Personalized Recommendation of Open Educational Resources in MOOCs

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Abstract. Today Online Learning Environments (OLE) like MOOCs and LMS are very commonly used and a huge number of students with very different profiles and backgrounds follow the same online courses. Still, personalized experience for attendees is not widely spread on the platforms hosting these courses. At the same time, there is a growing number of open educational resources (OER) that can helpfully enrich the content of online courses and even be chosen to match one-by-one the student tastes. Recommender systems may support personalization in OLE by providing each learner with learning objects carefully selected to help reaching their learning objectives. This kind of recommendation is more specific to compute than usual recommendations like consumer products: the recommendation depends not only on the learner profile, but also on the content of the course, because the recommendation needs to fit precisely with the course format at any point. In this article, we introduce MOORS, a MOOC-based OER recommender system that can be plugged in an OLE to dynamically provide recommendations of OER to learners on the basis of their profiles and the profile of the MOOC. We also describe the process for calculating recommendations from OER metadata, assuming these metadata follow the Linked Opend Data (LOD) principles. Our implementation has been done in Open edX, an open source MOOC platform widely used, however the same approach could be implemented in any OLE as long as the learners profiles and the course profile can be extracted. Finally, we discuss a life-size evaluation of our recommender system.

1 Introduction

For many years now, personalization in technology enhanced learning (TEL) is a major subject of intensive research. But, with the spreading of Massive Open Online Courses (MOOCs) and their open and massive nature, the personalization issue is becoming ever more important. Indeed, a learner who follows a MOOC, freely shared on the web and without any commitment related to a registration fees he paid or a diploma he must obtain, may decide not to finish it at any time, when the MOOC no longer meets his needs. To support personalization in MOOCs, recommender systems are increasingly introduced to enable learners to finish MOOCs and take the better advantage from its content. Recommendations

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offered to each learner are adapted to his needs and his learning objectives. They can take the form of pedagogical resources, other learners, discussions, etc.

At the same time, the amount of Open Educational Resources (OER) available on the web is permanently growing. These OERs have to be reused in contexts different from the initial ones for which they were created. Indeed, producing quality OER is costly and requires a lot of time. Reusing OERs can provide an efficient way to enrich online courses content and particularly MOOCs content. But the reuse of OERs depends on the ease with which we can identify them on the web and on the quality and the availability of their descriptions (metadata). In this context, linked Open Data principles are sometimes used for describing OERs in order to facilitate their discovery automatically by machines and then their reuse.

In this paper, we introduce a MOOC-based OER recommender system (MORS). MORS assists learners, who are attending a MOOC, by offering to them complementary OERs, in addition to the internal resources of the MOOC, when these resources are not sufficient for them. MORS recommendations aim to remedy some of learners deficiencies during the MOOC, in order to help them to assimilate the MOOC's knowledge. Recommendations provided by MORS are computed dynamically based on learner profile and on the MOOC profile. MORS is implemented in MOOCs but it can be integrated in other OLE as the course and the learner profiles can be extracted. We choose MOOCs because (1) their large number of learners with varied profiles make them good candidates for personalization, and (2) because targetting an open platform like Open edX will allow us to widely disseminate our system and to make it reusable.

This paper is an extended version of our previous work [8]. We extend our previous work by presenting the experiments conducted to evaluate our solution and discussing the results. This paper begins with related work. In Sect. 3 we introduce the recommendation scenarios proposed by our solution. Section 4 draws the architecture of the proposed system. Section 5 presents how we implemented our solution. The evaluation protocol and results are proposed in Sect. 6. Section 7 concludes the paper and presents future directions.

2 Related Works

Even though Personalization in TEL is a research topic with a long history, studies on MOOCs personalization have started since 2012 [17]. In order to address issues related to the open and the massive nature of MOOCs, different personalization approaches have been introduced. One of the most popular techniques relies on recommender systems. We have studied some of the proposed approaches to personalize MOOCs and adapt their content to the needs and objectives of each learner, based on different criteria.

The studied approaches offer different types of recommendations as pedagogical resources and other learners who can help the learner during the MOOC. Regarding the recommendation of pedagogical resources, we noticed that most approaches compute their recommendations based on internal resources of the

MOOC. For example, [1] targets learners who post a question in a MOOC discussion which reflects a confusion and recommends educational videos related to the confusion subject. [3] recommends additional learning activities to learners who show a lack of knowledge in a particular subject. However, it is interesting to offer to the learner external resources from the web, when the resources of the MOOC fail to meet his needs or do not allow him to assimilate the lacking knowledge.

For approaches that recommend external resources to the learner, we found that they rely on a static set of resources selected from the web. For example, [2] recommends to the learner a set of MOOCs which mostly match his learning objectives. Another approach [14] offers a scenario of activities to each group of learners according to the gap between their actual competencies and the target ones. This scenario can perform a number of recommendations of either internal or external educational resources, captured from the web. It is therefore interesting to be able to select external resources dynamically to take into account the changes on the web.

On the other hand, the approaches offering recommendations of external pedagogical resources to a learner who is following a MOOC are based on some of his characteristics: his knowledge, his preferences, his learning objectives, etc. They are therefore centered on the learner. But, these new resources will complement a MOOC, which represents an initial and main learning path and will enrich its content, for example to remedy the learner gaps or to present a set of alternative resources to those proposed in the MOOC. It is therefore important to propose resources that are both adapted to the characteristics of the learner and to the specificities of the MOOC that they will complete. It is also necessary to take into account the stage of the MOOC in which the recommendations are proposed. The interest of the dynamic calculation of the recommendations compared to the static calculation is that it allows taking into account, on the one hand the evolution of the profile of the learner throughout the MOOC and, on the other hand, the updates and the changes made on external pedagogical resources and repositories storing these resources descriptions.

We have also noticed that most of the approaches have been implemented in specific platforms, such as a specific university or laboratory, and are dedicated to a specific area. For example, the approach proposed by [13] is specific to health MOOCs in the area of Motivational Interviewing. It recommends to the learner the MOOC resources related to concepts they only need to know, by analyzing learners contexts. That is why it is important to introduce a generic solution, independent of the MOOC domain and implemented in one of the MOOC platforms which are accessible to everyone, such as Open edX.

In our work, we propose a generic solution providing recommendations of OERs in a MOOC platform when a lack of knowledge is detected for a learner. These recommendations are computed dynamically based on different learner characteristics and also on MOOC specificities.

3 Recommendation Scenarios

In this section, we describe how our system personalizes a MOOC for a learner. More precisely, we introduce some realistic scenarios of recommendation offered by MORS: where and when exactly the recommendation process is triggered for a learner during the MOOC.

Let's consider the MOOC as a set of sections. Each section offers pedagogical resources as video, text, quiz, etc. We consider also that studying the MOOC requires some prerequisites with a certain performance level defined by the MOOC creator who is the teacher. Each MOOC section provides some learning objectives with a certain performance level defined by the teacher. In our solution, we decide to recommend OERs to the learner at two different kind of stages of the MOOC: before starting the MOOC and after each MOOC's section.

Before Starting the MOOC. Once a learner is enrolled in a MOOC and decides to start its first section, MORS verifies if the learner has the prerequisites of the MOOC with the appropriate performance degrees. If a lack of knowledge is detected in at least one of the MOOC prerequisites, the recommendation process is triggered and a set of OERs dealing with the appropriate prerequisites are recommended to the learner.

At the End of Each MOOC Section. As stated earlier, each MOOC section has at least one learning objective. This learning objective can also be a prerequisite for the following section. So it is important to ensure that the learner has assimilated the section content. That is why at the end of each section, a quiz is presented to the learner where each question aims to assess his assimilation level of at least one of the section learning objective. Now if the learner gets bad results in the quiz, MORS triggers the recommendation process in order to recommend to him a set of OERs dealing with the learning objectives where he failed.

4 System Architecture

In this section we describe the architecture of our system for recommending OERs in a MOOC (MORS). MORS is composed of four major process (Fig. 1): process of generating the MOOC profile, process of generating the learner profile, PreSelection process and refinement process.

Once MORS is integrated in the MOOC to be personalized, the process of generating the MOOC profile generates the profile of the MOOC based on the MOOC model defined in our solution. Then the process of generating the learner profile generates the learner profile based on the learner model defined in our solution. When the system identifies gaps in student mastery of a certain topic, before starting the MOOC or at the end of one of its sections, the PreSelection process requests the external OERs descriptions repositories to collect an initial set of OERs dealing with this topic. This initial set is transmitted to the refinement process that performs selection and ranking operations based on the learner and the MOOC profiles content at the time of the calculation of the recommendations.

4.1 Process of Generating the MOOC Profile

The role of this process is to generate the profile of a specific MOOC from the MOOC model defined in our approach.

MOOC Model. In the MOOC Model, we represent some of its characteristics: the knowledge elements of the MOOC and the corresponding performance degrees, the domain of the MOOC and the effort needed in terms of time. We consider two types of knowledge elements: learning objectives of each MOOC section and prerequisites of the MOOC.

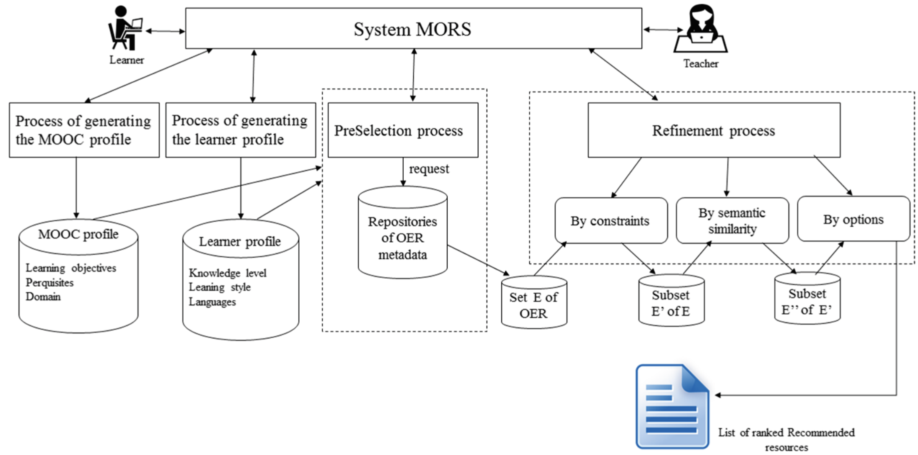

Fig. 1. The architecture of MORS.

Notations. In this paper, we denote the number of MOOC sections by $n_{section}$, the set of MOOC knowledge elements as KE, the set of MOOC prerequisites as P, the set of the learning objectives provided by the kth section as LO_k, where $1 \leq k \leq n_{section}$ and the set of the learning objectives provided by the entire MOOC as LO. Then $LO = \cup_{k=1}^{n_{section}} LO_k$ and $KE = LO \cup P$.

The teacher defines the MOOC knowledge elements together with their performance degrees. In this work, we use the performance degrees as introduced in [9] (1: beginner, 2: intermediate and 3: expert) to which we add (0: no performance).

Definition 1 (Performance Degree by Teacher): *Given a knowledge element ke from KE, the performance degree of ke, set by the teacher, is defined by the function LP_T.*

$$LP_T : \begin{cases} KE \longrightarrow \{0, 1, 2, 3\} \\ ke \longmapsto lp \in \{0, 1, 2, 3\} \end{cases}$$

The prerequisites and the learning objectives of the MOOC associated to their performance degrees are modeled respectively by the vectors $V_{P,MOOC}$ and $V_{LO,MOOC}$. We represent in (Fig. 2) the evolution of knowledge elements during the MOOC. As input, we represent in $V_{P,MOOC}$ the required performance degrees for each prerequisite. Then we represent the evolution of $V_{LO,MOOC}$ during the MOOC. At first, $V_{LO,MOOC}$ is initialized to zero. Thus, at the end of each section, $V_{LO,MOOC}$ is updated with new values. These values correspond to performance degrees expected to be acquired in learning objectives provided by the section.

The MOOC domain and the MOOC effort are represented respectively by the variables D_{MOOC} and Eff_{MOOC}.

Generation of the MOOC Profile. The data required to generate the profile of a specific MOOC based on our MOOC model are collected from the information entered by the teacher when creating this MOOC. The teacher defines the prerequisites of the MOOC, the learning objectives of each of its sections and the corresponding performance degrees. He defines also the domain and the effort of the MOOC.

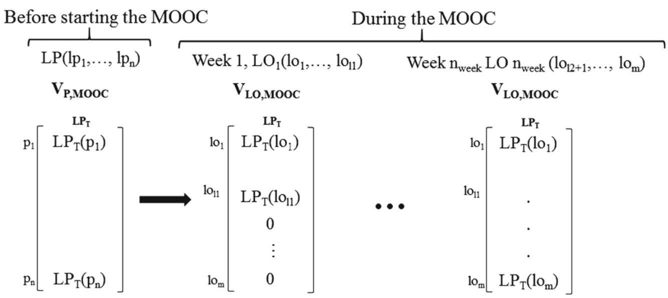

Fig. 2. The evolution of the knowledge elements during the course (from [8]).

4.2 Process of Generating the Learner Profile

The role of this process is to generate and update the profile of a specific learner from the learner model defined in our approach.

Learner Model. In the learner Model, we represent some of his characteristics: his knowledge level, his learning style and the languages he knows. Concerning the learner knowledge level, we consider only his level in the knowledge elements of the MOOC. More precisely, the learner model contains the performances degrees of the learner in the prerequisites and the learning objectives of the MOOC.

Definition 2 (Performance Degree of Learner): *Given a knowledge element ke from KE, the learner performance degree in ke is defined by the function LP_L.*

$$LP_L : \begin{cases} KE \longrightarrow \{0,1,2,3\} \\ ke \longmapsto lp \in \{0,1,2,3\} \end{cases}$$

The prerequisites and the learning objectives of the MOOC associated to the learner performance degrees are modeled respectively by the vectors $V_{P,Learner}$ and $V_{LO,Learner}$. A quite similar modeling process is proposed in [15]. In (Fig. 3) we represent the evolution of the knowledge elements in the learner profile during the MOOC. Before starting the MOOC, the learner performance degrees in MOOC prerequisites are stored in $V_{P,Learner}$. During the MOOC and after each section, $V_{LO,Learner}$ is updated with the new learner performance degrees acquired with the learning objectives provided in this section.

The learning style refers to the way a learner receives and processes information [6]. In the literature, many profiles are defined to analyze learners learning styles like Kolb [10] and Felder and Silverman [6]. In our work, we use the frequently used, Index of Learning Style (ILS) questionnaire [16]. It was developed by Felder and Soloman to identify learning styles based on Felder and Silverman Learning style Model (FSLSM) [6]. The FSLSM classifies learning styles along to four dimensions which are active/reflective, sensorial/intuitive, visual/verbal and sequential/global. In our work we also use the patterns introduced by [5] to identify the type of learning resources to be provided to the learner based on his answers to the ILS questionnaire. For example, sensing learners prefer to get more examples and exercises [5]. We model the learning style by using the term $S_{learner}$.

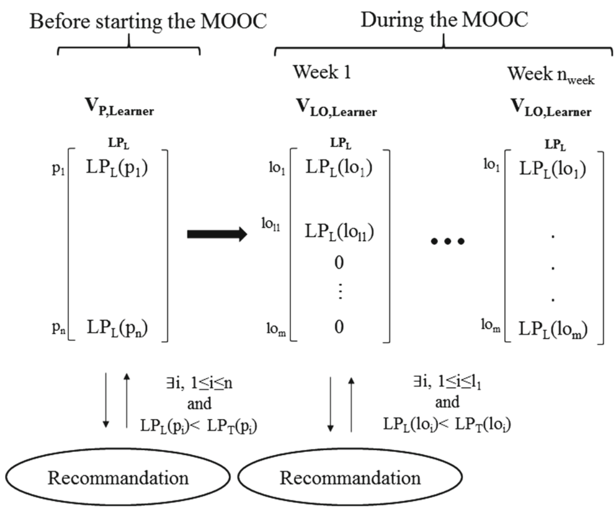

Fig. 3. The evolution of the knowledge elements in the profile of the learner during the course (from [8]).

The languages known by the learner are modeled by using a list $L_{learner}$.

Generation of the Learner Profile. The data required to generate the profile of a specific learner are collected with different methods. The learner performance degrees on MOOC prerequisites are determined by browsing his knowledge base storing the knowledge elements acquired by the learner previously on the same MOOC platform. If no significant evidence is collected this way, because the learner is a new user of the platform for example, then we ask the learner a few questions about the prerequisites in order to evaluate his performance degrees.

Each MOOC section ends with a quiz. The learner results on those quiz are used to compute the learner performance degrees on MOOC learning objectives. For the learning style of the learner, we use his answers to the questionnaire ILS [16] to deduce his learning style. We ask him also about the languages he knows.

4.3 PreSelection PROCESS

As indicated in (Fig. 3), the recommendation process is triggered for a learner L at two different kind of steps of the MOOC.

Before Starting the MOOC. Let $LP_L(p)$ the performance degree of a learner L in $p \in P$, the recommendation process is triggered if:

$$LP_L(p) = V_{p,L}(p) < LP_T(p) = V_{p,MOOC}(p)$$

During the MOOC. At the end of the kth section of the MOOC, let a learner L who acquires $LP_L(lo)$ in $lo \in LO_k$, the recommendation process is triggered when:

$$LP_L(lo) = V_{LO,L}(lo) < LP_T(lo) = V_{LO,MOOC}(lo)$$

Where $V_{LO,MOOC}$ and $V_{LO,L}$ considered are those updated after the kth section.

The aim of this module is to select a set of candidate OERs dealing with the knowledge element for which the recommendation process has been triggered. In order to find these resources, the system performs a keyword search in metadata stored in external accessible repositories of OERs metadata [7]. The metadata used in this search is "the description of the resource" introducing the subject and the global idea of the resource.

For keywords, the first keyword is the knowledge element which is the subject of the recommendation. The objective of the search is, therefore, to select resources with descriptions containing this knowledge element. However, we must also solve the problems of synonymy and polysemy that may arise in our search.

Polysemy. The same knowledge element can be expressed differently. For example "conditional statements" in computer science are also "if-then-else".

Synonymy. The same expression can be used to represent different knowledge elements that belong to different domains. For example the notion of "graph" is used in a variety of disciplines as "computer science", "mathematics", etc.

To solve synonymy problems, we used a second keyword, in addition to the knowledge element, which is the domain of the MOOC. We introduced also a module of synonyms detection[1] to address synonymy problems. This module is based on DBpedia[2] structured data that has been extracted from Wikipedia. Some possible synonyms of the knowledge element and the MOOC domain are inferred using this module that will increase the number of selected resources.

Overall, we select descriptions including the knowledge element and the MOOC domain or at least one of their synonyms.

In a formal way, let OER be the set of Open educational resources, $R \in OER$, $ke \in KE$, $Meta_R$ is the set of the metadata of R where $\mathrm{Meta}_R = \{\mathrm{Descript}_R, \mathrm{Lang}_R, \mathrm{Prereq}_R, \ldots\}$, $Syn_{D_{mooc}}$ the set of the synonyms of the domain of the MOOC, D_{mooc} and Syn_{ke} is the set of the synonyms of the ke generated by our module of synonyms detection.

$$(R \text{ is dealing with } ke) \equiv ((ke \in \mathrm{Descript}_R) \text{ OR } (\exists i : Syn_{ke}[i] \in \mathrm{Descript}_R)) \text{ AND } ((D_{mooc} \in \mathrm{Descript}_R) \text{ OR } (\exists j : Syn_{D_{mooc}}[j] \in \mathrm{Descript}_R)).$$

To select the candidate resources, our PreSelection process requests external repositories providing SPARQL endpoints with an initial query. In order to manage the diversity of metadata schemas employed by these repositories, we use classes and properties as defined in the Learning Object Ontology of Mapping (LOOM) introduced in [7].

4.4 Refinement Process

The PreSelection process returns as result an initial set E of OER and as we explained in the previous part the PreSelection is based on keywords. This initial set E is transmitted to this refinement process which applies selection and sorting operations according to several criteria. These operations are performed in three stages.

- Selection by constraints.
- Selection by semantic similarity.
- Sorting by options.

Selection by Constraints. In this first step, we select a subset E' of E which contains only the resources that respect certain constraints. The constraints are firm criteria that must be respected by the resources recommended to the learner. In other words, these are criteria without which it will be difficult for the learner to understand the content of the resource or it will impact the MOOC follow up. The three constraints we consider are the following. The first one is: "Resources must not require prerequisites not assimilated by the learner" **(C1)**. The second constraint is: "Resources must be presented in a language known by the learner" **(C2)**. The third constraint is: "The resource has to bring a performance level which is greater than or equal to the level defined in the MOOC" **(C3)**.

[1] https://davidallenfox.wordpress.com/2013/09/05/generating-synonyms/.
[2] http://wiki.dbpedia.org/.

Constraint C1 Violation. Let $R \in E$, R doesn't respect the constraint C1 if:

$$\exists ke \in \text{Prereq}_R : (LP_L(ke) = 0) \vee (\exists i, LP_L(\text{Syn}_{ke}[i]) = 0)$$

In order to identify the performance degree $LP_L(ke)$ of the learner in the prerequisite ke of the resource R, we start with browsing his knowledge base looking for the information. Otherwise, we ask the learner some questions to deduce his $LP_L(ke)$.

Constraint C2 Violation. Let $R \in E$, R doesn't respect the constraint C2 if:

$$(\text{Lang}_R \notin \text{L}_{learner})$$

Where $\text{L}_{learner}$ is the set of the languages known by the learner and Lang_R the metadata presenting the language of the resource.

Constraint C3 Violation. As we did previously for the learner and the MOOC, each resource $R \in E$ is modeled by a vector $V_{KE,R}$ that represents the performance degrees acquired in each ke of the MOOC after following this resource.

Definition 3 (Resource Performance Degree): *The performance degree acquired by the learner with regard to a specific knowledge element ke, from KE, after following the resource R is defined by the function LP_R.*

$$LP_R : \begin{cases} KE \longrightarrow \{0, 1, 2, 3\} \\ ke \longmapsto lp \in \{0, 1, 2, 3\} \end{cases}$$

As shown in (Fig. 3), the recommendation process is triggered when $LP_T(ke) > LP_L(ke)$. Indeed, the goal of the recommendation of the resource R to the learner is the improvement of his level of performance in the knowledge element ke.

So, Let $R \in E$, R doesn't respect the constraint C3:

$$LP_R(ke) < LP_T(ke).$$

As the OERs metadata do not specify the performance degrees of OREs, we need to estimate them from learners who have already used the resources. For a new OER we use two performance degrees 0: a resource doesn't deal with the knowledge element and 1: the resource deals with the knowledge element. Then once the resources are studied by the learners, we plan to collect the results from them according to their responses to the knowledge test once they have followed a recommended resource.

Definition 4 (A Knowledge Element derived from a Resource):

$$(ke \textit{ is provided by } R) \equiv (\text{V}_{KE,R}(ke) \neq 0) \equiv$$
$$\{ke \in \text{Descript}(R) \vee \exists i : \text{Syn}_{ke}[i] \in \text{Descript}(R)\}.$$

Selection by Semantic Similarity. Once resources respecting the defined constraints have been identified, we select resources which are close to the initial query (the query defined in the PreSearch module). For that purpose, we calculate the similarity between selected resources and the initial query terms (IQT). The IQT are the terms used in the initial query: the knowledge element, the domain of the MOOC and their synonyms generated by our module of synonyms detection. We denote IQT as a set.

$$IQT = \{\mathrm{T}_1, ..., \mathrm{T}_{nt}\}$$

Where T_{nt} is one of the initial query terms and nt is the total number of terms used in the initial query.

We start with using Term Frequency Inverse Document Frequency (TF-IDF) [4] to identify the importance of IQT inside the selected resources descriptions. Each selected resource R is represented by a vector V_R.

$$\mathrm{V}_R = (\mathrm{V}_{R_{T_1}}, ..., \mathrm{V}_{R_{T_{nt}}})$$

Where $\mathrm{V}_{R_{T_1}}$ is the TF-IDF value of the term $operatorname T_1$ in the description of the resource R.

The IQT is also represented by a vector V_{IQT}.

$$\mathrm{V}_{IQT} = (\mathrm{V}_{IQT_{T_1}}, ..., \mathrm{V}_{IQT_{T_{nt}}})$$

Where $\mathrm{V}_{IQT_{T_1}}$ is the TF-IDF value of the term $\mathrm{V}_{R_{T_1}}$ in the descriptions of all selected resources.

Then a cosine measure is employed to compute the similarity between each resource vector V_R and the initial query vector V_{IQT}. As result each selected resource R is characterized by one measure which is his cosine measure, $\mathrm{CosSim}(R)$. The resource R with higher value of $\mathrm{CosSim}(R)$, is the closest to the initial query.

At the end of this step, the result is the set E' of resources ordered by their semantic similarity with the IQT. We select the subset E'' of the first n ones to be the input of the next step. We take a limited number of resources because the objective of our recommendations is to help the learner to improve his knowledge level in a certain knowledge element by following at least one resource rather than recommending a large number of resources. The number n is defined arbitrarily and in our case study, n has been fixed to 4 but the teacher can change its value. We define the relation of preference ($\geq$).

Definition 5 (Preference Relation $\geq$): *Given two resources $R_1 \in OER$ and $R_2 \in OER$:*

$$R_1 \geq R_2 \textit{ means } R_1 \textit{ is at least as good as } R_2.$$

In this first step $R_1 \geq R_2 \Leftrightarrow \mathrm{CosSim}(R_2) \geq \mathrm{CosSim}(R_1)$.

Sorting by Options. The last step is to classify resources based on options. The options are other criteria defined to reflect the adaptation to some characteristics of the MOOC and the learner. However, these options are not mandatory criteria as the constraints used in the first step. In other words, recommended resources may not be consistent with all options, but they are presented to the learner in an order depending on how much they satisfy the options. Let Op the set of options and n_{op} the total number of options.

Definition 6 (Score Function): *For each $op_i \in OP$, where $1 \leq i \leq n_{op}$, we define the score function U_i:*

$$U_i\colon \begin{cases} E'' \longrightarrow [0,1] \\ R_j \longmapsto a_i^j \end{cases} \tag{1}$$

U_i assigns a score a_i^j, between 0 and 1, to each candidate resource R_j depending on how much it satisfies the op_i. The scores a_i^j are calculated differently depending on the options op_i type.

For each option, the resource score represents its option satisfaction percent. Then we consider each option as a fuzzy set and the score of each resource as its membership degree to this set. We represent each resource R_j by a vector S_{R_j} whose components are the values of its score for each option.

$$S_{R_j} = (a_1^j, a_2^j, ..., a_2^{n_{op}})$$

The ideal resource id has a vector S_{id} whose components are equal to 1. This means that the resource meets all the options at 100%.

A weight value $p_i \in 1, 2, 3$ is assigned to each option in order to characterize its importance (1: less important, 2: important and 3: very important).

Initially all options have the same importance ($p_i = 3$) but we give the teacher the possibility to change weights values of options defined to reflect coherence with the MOOC. In MORS, we defined these options: "Recommended resources should respect the learning style of the learner." (Op_1) and "Recommended resources should have a 'typical Learning Time' similar or bellow the mean effort needed to assimilate a MOOC resource, as defined by the teacher." (Op_2).

For Op_1, we define the corresponding score function U_1 as below:

$$U_1(R) = \begin{cases} 1 \text{ if } \text{Typ}_R \in RT_L \\ 0 \text{ else.} \end{cases}$$

where Typ_R is the type of the resource $R \in E''$ and RT_L is the set of resources types corresponding to the learner L learning style.

Concerning op_2, we define the corresponding score function U_2 as below:

$$U_2(R) = \begin{cases} 1 & \text{if } LT_R \leq ME_{W/R} \\ (\varepsilon + ME_{W/R} - LT_R)/\varepsilon & \text{elseif } LT_R \\ & \in [ME_{W/R}, ME_{W/R} + \varepsilon] \\ 0 & \text{else } LT_R \geq ME_{W/R} + \varepsilon \end{cases}$$

where $R \in E''$, $ME_{W/R}$ (Mean Effort section) corresponds to the quotient of the section effort defined by the teacher and the number of the section resources and LT_R corresponds to the value of the metadata 'typical Learning Time' for R. The value ε is defined arbitrarily and has been fixed to ME_W in our case study.

To rank candidate resources, we use the Chebyshev distance to compute the distance between the ideal resource and each resource to recommend. The smaller the distance is the better the resource is. This distance is defined as below:

$$\mathrm{DCH}_{R_j,id} = max_{i \in n_{op}} \lambda_i |V_{R_j}[i] - V_{id}[i]|$$

where λ_i is defined as below:

$$\lambda_i = p_i / (\mathrm{Sup}_{R_j \in E''}(V_{R_j}[i]) - \mathrm{Inf}_{R_j \in E^*}(V_{R_j}[i]))$$

where E^* is a subset from E'' of candidate resources that not have a maximal satisfaction degree for any option.

In conclusion,

$$R_1 \geq R_2 \Leftrightarrow \mathrm{DCH}_{R_2,id} \geq \mathrm{DCH}_{R_1,id}$$

5 Implementation

In order to implement our solution, we choose edX as the MOOC platform. First, it is an open platform which is widely used. Then, this choice allows us to offer our solution to the vast community of OpenEdX users and hope to replicate experiments about personalization, then gather more data about its efficiency. Furthermore, the documentation of Open edX is well detailed and the community is very active. Finally, the platform is characterized by a modular architecture thanks to XBlocks [11] that we will detail later.

The XBlock is a component architecture developed in 2013 by edX, which allows developers to create independent course components (xBlocks). These components can be combined together to make an online course [11]. The advantage of XBlocks is that they are deployable. The code that you write can be deployed in any instance of the edX Platform or other XBlock runtime application[3]. We found also that there is a recent focus on using these XBlocks to add personalization in MOOCs, for example the work [12] where a recommender XBblock was created in order to recommend resources for remediation in a MOOC. Once developed, each XBlock can be installed and added by the MOOC creator, in the appropriate unit of the appropriate section of his MOOC[4]. In fact, Open edX organized the courses in a hierarchy of sections, sub-sections and units, where the unit is the smallest component in the MOOC.

[3] https://open.edx.org/about-open-edx.

[4] http://edx.readthedocs.org/projects/open-edx-building-and-running-a-course/en/latest/.

For these reasons, we use XBlocks to implement our solution in edX. Three XBlocks have been implemented.

An XBlock to Generate the MOOC Profile and the Static Part of the Learner Profile. This XBlock is developed to be added at the first unit of the MOOC first section. It is responsible for collecting information about the learner and the MOOC: learner languages, learner learning style, MOOC knowledge elements and corresponding performance degrees (see Fig. 4).

An XBlock to Compute Recommendation at the Beginning of the MOOC. This XBlock checks the performance degree of the learner in the pre-requisites of the MOOC. In order to ensure this, it starts with determining whether this prerequisite is stored in the knowledge base of the learner. In case the prerequisite is not found in the knowledge base, the XBlock asses the knowledge level of the learner in the MOOC prerequisites by asking him some questions (an example for the prerequisite "structure data" (Fig. 5)). Then if he doesn't answer the questions correctly, a set of OERs links are recommended to him. These links are ranked by descending order by satisfaction of the criteria defined at the previous section (Fig. 6).

An XBlock to Compute Recommendation after Each MOOC Section. A third XBlock is developed to be added at the end of each section. This XBlock computes recommendations of OERs to the learner based on his answers to the quiz presented at the end of the section. These OERs links are presented to the learner sorted based on the criteria we defined in the previous section.

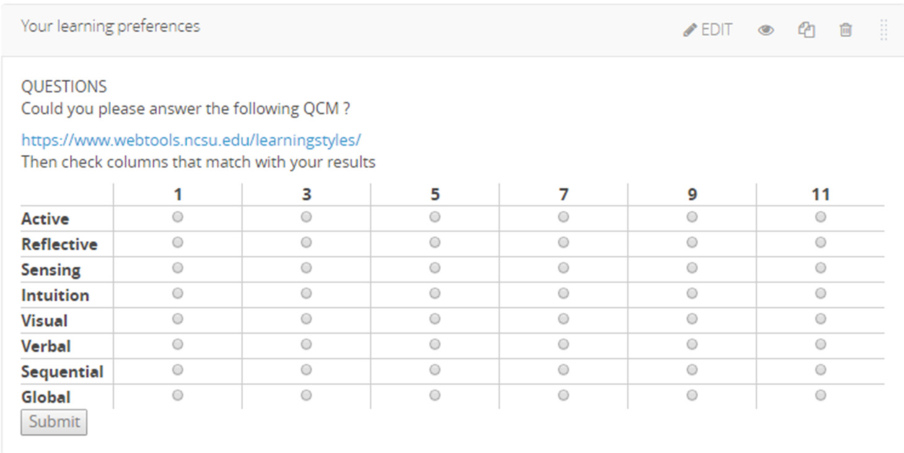

Fig. 4. Interface to collect information about the learning preferences of the learner (from [8]).

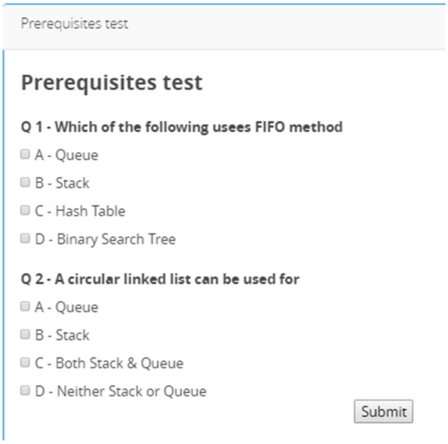

Fig. 5. Interface for testing the assimilation of the prerequisites (example "Data structure") (from [8]).

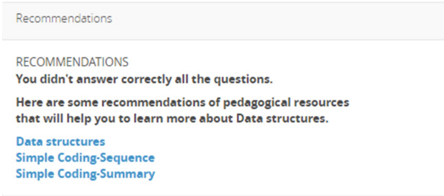

Fig. 6. Interface for recommended resources (from [8]).

6 Evaluation

Our recommender system MORS presents some specific characteristics that come firstly from the open and the massive nature of MOOCs and secondly from OERs referenced in external and dynamic repositories. For this reason, it is difficult to reuse evaluation protocols mentioned in the literature for classic recommender systems and it is important to introduce a new evaluation protocol.

This section presents a set of experiments conducted to evaluate our solution and discuss the results. The purpose of the evaluation is to assess our algorithm of recommendation and the relevance of the recommended resources. The recommended resources have to be adequate with the criteria defined previously, to exhibit some characteristics consistent with both the learner and the MOOC. The scalability and the versatility of OERs repositories means that OERs and their descriptions change dynamically, so there is no "best OERs", only best OERs at some time point. Given OERs vary over time, during the evaluation process, we are not interested in assessing whether our system recommends all the "good" resources, but rather in assessing whether the retrieved resources are "good" resources.

6.1 Evaluation Process

In order to evaluate our system, we chose the MOOC[5] "Design a Database with UML" in the domain of computer science, from the platform OpenClassrooms. This MOOC is composed of three sections. Each section represents a set of pedagogical resources. An assessment quiz is presented at the end of the section to

[5] https://openclassrooms.com/courses/faites-une-base-de-donnees-avec-uml.

evaluate the assimilation of its learning objectives by the learner. In our evaluation, we were interested in a learning objective of each section: "Relationnel model" presented in the first section, "Database management system (DMS)" presented in the second section and "SQL" presented in the third section.

Our evaluation process is based on two questionnaires. The first one is dedicated to experts and the second one is intended to learners. The questionnaire for experts has been sent by e-mail to four teachers which are experts in the domain of database. We had several constraints to respect for learners. The MOOC can be followed by a large number of learners with various profiles. To collect a large number of various users profiles without having to wait until they subscribe and follow the MOOC from the beginning to the end, we used the website Foule Factory. It is a micro-service platform which offers the possibility to ask the crowd to do some tasks as answering questions or finding data. It also allows recovery of rapid results. 117 Foule Factory respondants answered our questionnaire.

In the questionnaire dedicated to teachers, we present the REL selected by the initial query which are expected to provide the three learning objectives of the MOOC as well as some questions to assess these resources. Concerning the questionnaire for learners, we start with assessing the knowledge level of each learner in each learning objective. Therefore, we invite the learner to answer a set of questions about the learning objective, selected from the assessment quiz of the corresponding section. In this context, we chose three questions to evaluate his knowledge in the notion of "relational model", three questions to evaluate his knowledge in the notion of SMD and two questions to evaluate his knowledge in the notion of "SQL". For each set of questions, if the learner answers correctly, he is redirected to the questions about the learning objective of the next section. Otherwise, we consider that the learner has not sufficiently assimilated the corresponding notion and we present to him the resources selected by the initial query as well as some questions to evaluate these resources.

Adequacy of Recommendations with the MOOC and the Learner Profiles

A set of questions asked to Foule Factory respondents and to the teachers had the objective to assess the adequacy of selected OER with the criteria fixed, with regard to our approach, to express the recommendations adaptation with the learner and the MOOC profiles.

Application of Semantic Similarity Measure. The first criterion to evaluate is the selection of the closest resources to the initial query by applying the semantic similarity measure. In this context, for each learning objective: "relational model", "DMS" and "SQL", we present the initial set selected using the initial query to the teacher. For each resource, a closed question is presented to the teacher asking whether this resource is relevant or not. Relevance in this context refers to the fact that studying the resource allows the learner to acquire knowledge on the notion.

The synthesis of teachers replies will help us to assess the interest applying the semantic similarity measure on REL descriptions is interesting and whether it allows eliminating non relevant resources selected by the initial query and keeping the most relevant resources.

Adequacy of Recommended Resources with the MOOC Profile. In order to assess the adequacy of the OER recommended by our solution with some specificities of the MOOC, the teachers are invited to rate the relevance of the recommended OER in accordance with the criteria fixed in our approach: the granularity, the learning time and the provided performance degree.

For each resource that provides the learning objective, according to the teacher, he is invited to answer three questions:

1. A closed question asking the teacher to rate the resource on a scale of 1 to 5 according to how much its granularity is more or less adequate with the MOOC content.
2. A closed question asking the teacher to rate the resource on a scale of 1 to 5 according to how much its learning time is more or less adequate with MOOC specificities.
3. A closed question asking the teacher to rate the resource on a scale of 1 to 5 according to how much the knowledge level provided by the resource in the notion in question is more or less adequate with the level supposed to be provided in the MOOC.

Adequacy of Recommended Resources with the Learner Profile. The assessment of the adequacy of the resources recommended by our solution with some characteristics of the learner is conducted according to this protocol. As a first step, we ask Foule Factory respondents to rate the pertinence of the OER in accordance with the criteria fixed in our approach: the learning style and the knowledge of the learner. For each resource, they are invited to answer two questions:

1. A closed question asking the respondent to rate the resource on a scale of 1 to 5 according to how much the resource is more or less pleasant to follow and matches with his learning habits.
2. A closed question asking the respondent to rate the resource on a scale of 1 to 5 according to how much the resource is more or less easy to follow.

In a second step, we ask the respondents to choose one resource to follow from the list of OER presented to them for each notion. Our aim is to examine the learner's choice to compare it with his characteristics and then to detect what makes him choose one resource over than other. Learners are invited to answer two questions.

1. A closed question asking them to tick the resource they choose to study.
2. An open question asking them to justify choosing this resource and abandoning the others.

Evolution of learners Knowledge after Recommendations

Another set of questions proposed to Foule Factory respondents aims to evaluate the effect of the recommended resources on the evolution of learner knowledge in general and on the evolution of his knowledge in the learning objective of the MOOC.

For this purpose, learners are invited, firstly to answer a closed question asking him whether the recommended resources allowed him to acquire new knowledge. Secondly, the same questions selected from the evaluation quiz and asked to evaluate his knowledge level in each notion, are addressed to the learner for a second time after he studied at least one recommended resources for each notion. The purpose is to study and compare his answers before and after recommendations.

Overall evaluation of the Approach

A last set of questions asked to learners and teachers concerns assessing globally our solution. As experts, after consulting the recommended resource for each notion, the teachers are invited to express their views on the interest of recommendations, the method we use to propose recommendations and more precisely the importance of the criteria used to adapt the resources to the specificities of the MOOC and to propose other criteria they find interesting.

The teachers questionnaire contains 4 questions dedicated for that purpose.

1. An open question asking the teacher's view on the idea of recommending external resources for a learner who is attending a MOOC.
2. A closed question presenting the different criteria used in our solution to the teacher and asking him to rate them according to their importance on a scale from 1 to 3 (not very important, important, very important).
3. An open question inviting the teachers to propose other criteria to take into account when choosing resources to recommend, in order to respect the specificities of the initial course and to facilitate the integration of the resources in its content.
4. An open question asking teachers to propose other suggestions.

As playing learner role, Foule Factory respondents are also invited to express their views on recommending external resources, after consulting the recommended resources and studying some of them.

The learners questionnaire contains 3 questions dedicated for this purpose.

1. An open question asking the respondents to suppose they are attending an online course and express their views about recommending to them other resources when they don't answer correctly to the evaluation test of a certain course's section. The respondents are invited to choose between: (1) It is a good idea but I will study some of them; (2) It is a good idea but I don't have the time to study them; (3) It is not a good idea, because I don't want to disperse myself with studying external resources; (4) other point of view.

2. A closed question asking respondents to suppose they are attending an online course and to precise their behavior when they don't understand some of its notions. Do they repeat the course or look for other online courses ?
3. For the learners who prefer looking for other courses, another closed question asks them to precise whether the recommended resources allow them to save time compared to the time they spend to look for external resources by themselves.

6.2 Evaluation Results

In this chapter we summarize the responses of teachers and learners to the questions presented in the evaluation questionnaires.

Overall evaluation of the Approach

Experts Opinions. After consulting the resources selected by our system, all experts agreed that recommending external resources, during a MOOC, is a good idea. Regarding the criteria defined in our solution to take into account the specificities of the MOOC in the recommended resources, we obtain these results. All experts assigned the maximum score of 3 to the criterion relating to the level of knowledge provided by the resource. All experts agreed on the importance to recommend resources allowing the learner to acquire the knowledge level supposed to be acquired by attending the MOOC. Three of the experts assigned the maximum score of 3 to the criterion relating to the learning time. According to them, it is very important to take into account the learning time of the recommended resources. The fourth expert assigned the score of 2 to this criterion. He considers that it is an important criterion but still less important than the one relating to the knowledge level.

Two experts assigned the maximum score to criterion relating to the granularity of the resource. The other two experts assigned the score 2 to this criterion. For them, the fact that the granularity of the recommended resources is adequate with the internal resources of the MOOC is important, but it is less important than the adequacy of the knowledge level and the learning time.

Learners Opinions. After consulting the resources selected by our solution, 60% of Foule Factory respondents endorse the recommendation of external pedagogical resources, when they didn't correctly answer the evaluation test presented in a course they are attending. Another 25.7% of the respondents consider that it is a good idea but they have a problem with the time they will spend to learn additional resources. The lack of additional time available to study the recommended resources, confirms the importance of the learning time criterion taken into account in our solution. The last 14.3% of respondents don't consider the recommendation of external resources as a good idea and they do not want to disperse themselves by studying external resources in addition to the course they are attending.

On the other hand, 55.2% of the respondents prefer to search for other online courses when they are taking a course and they don't understand some of its notions. The remaining respondents prefer to repeat the same course. Among those who prefer to search for other online courses, 72.4% find that the recommended resources allow them to save time, compared to the time they would have spent looking for resources on the web.

Evolution of Learners Knowledge after Recommendations

After consulting the recommended resources, 81.6% of Foule Factory respondents find that those recommended for the notion "relational model" allowed them to acquire new knowledge. 69.5% find that those recommended for the notion "DBMS" allowed them to acquire new knowledge about this notion and 60.5% find that those recommended for the notion "SQL" helped them to learn new knowledge.

Based on the respondents answers to the same quiz presented before and after recommendations, the Table 1 resumes the percentages of correct answers. By examining the results, we note an improvement in all the answers after the recommendations except for one question dealing with the notion of "Relational Model" Q_2 for which the percentage of correct answers decreased. To understand the causes of this decrease, we started with studying the resources we recommend to the respondents to help them to acquire the notion of "Relational Model". Among the four recommended resources, there is R_1 that does not contain the information which is the subject of the question Q_2. There are also two resources R_2 and R_3 that include the information and the resource R_4 that includes the information but that is very voluminous with 37 modules and that require at least 3 hours to learn its content.

Table 1. Answers to the evaluation quiz before and after recommendations.

Recommandations	Relationnal model			DBMS			SQL	
	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	Q_7	Q_8
Before	48%	42%	41%	31%	51%	24%	42%	16%
After	76%	34%	52%	41%	68%	28%	43%	20%

Then we selected the 15 respondents who answered correctly the question Q_2 before the recommendations and incorrectly after the recommendations. By looking the resources attended by these respondents, we found that 10 of them have opted to attend the resource R_1 not dealing with the information processed by the question Q_2 and 3 of them choose the voluminous resource R_4. So, a possible explanation for these results is that the respondents didn't find the answer in the chosen resource or they didn't follow it until the end and they replied randomly to the question.

It is also important to note that two of the three respondents who opted to attend R_4 left some comments about its length: *"many pdf documents to open"* and *"too long"*. Hence the importance of the criteria relating to the granularity and the learning time of the recommend resources, defined in our solution and the importance of describing these information in the metadata of the OER to improve the recommendation's results.

Adequacy of recommendations with both the MOOC and the Learner Profiles

Application of Semantic Similarity Measure. For each MOOC's notion, the fourth experts ticked the resources allowing to acquire knowledge about this notion, from the set of all the resources selected by the initial query of our MORS system (the query defined in the PreSearch module). To assess the benefit of using the semantic similarity measure, we define two measures of precision. The first one is carried out on the resources selected by the initial query to assess whether the keyword search adopted in this query allows selection of relevant resources dealing with of knowledge element (subject of the recommendation). The second measure of precision aims to assess whether the refinement of the initial set of resources by using the semantic similarity measure increases the precision rate. Our objective is to have a precision rate closer to 100% after applying the semantic similarity on the descriptions of the resources selected by the initial query.

As explained previously, our goal is not to select all the relevant resources that exist in the external repositories but to be assured that the limited resources recommended to learners are relevant. In this context, the relevance is that the resource allow the acquisition of the notion which was not well mastered by the leaner and whose lack of knowledge triggered the recommendation process. For this reason, we define to measures of precision adapted to our goals:

- A first precision rate Precision_{ad1}. Precision_{ad1} represents the percentage of relevant resources among all the resources selected by the initial query.

  $$\text{Precision}_{ad1} = \frac{|R_{RT}|}{|R_{IQ}|}$$

  Where R_{RT} represents the resources ticked by experts as relevant resources and R_{IQ} represents the set of the resources selected by the initial query of our system MORS.
- A second precision rate Precision_{ad1}. Precision_{ad2} represents the percentage of relevant resources among all the resources selected after the refinement using semantic similarity.

  $$\text{Precision}_{ad1} = \frac{|R_{RT}|}{|R_{SS}|}$$

  Where R_{RT} represents the resources ticked by experts as relevant resources and R_{IQ} represents the set of the resources selected after applying semantic similarity.

By reviewing the results, we notice a significant increase in precision rates for resources related to the notion “Relational Model” and “DMS”. For the notion “SQL”, an increase is detected depending on the answers of two experts (expert 1 and expert 3) whereas a decrease is detected depending on the answers of the two others (expert 2 and expert 4). To understand this decrease, we studied the answers of the fourth experts on the relevance of the resources selected after applying the semantic similarity. Among the four selected resources, there is a resource which is considered as relevant by the expert 1 and 3 and no relevant by the expert 2 and 4. This is a course on database with a section introducing the notion “SQL”, without giving details. A possible explanation of the difference between experts’ opinions is that presenting not detailed information about the notion is considered, by some experts, sufficient to acquire some basic knowledge about the notion and not sufficient by the others.

In our case, the objective of recommendations is to help the learner to acquire a knowledge level allowing him to attend the MOOC until the end. From that comes the importance of the constraint defined in our solution to just retain resources which provide a knowledge level in a specific knowledge element (prerequisite or learning objective) upper or equal to the knowledge level defined in the MOOC. Unfortunately this information doesn’t exist in the metadata of OER but recovering it later from learners who consult the recommendations may improve the results.

Adequacy of Recommendations with the MOOC Profile. In this step, we calculated the averages of scores given by the experts to each resource according to its satisfaction to the criteria related to the granularity and the learning time and the knowledge level.

It is important to note that in this step we are interested in the resources of the final set which is recommended to the learner (after applying the selection by constraints and the selection by semantic similarity).

Concerning the criterion related to the learning time of the resource, we obtain these results. For the notion “Relational Model”, the resource with the worst note, represents a voluminous course with 37 modules and 3 hours at least to learn its content. The resource which receives the best note is a pdf of 84 pages in the form of slides where each page some lines. Therefore, we can deduce that the resource’s volume (the number of its pages in this case) cannot give the exact information about the duration needed to assimilate its content.

Having the exact information about the learning time of the resource could support its recommendation by our approach. Unfortunately, information about learning times, in the majority of cases, is not included in the OER descriptions.

Concerning the notion “DBMS”, the two best notes were assigned to resources presented as HTML pages. Although these courses are long, the notes can be explained by the fact that each of them offers a well presented summary that allows learners to go directly to a section dealing with a specific notion. The worst rating was assigned to a resource in the form of a quiz. A quiz presents questions and answers to learners and in most cases, it is used for the assessment of knowledge. Therefore, to answer a quiz, the learner is, in many cases, obliged to consult other courses which will increase the duration necessary to master the knowledge.

For the notion "SQL", the best note was assigned to a resource presented as a set of short videos of 2 to 4 min. A quiz resource is considered as the resource that requires the longer learning time.

Based on the experts responses on the relevance of OERs according to the criterion of the learning time, we can notice that two learning durations are to be taken into consideration.

The first duration concerns that necessary to assimilate the total content of the resource, and the second duration concerns that necessary to acquire knowledge about a specific notion, by consulting the resource. We can also notice that the way in which the resource is presented influences the duration to be spent by the learner to master its content.

In some cases, we noticed that experts have difficulty to rate resources criterion-by-criterion and their scores are influenced by several criteria at once. Such is the case of the criterion of granularity and knowledge level. For example, for the notion "DBMS", the same resource received the worst notes about its satisfaction to the criterion of granularity and knowledge level. The same resource received also the best note for its satisfaction to the criterion about granularity and knowledge level.

Adequacy of Recommendations with the Learner Profile. A large proportion of respondents, between 40% and 90%, considered the recommended resources as difficult resources in relation to their knowledge. Some of them left comments to express this difficulty: *"quite complex"*, *"very technical"* and *"I do not have the necessary bases"*.

This highlights the constraint defined in our approach that the prerequisites of recommended resources must be mastered by the learner.

As regards the criterion about learner's learning style, we calculated the average values of the scores assigned by respondents. After reviewing the results, we noticed that the resources presented in the form of videos and HTML pages with a properly presented menu to access resources' sections, are the most appreciated. Long resources are less appreciated. The worst notes were assigned to quizzes. This can be explained by the fact that a quiz does not explain the notion especially for beginner learners.

By studying respondents' learning styles based on their answers to the (ILS) questionnaire [16], we found that 29% of respondents are visual rather than verbal and 16% are 100% visual. This can explain the fact that the resources properly presented and including videos and images received better notes. We also found that 36% of respondents are sensorial rather than intuitive and 18% are 100% sensorial. This can explain the fact that resources containing exercises and applications were more appreciated than those based solely on theory.

7 Conclusions

In this article, we have presented our recommender system MORS. It dynamically recommends external OERs during a MOOC when a lack of knowledge of the learner is detected. To this end, we use performance degrees to qualify the difficulty of the MOOC knowledge elements and also to measure the acquisition of these elements by the learner. MORS adapts the results according to the progress of the MOOC and the knowledge acquired by the learner.

The resources to be recommended by MORS, at the beginning of the MOOC or at the end of each section, are calculated so that they are adapted to some characteristics of the learner and of the MOOC he is attending, at the moment of the recommendation. Therefore, our system consists of two processes responsible for generating and updating the learner profile and the MOOC profile throughout the MOOC, by extracting the necessary information. Based on these two profiles, if a lack of knowledge is detected for a certain knowledge element, the calculation of the recommendation is triggered. It starts with the PreSelection process that requests the repositories of OERs descriptions to select an initial set of OERs dealing with the knowledge element. Then, the refinement process generates the final set of OERs to be recommended to the learner. To his end, the refinement process performs selection and ranking operations based on mandatory and optional criteria. These criteria are defined to take into account both some characteristics of the learner and some specificities of the MOOC.

The first assessment of our system showed the importance of the criteria used in our recommendation algorithm to satisfy some learner and MOOC characteristics. This also allowed us to have an idea about the criteria priority according to the experts and to retrieve other proposals of criteria like the difficulty and the creation's date of the resource to enhance our solution. The evaluation also showed that in most cases, the resources recommended to the learners allowed them to acquire better knowledge in the notions of the MOOC. It is also necessary to perform another qualitative assessment to understand some of the experts answers that were not clear and easy to interpret. It is important to note that our solution uses the OERs metadata stored in accessible repositories, hence depends on the availability and the quality of these metadata. Therefore, in some cases, we have not been able to verify the fulfillment of certain criteria by the recommended OER because of the lack of metadata information, which affects the quality of recommendations.

Our short-term objective in the intermediate future is to improve our solution in the light of the results obtained from the evaluation, for example by adding other criteria in the recommended resources and assigning weights values to the optional criteria based on the experts answers. We also seek to integrate our recommender system in an existing MOOC in order to assess how it will be working under real conditions. This integration will allow us to get better feedback on the quality of recommended OERs and how much they support learners during the MOOC. We will be able also to deduce the performance degrees provided by the OERs based on learners responses to the MOOC quiz, after attending the recommended OERs.

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