend a sequence of learning resources to be provided to the learner. 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 has a long history of researches contributing to the design and development of personal assistants and recommender systems (RS) which provide personalized instruction tailored to each student's needs [Berlanga and García-Peñalvo, 2008]. Personal assistants and RS are also capable of recommending activity plans adapted to the student's profile and context. For instance, Koper [Koper, 2005] proposed analyzing the social context of the user (user's social interactions) for recommending learning paths formed by sequences of units of learning. The results of applying these RS in lifelong learning scenarios show that the learners' effectiveness increases [Janssen et al., 2007]. Hummel et al. [Hummel et al., 2007] proposed an evolution of Kopers' idea designing a RS that combines social information, learning profiles and characteristics of the learning activities to provide the appropriate learning path to each user.

More recently, research in *adaptive planners* has been applied to support ubiquitous learning, taking advantage of the affordances of mobile technologies. These planners adapt the learning paths using physical contextual information. For instance, Yau and Joy [Yau and Joy, 2007] proposed the Context-aware and Adaptive Learning Schedule (CALS) framework to support students in their daily routines. This framework was used to develop an application that takes into account students' learning style and current learning context for recommending a particular activity or learning path. In their proposal, students explicitly introduce information to predefine schedules, activity types and time slots, and propose an activity to be performed during this particular time.

MLM takes these studies as a reference to propose learning paths, considering learners' needs and the structure of MOOCs. MLM differs from the current research in personal assistants, RS, and adaptive planners in two main aspects. On the one hand, the context of application is different: MLM proposes scheduling tasks to improve the overall learning experience in a MOOC by guiding the learner, looking for a continuum between traditional and connectivist MOOCs [Gillet, 2013]. On the other hand, MLM considers explicit feedback introduced by the learner. This learners' feedback will be incorporated to make adjustments and refinements in future planning [Wang and Wu, 2011].

3 MyLearningMentor

This section presents MyLearningMentor (MLM), an application that addresses the lack of support and personalized advice for learners participating in MOOCs and that is built upon existing research on mobile context-aware recommender systems and adaptive learning planners. First, the requirements of MLM are defined. Next, the design of MLM is discussed according to these requirements, including the functional architecture and a brief overview of the planning algorithm. Finally, the current implementation of the application is briefly described. Despite the separation of the requirement analysis, design and implementation in three subsections, the process of building MLM follows an iterative process on these three issues.

3.1 Requirements analysis

MLM targets less experienced learners that enroll in MOOCs. In order to gain insights on the work habits and study skills of today's learners (both in face-to-face and in online instruction), a 5-point Likert scale questionnaire was distributed among second-year engineering students from a Spanish university. This questionnaire covered topics such as the selection of a proper workplace to study, the presence of distractions while studying, the habit of studying with peers (face-to-face or remotely), the planning of the time to study (and the need for rescheduling it during the week), and students' experience with online education [Gutiérrez-Rojas et al., 2014a]. The questionnaire was answered by 41 students. These students had extensive experience in face-to-face and blended learning but little experience in online learning. The data extracted from this questionnaire point out that today's students lack many of the study skills and work habits that are necessary for becoming self-learner, which, according to Laplante [Laplante, 2013], is a skill to be developed in order to follow up and complete most MOOCs. In addition, there is a general lack of experience with online courses; the few students that tried online education recognized having difficulties that prevented them from completing online courses. From the answers to this questionnaire, and considering the overall objectives of MLM, the following five requirements were collected.

The first requirement (REQ1) is that MLM must be **offered as a mobile application**. According to most of the reports published, MOOC participants are typically in the range between 25-40 years old [Christensen et al., 2013] [Ho et al., 2014], an age in which mobile technologies are having a big impact. As a matter of fact, MOOC participants with mobile devices tend to interact more with their peers, this social component being a key element in MOOCs [DeWaard, 2013]. In addition, most MOOC platforms are being optimized to display courses in a responsive way, enabling the download of videos to watch them in places with poor connectivity, such as the public transport.

The second requirement (REQ2) is that MLM must be **personalized to the different participants that enroll in the different types of MOOCs**. Regarding differences between participants, MLM will collect information from them and react accordingly. This information will be classified in 4Ps: *Profile* (e.g., background, age…), *Preferences* (e.g., available hours, best time to study…), *Priorities* (e.g., MOOCs that the participant wants to address with a higher priority) and *previous Performance* (e.g., tasks that the participant was able to complete and time spent on them). Regarding differences between MOOCs, MLM will take into account the amount of workload and its expected distribution (e.g., sequence of tasks and distribution throughout the MOOC), the nature of each task (mandatory, recommended or optional), and the deadlines (if any).

The third requirement (REQ3) is that MLM must **provide an adaptive planner** that organizes the tasks that each participant needs to complete in the short-term (e.g., the next week) and in the long-term. The adaptive planner will take into account the 4Ps that define the participant and also the tasks that define each particular MOOC, as described in REQ2. In order to improve the correctness of the planning, the adaptive planner will react when the participant provides new information (e.g., adding information about the completion of tasks as part of the *previous Performance*) or updates existing one (e.g., updating the available hours for the next week as part of the *Preferences*), or when new tasks and/or deadlines are set in the MOOC.

The fourth requirement (REQ4) is that MLM must **enable learners to publish and curate information** about the MOOCs and their tasks (following a social, or *crowdsourced*, model) so that the adaptive planner can provide a rich planning, as described in REQ3. Although ideally MLM should be able to collect all the information related to the MOOCs from the platforms in which they are deployed, currently most platforms do not offer APIs suitable for this purpose. The alternative of scraping the information from the website is feasible, but cumbersome and error prone, which motivates the appearance of this requirement. It may also happen that teachers decide to publish new tasks during the course, or include changes between two editions of the same course, requiring in both cases the update of the information stored in MLM.

Finally, the fifth requirement (REQ5) is that MLM must **provide advice to learners** that have problems to follow the MOOCs. This advice will be provided in the form of tips and hints. Tips and hints can cover generic issues that learners should take into account to follow a MOOC, or specific issues related to a particular MOOC. Examples of the former can be tips for increase concentration while working on a task, or for reviewing and assessing peer's work. Examples of the latter can be recommendations of particular references or videos to get an additional explanation of the most difficult contents in a MOOC.

3.2 Design

Figure 2 shows the functional architecture of MyLerningMentor (MLM). This architecture follows a client-server model and makes use of external services. These external services are the platforms in which the MOOCs are deployed (e.g., edX, Coursera, MiríadaX, etc.).

The client of MLM is a mobile application (*MyLearningApp*). This design decision is a consequence of requirement REQ1. The server of MLM contains three databases, five services, and several independent processes. *MyLearningApp* communicates with the services sending requests to a REST interface. The independent processes collect information from the external services populating the databases.

The three **databases** are: *User data*, *MOOCs data* and *Tips and Hints data*.

- **MOOC data.** This database contains information about the existing MOOCs. This information will be general information of the MOOC and specific information of the tasks in the MOOC. We consider as a task any activity that the learner can do in the course, such as watching a video, answering a question, reviewing a work, consulting additional links. General information includes course name, number of weeks, expected weekly workload, platform, URL, and knowledge area. Specific information includes name of the task, order in the course, type of task (e.g., video, exercise…), nature of the task (required, recommended, optional) and deadline (if any).

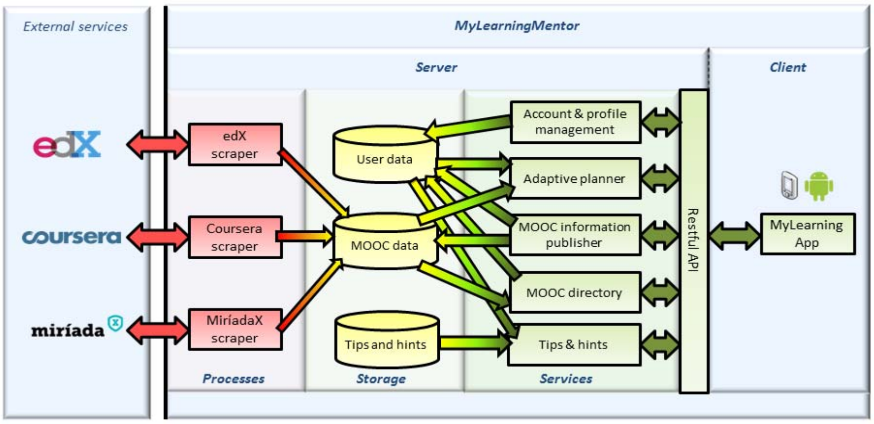

Figure 2: Overview of the functional architecture of MLM. This is a client-server architecture that makes use of external services (MOOC platforms). The client is a mobile application. The server includes 5 services, 3 databases, and several processes (3 in this example) that collect information from the external services. Arrows pointing at the databases indicate services or processes that store information in them. Arrows coming out of databases indicate services that retrieve information from them.

- **Tips and Hints data.** This database contains a set of preloaded tips and hints oriented to provide generic or specific advice to users, as indicated in requirement REQ5. Each tip and hint contains a name, the text with the advice, the category, and, in the case of specific advice, the MOOC to which it refers.

The five **services** are: *Account and profile management*, *Adaptive planner*, *MOOC information publisher*, *MOOC directory*, *Tips and hints*.

- **Account and profile management.** This service stores information about the user in the *User data* database. That includes the generation of new information and the modification of existing information related to the user account and the user profile. The first time the user downloads and clicks on *MyLearningApp* this service will be accessed in order to complete the account and profile information.
- **Adaptive planner.** The adaptive planner is the main service in MLM. It provides each learner with a detailed planning of the sequence of tasks to be completed in the short-term (typically a week) and in the long-term, indicating the number of tasks, their order and the best times to complete them (see REQ3). In order to calculate the planning in a personalized way, as stated in REQ2, the adaptive planner collects information from the *User data* and *MOOC data* databases (see Figures 2 and 3). The adaptive planner collects the 4Ps from the *User data* database: Profile, Preferences, Priorities and previous Performance. It also collects the sequence of tasks in each MOOC, including their types, deadlines and nature: required, recommended or optional.

- **MOOC information publisher.** This service enables users to publish two kinds of information in the databases. First, users can publish in the *User data* database information about their previous performance, indicating the time devoted and if they were able to complete the tasks that the adaptive planner assigned to them on time. This previous performance is taken into account by the adaptive planner in the next iterations in order to adjust the planning provided to each learner. Second, users can complete, update and curate the information about MOOCs stored in the *MOOC data* database (REQ4). This ensures a higher accuracy in the sequence of tasks for each MOOC and, eventually, a better planning.
- **MOOC directory.** This service enables users to search for MOOCs in the *MOOC data* database, indicating the URL, or alternatively, the platform and name of the MOOC. Once the MOOC is found, the user can add it to his profile in the *User data* database and establish the priority for this MOOC. The user can register new MOOCs that are not available in the *MOOC data* database, but only through the MOOC information publisher.
- **Tips and hints.** This service provides advice to learners in the form of short tips and hints (REQ5), which are collected from the *Tips and Hints data* database. Tips and hints can be adapted also to the 4Ps of each learner (collecting this information from the *User data* database), and can be either generic (about MOOCs in general), or specific (about one MOOC in particular).

MLM also incorporates several independent **processes** that scrape information from the platforms web sites. Due to the different organization of information, every platform needs a different process. These processes run periodically collecting (and updating) information that is stored in the *MOOC data* database, although they can also be invoked by the MLM services at certain moments.

The **planning algorithm** followed by the adaptive planner has already been published by the authors and is detailed in depth in (Alario-Hoyos et al., 2014). A summary of the planning algorithm is presented here so that the reader can get a feeling of what the main steps in the planning algorithm are. The planning algorithm starts from the assumption that a learner should complete all the required tasks before their deadlines. Therefore, it prioritizes required tasks over recommended and optional tasks, taking into account the available study time indicated by the learner:

1. For each MOOC in which the learner is enrolled, the algorithm initially allocates the amount of time required to complete the entire sequence of tasks (including required, recommended and optional tasks), multiplied by a factor that represents learner's profile and previous performance;
2. MOOCs are ordered according to the list of priorities given by the learner, and the time allocated for each MOOC is adjusted according to this order;
3. The algorithm generates the sequence of *required* tasks for each MOOC, computing if it is possible to complete all the required tasks for all the MOOCs according to learner's preferences, recommending withdrawing MOOCs with a lower priority otherwise;
4. The remaining time is allocated for the *recommended* tasks, starting from those that belong to the MOOC with a higher priority;
5. If there is still time, *optional* tasks are scheduled following the list of priorities.

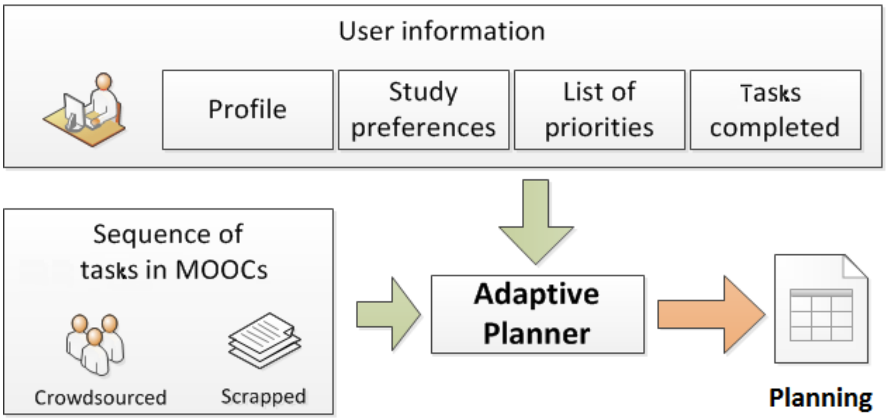

Figure 3: Input sources of the adaptive planner. From User data database the 4Ps: profile, preferences, priorities and previous performance (time devoted to complete previous tasks). From MOOC data database: sequence of tasks in MOOCs.

3.3 Implementation

The implementation of MLM follows an incremental approach. Currently a first version of the client, of the five services, of the three databases and of one of the processes is developed.

The mobile client is developed for Android OS, using the Android SDK 4.4.2, the Java language and an Android emulator; Figure 4 shows two screenshots with the planning for a learner, where the left screenshot shows the next tasks that the learner has to complete and the right screenshot shows further information on one particular task.

In the server side, the five services are developed in PHP. The information exchanged between client and server is formatted in JSON documents. The three databases are developed using SQL or MongoDB, depending on the characteristics of the information to be stored. Particularly the *User data* and the *Tips and Hint data* databases are developed as relational databases in SQL, while the *MOOCs data* database is developed using a document-oriented database in MongoDB. The implementation process has resulted in the need for a new database in order to store the relationship between users and the tasks they complete (previous performance) as a document-oriented database in MongoDB.

Finally, an edX scraper built on three Python scripts is currently under development. These scripts are used to access all the MOOCs in edX and to obtain the public information from the courses, their structure, and the tasks learners need to complete. Two of these scripts are based on the Selenium browser automation framework (http://www.seleniumhq.org).

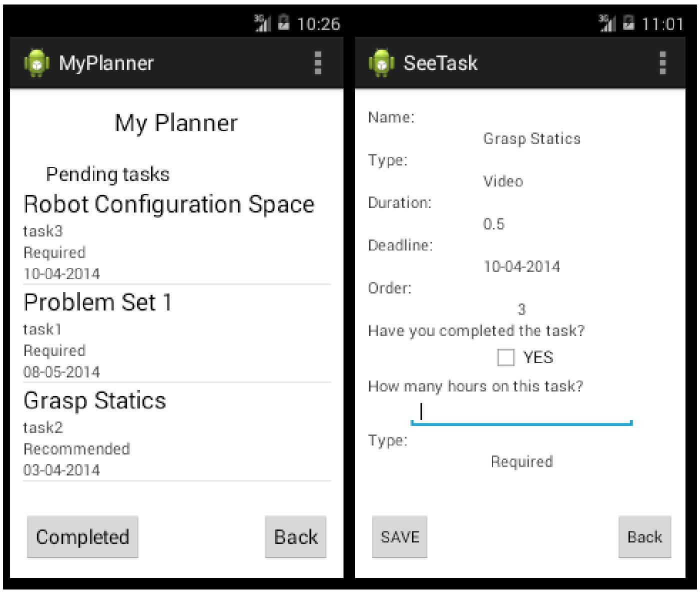

Figure 4: Screenshots of the adaptive planner obtained from the Android emulator. Left side shows the next tasks to be completed. Right side shows more information for one task, and the user providing feedback about the completion of that task.

4 Use cases and practical examples of use

From the definition of the architecture, MLM supports the following main use cases:

1. **Registering and completing user profile**. The user will interact with the *Account and Profile Management* service and, as a result, the *User data* database will be updated.
2. **Searching for a MOOC**. The user will interact with the *MOOC directory* service in order to search for a course (or for information about a course) in the *MOOC data* database. This search may result in invocations to the independent processes to collect the courses (or information about the courses), updating the *MOOC data* database.
3. **Adding a new MOOC**. The user will interact with the *MOOC directory* in order to add a new MOOC to his profile. As a result, the *User data* database will change. This use case includes use case 2 (“Search for a MOOC”) as a previous step to the addition of the MOOC to the user’s profile.
4. **Completing MOOC information**. The user will interact with the *MOOC Information Publisher* to add more information about a MOOC. As a result, the *MOOC data* database will be modified.
5. **Asking for personal planning**. The user will interact with the *adaptive planner*, which will collect information both from the *MOOC data* database and the *User data* database for calculating the personalized planning.

6. **Adding feedback about performance**. The user will interact with the *MOOC Information Publisher* adding his performance in the *User data* database.
7. **Asking for tips**. The user will interact with the *Tips and Hints* service which will collect information from the *User data* and the *Tips and Hints* databases.

Given the former use cases, this section will focus on the third and fifth ones, explaining them through user stories. Alice and Bob have recently discovered MOOCs and they would like to take advantage of them to enhance their professional careers. Nevertheless, they feel that they do not have enough time to dedicate to MOOCs after work, and that they are not able to properly organize their time by themselves, given the number of tasks that are required to complete the MOOCs they have been scouting. In addition, Alice and Bob have no experience with online education and they feel they may need some mentoring on how to make the most of MOOCs. A friend of them recommends Alice and Bob MyLearningMentor, a new mobile application that offers personalized planning and advice to MOOC learners, and both Alice and Bob decide to install MLM in their smartphones.

After checking the available MOOCs in Coursera, edX and MiríadaX, Alice and Bob decide to start the edX course entitled *Mentoring 101,* whose URL is *urlMentoring101*. Alice enrolls in *Mentoring 101* directly in edX and then she wants to add this course in MLM to receive personalized planning and advice. Alice logs in *MyLearningApp* and requests to add a new course, indicating the URL. *MyLearningApp* sends this request to the server. Within the server, her request is processed by the *MOOC Directory* service, which searches within the *MOOC data* database if there is information stored about *Mentoring 101*. As Alice is the first user interested in this MOOC, there is no information about it in the database. As a consequence, the *MOOC Directory* asks the suitable scraper (*edX scraper*) for information about *Mentoring 101*. The information returned by the scraper is inserted in the *MOOC data* database. Finally, *Mentoring 101* is added as one of Alice's courses in the *User data* database. Notice that if, later, Bob wants to add *Mentoring 101* to his courses, the general information about this MOOC will be already available in MLM and there will be no need to perform the web scraping from the edX platform.

As Alice is eager to start working in the MOOC, she asks for her personal planning to MLM. Her request is processed by the *Adaptive Planner*, which gets Alice's 4Ps, including the MOOCs she is enrolled, from the *User data* database. It is noteworthy that the *Adaptive Planner* also collects, for each MOOC, the sequence of tasks from the *MOOC data* database (see Figure 3). If there is no information about the tasks (or if outdated), the suitable scraper will be notified in order to obtain the sequence of tasks, updating the corresponding entry in the *MOOC data* database and returning the sequence of tasks to the *Adaptive Planner*. Once the *Adaptive Planner* has the whole sequence of tasks, it will check Alice's status on them (if they are completed or not) in the *User data* Database. Then, the *Adaptive Planner* will execute the planning algorithm as explained in section 3.2, returning the personalized planning to Alice.

It is important to note that scraping the information about the tasks in a MOOC is a computationally expensive process. Therefore, it cannot be performed every time a user wants to get his personalized planning. As MOOCs are available anytime and anywhere, the usual approach of updating the *MOOC data* periodically (e.g., once a week at night) is not suitable. Alternatively, MLM sets both an expiration date and a validity period for the information stored in the database that was scraped from MOOC platforms (this is not applied to the information crowdsourced by the community of users). If Bob asks for his personal planning immediately after Alice, the list of tasks of *Mentoring 101* will not be updated (unless they reached their expiration date). However, if the system asks for the list of tasks of *Mentoring 101* once their validity expires, their update will be mandatory.

5 Discussion

The architecture of MLM involves several services that require a more detailed design and analysis. This is for instance the case of the *adaptive planner* [Alario-Hoyos et al., 2014], the *tips and hints* service and the scrapers. For this reason an incremental process is followed for implementing the architecture, according to which the different services are refined and improved iteration by iteration. Once all the services are ready, and before releasing the application to such a potentially large community of learners, a preliminary evaluation will be conducted with a limited number of users and courses. These users will be university students with a similar profile to those who completed the questionnaire that led to the capture of requirements for MLM. Then, MLM will be offered as a supporting tool for learners who take part in the MOOCs. The purpose of this evaluation will be to assess the usefulness of MLM and the correctness of the planning and advice provided by this tool. The outcomes of this evaluation will be used to continue to refine the design and implementation of MLM.

One of the most important aspects when providing a personalized planning is to have accurate and updated information about the tasks learners need to carry out, as well as about the sequence they form. MLM follows a mixed approach, combining web scraping and crowdsourcing to get this information. Web scraping is the alternative to the lack of APIs for retrieving information from the MOOC platforms, and alleviates the workload of users writing all the tasks from scratch, as well as the well-known cold start problem in social systems. Nevertheless, this strategy is very sensitive to changes in the design of web interfaces and may cause inconsistencies if information updates are not properly addressed. Crowdsourced information contributes to increasing the accuracy of the data, but relies on the willingness of users. Furthermore, crowdsourced information may need manual checking or community approval before becoming part of the MOOC data database. Gamification or the assignment of special roles (e.g., curator) to expert and proactive users are recurrent strategies to promote the sustainable collaborative knowledge construction in systems that rely on crowsourced information.

The planning and advice MLM provides to users can be delivered following different approaches. Currently, it is the user who explicitly requests the planning and advice to MLM. However, MLM can also be redesigned to introduce mobile alerts reminding users the best moments to work on pending tasks (according to users' preferences and weekly planning). Nevertheless, an excess of alerts can be annoying or disruptive when they occur at inappropriate times and does not necessarily improve the responsiveness and attitude of the user towards the commitment with their duties, as discussed in section 2.2. It is therefore necessary to conduct a study with MOOC learners to find out the best way to deliver the personalized planning and advice through MLM.

Regarding the personalized planning, the algorithm designed to calculate it prioritizes the required tasks of every single MOOC where the user is enrolled; recommended and optional tasks are only allocated if there is enough available time (Alario-Hoyos et al., 2014). As a result, the personalized planning always shows required tasks first, then recommended tasks, and, finally, optional ones. Within each type, tasks are ordered by MOOC personal priority. This design decision aims to ensure that the learner is able to pass all the MOOCs he enrolled (even if he is not able to complete all the recommended and optional tasks). However, other approaches are possible with users selecting the type of approach as an input parameter of the *adaptive planner*. An alternative approach would be, for instance, allocating time for all the tasks (required, recommended and optional) in the MOOC with a higher priority; and using the remaining available time for the other MOOCs, allowing the user to deepen in the knowledge of the MOOCs he is more eager to follow up.

Regarding the personalized advice, the *tips and hints* service provides different advice depending on the profile, preferences and previous performance of the learner. In the current design, these tips and hints are preloaded in the *tips and hints* database. Alternatively, a crowdsourced approach where teachers and peers generate and classify new tips and hints could be implemented. It would then be possible not only to have teachers' advice for a specific MOOC as static information loaded before the start of the course, but also as dynamic information that teachers create and update as a reaction to learners' progress throughout the MOOC.

The search of MOOCs is carried out in MLM through the *MOOC directory* service, either indicating the URL, or the platform and name of the MOOC. Nevertheless, the user needs to know beforehand the course in which he wants to enroll and register directly through the corresponding MOOC platform. Alternatively, it can be consider the possibility of integrating a richer MOOC search system, such as Class Central (http://class-central.com) or moocrank [Gutiérrez-Rojas et al., 2014b] to help users search and discover new MOOCs that match their expected learning objectives. This way, MLM users could easily discover and enroll in new MOOCs for which they would receive planning and advice, all in one single mobile personal learning environment [García-Peñalvo and Conde, 2014].

The current design of MLM is decoupled from MOOC platforms, with the only exception of the web scraping processes retrieving information about MOOCs and tasks. Nevertheless, it would also be possible to design and implement a tighter integration with certain platforms, so that MLM would be a generic service offered, for instance, to edX learners in the edX platform. The shortcoming of this tight approach is that MLM would not be able to support learners that want to enroll in MOOCs offered by different platforms.

6 Conclusions and future work

The lack of work habits and study skills is a significant factor that hinders the follow up and completion of MOOCs, affecting particularly learners with little or no experience in online learning. MOOC teachers cannot give personalized support to learners and therefore there is a need for approaches that provide learners with planning and advice to face the challenge of participating in MOOCs and, eventually, become self-learners. MyLearningMentor (MLM) addresses this problem providing personalized planning and advice to learners in MOOCs. Nevertheless, MLM is still in the process of implementation through an iterative construction of the different services, processes and databases that are defined in its architecture. And a proper evaluation with real users is already planned to understand its benefits and impact.

Although MLM was conceived to help less experienced learners that enroll in MOOCs, it needs to be researched if MLM can be useful for learners with other profiles, such as people with study experience but with problems for self-managing their time. Further research is also planned in order to see if MLM can be beneficial in other educational contexts. Examples of these contexts in formal education are face-to-face courses, blended learning courses (e.g., university courses with a strong workload outside the classroom), online (but private) courses, or vocational training. Non-formal educational settings, such as workplace learning and professional development can also serve to assess the usefulness of MLM in different contexts. The particular educational context, as well as the particular user profile will very likely have an impact on the type of planning and advice that MLM has to provide. Finally, MLM is intended to be extended in order to serve as a communication channel between alumni, teachers and other mentors around MOOCs.

In conclusion, MLM is a first approach towards the objective of reducing the education gap between those people that are qualified and those that are not; gap that MOOCs are otherwise contributing to increase, considering the profiles of most of the participants taking advantage of these courses. Moreover, MLM goes beyond current research on MOOCs by considering the affordances of mobile and context-aware technologies to provide a more adaptive environment to improve learners' learning experience.

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