CHAPTER 10

INTELLIGENT TUTORING OF LEARNERS IN E-LEARNING SYSTEMS AND MASSIVE OPEN ONLINE COURSES (MOOC)

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DOI: 10.26650/B/ET06.2020.011.10

Abstract

In the last few years, many terms related to learning environments have emerged. Each one of these terms is distinguished by a set of criteria such as the target audience, the duration of learning, the type and nature of the educational content, the manner of dissemination of knowledge, etc. Among problems encountered in these environments, the lack of support for learners seems to be a serious problem that requires special attention. Tutoring can be seen as a good solution for this problem; it consists of giving assistance to learners who are in need for help. Regardless the nature of this assistance (pedagogical, social, etc.), it can be delivered in many forms: advice, guidance or even recommendation. If tutoring has been applied for a long time in traditional e-learning environments, its application in new systems such as Massive Open Online Courses (MOOC) is still under study. In fact, a considerable number of studies driven on MOOCs had reported the problem of learners' dropout. Several reasons can be listed as causes of such a problem. Among these reasons, we can find learners' isolation as well as learners' loss of motivation. This same problem has been reported by researchers working in the field of Computer-based Environments for Human Learning. In this article, we propose a new vision on how to apply an intelligent tutoring process in human learning systems in general and in MOOCs in particular. This new vision is based on the behaviors and skills of learners. This activity can take many forms and can be carried out by different types of actors (teachers, learners, etc.).

Keywords: E-learning, MOOCs, Intelligent tutoring, Social tutoring, Traces

1. Introduction and Motivation

Computer-based systems and networks have been in widespread use since the emerge of the internet and the technological boom of the early 21st century, and as dedicated to human learning they keep growing faster each year. These systems use a set of informational and educational resources that serve thousands of learners' needs. As uniquely designed for colossal number of learners, Massive Open Online Courses (MOOCs) allow the acquisition of knowledge easily with the advantage of being transmitted in different forms, audible, textual, or visual (Jordan, 2014; Khalil & Ebner, 2016; Zhang et al., 2016). These courses are freely accessible without any enrollment conditions in most cases due to participants' turnout in such systems. Moreover, learners are quite offered a set of tools that help carrying out the required activities and duties that can be traced or even tracked simultaneously. Such specialized use of MOOCs makes it highly sustainable for learners' to have accessible data that is to be traced whether implicitly or explicitly.

Many results can be found just by typing the word MOOC on any search engine, the thing that stands for the provability of several academic and professional bodies' work on this axis. In some developed countries, the development of MOOCs was one of the goals of their governments and their policies for research and development. Therefore, several educational institutions and companies come to offer their own MOOCs for they have some characteristics that encouraged thousands or even hundreds of thousands of learners to enroll online.

What really distinguishes these MOOCs from other learning formats is that they provide free access though its limited nature, demand no high degrees or even qualified-knowledgeable geeky learners, and immediately attract the attention of participants who face some difficulties on the audible and textual level.

The gathered data on the number of participants' access and enrollment in such systems sumps up its efficiency, however, the majority of participants would shy away and keep the programmed training unfinished although the splendid display that these MOOCs demonstrate. Many researches have shown that the percentage of learners who accomplished their courses is around 10%. Their withdrawal generated a sort of fear (Boyatt et al., 2014).

As an attempt to look for the reasons behind this quitting, results have shown that the main cause is their isolation and the lack of an adequate follow-up. The letter became very crucial and demands an immediate resolution.

In the wake of these findings, this framework is ultimately conducted to present an approach that offers an intelligent tutoring for learners using an e-learning system through different ways that work on eliminating the participants' isolation, and further guide them according to their needs and social profiles. It aims also to empower the teachers and tutors' roles as supporters, and interaction makers. The latter can intervene to answer all different questions asked from the part of the enrollers whether they are pedagogical, social, administrative, technical, etc. (Bendjebar et al., 2016). Moreover, the process involves real identification of the participants' categories and their exact level/situation (very serious situation, serious situation, rather serious situation, etc.), so that the smart intervention take place, and assign them with the appropriate type of tutoring. We come to raise these questions, under what category learners are to be classified during the learning process? How can we associate this system to meet the supported needs? What is the possible means that serve best the proposed intervention? These questions are best answered under full examination, which is the main goal of this approach.

To validate our approach, we have implemented a system called 'TutMOOC' (http://www.mooc24.net/MC/) dedicated to learning "algorithmic" subject. TutMOOC has been tested for one month. The obtained results were very promising and encouraging.

This paper is divided into three parts; section 2 is a full presentation of previous researches on tutoring and social tutoring in MOOCs. Section 3 involves a very detailed demonstration of the proposed approach. The last section is highly dedicated to the conclusion and further perspectives.

2. Related Works

Traditional learning environments involve backing up tasks, and one of the most functioning is tutoring. It takes several forms: supervision, pedagogical and psychological support, reinforcement of knowledge, answers to questions, motivation, etc. The main objectives of this activity are essentially to increase learners' motivation, break their isolation and increase opportunities to improve learners' levels of knowledge.

This tutoring task is performed by actors called tutors. They follow and accompany a number of learners. In some cases, learners themselves may be tutors; this is known as peer-tutoring. In all cases, tutors have several skills and perform a set of functions.

Several research studies have investigated the detection and the description of the tutor's roles and functions in human learning environments that can support hundreds of learners.

The reader can consult (Lafifi et al., 2010) to get an idea about the extraction and the desciption of the roles of online tutors in e-learning environments and how to assign roles to tutors.

In the case of MOOCs that contain thousands of learners and more, the tutoring task becomes very delicate and requires a special attention. From our findings, only few works that focused on figuring out what is exactly with applying tutoring in MOOCs, and why it is not working; these systems turned to be creating of more problems when testing it and the main reason is the huge number of learners enrolling in such online environments.

We found a first attempt that was the subject of a startup, Livementor (mentor or tutor live). Livementor (https://www.livementor.com/about-LiveMentor) is an online tutoring service that allows the user to benefit from an instant support, to have an excellent tutor according to the needs of the applicants and to ensure this task of tutoring at any time. The advantage of this system is that it can be applied to several types of learners (schoolchildren, students, young entrepreneurs, etc.). Nevertheless, the services offered by this system are not free.

Another system is Openclassrooms (https://openclassrooms.com/), which offers learners a video conferencing mentor. According to the developers of this platform, the tutor is “an expert” who adapts learning to the level of learners and “a tutor” to motivate them and lead them to achieve their goals.

In (Collect et al., 2017), the authors proposed peer tutoring to be applied in MOOCs. This tutoring technique has been applied in the POEM platform (Personalised Open Education for the Masses platform of the UNESCO UniTwin Digital Campus Systems). The authors indicated the impossibility of managing teacher-learner interactions in MOOCs given the very high number of learners. According to the authors, POEM offers each learner a tutor who is only another learner with a higher level in the same course. In this sense, the learner can ask questions to his tutor. Of course, if the tutor can not answer a question, he can send it to his own tutor, and so on until a question is sent to a teacher in case of difficulty.

3. Intelligent tutoring in e-Learning and MOOC environments

The main objective of this work is to offer learners a variety of mechanisms and tools of social tutoring to support and motivate them in order to reduce the risk of quitting the training. “Social tutoring” can be defined as the adoption of social indicators in the activity of human tutoring. In other words, social tutoring is attached to the application of tutoring through the interactions between the learners themselves and by adopting some indicators, terms and tools used in social networks. The ultimate goal is to create a friendly and a social environment in which promoted learning is in turn essential for successful tutoring, that is to say, social tutoring means taking into account the social aspect when applying the tutoring task. Moreover, this smart social tutoring states that each learner's situation is associated with an appropriate tool to intervene before the learner's situation worsens. Indeed, for example if the learner is in a situation very close to giving up, the system offers a specific tutoring (semi-collaborative or TWISA (a term used by Algerian farmers during the periods of work of the land .... ..)).

In order to benefit from these tools and mechanisms, we must take into account information about learners. These information concern all the actions taken by the learners during the course follow-up once the learning, evaluation, tutoring and interaction with other human actors in the system have taken place. Furthermore, to make use of these gathered data, we propose to group them according to the nature of the activity and present them in a model or profile. For taking into account all these functionalities, the proposed approach is divided into three phases: the information collection phase (modeling), the zone detection phase and the intelligent tutoring phase (c.f. figure 1).

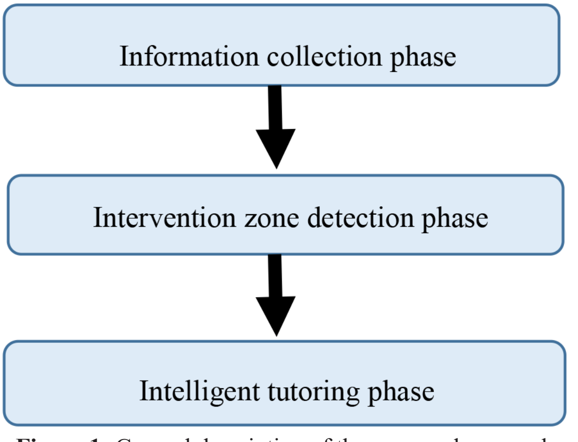

Figure 1: General description of the proposed approach

For validating our contributions, the proposed approach was supported by a system dedicated to learning "the algorithmic" subject, called "TutMOOC". The general architecture of this system is presented in Figure 2.

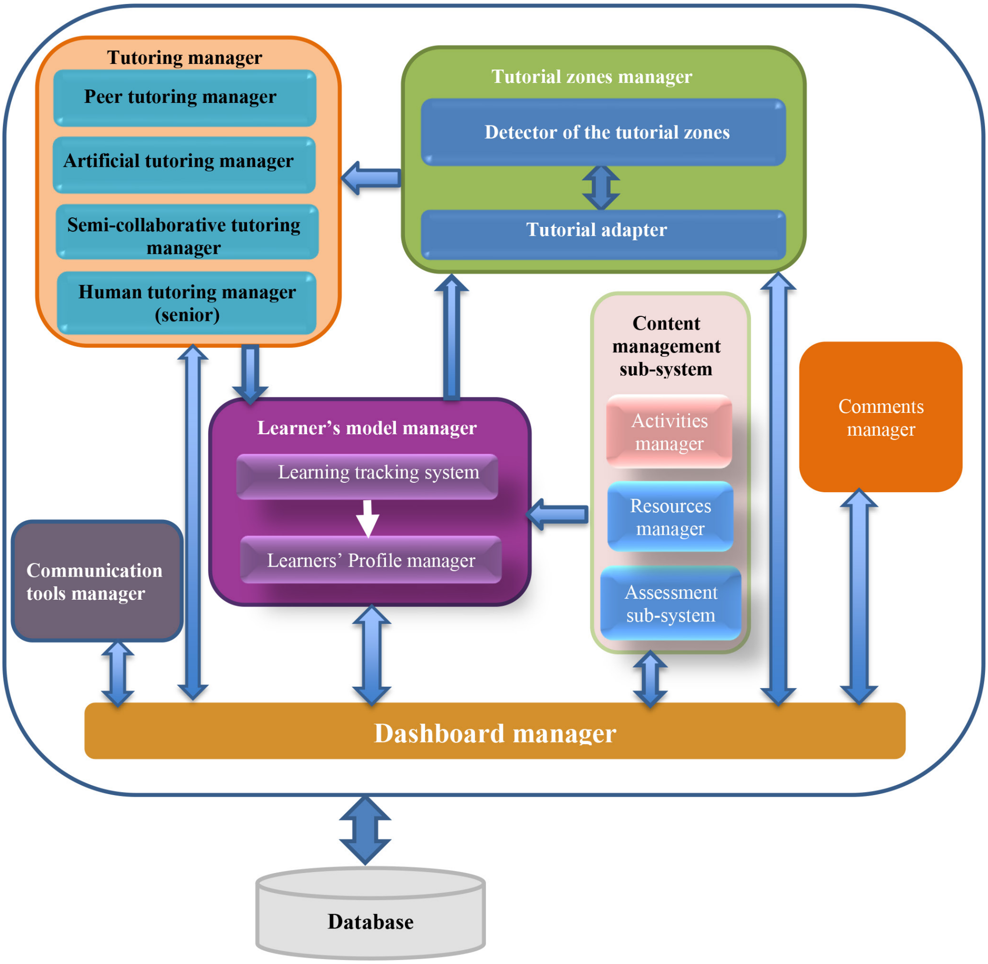

Figure 2: General architecture of the system

3.1. The collection of information (modeling)

In this phase, the system collects all the actions (traces) of the learners. These traces may be the result of the learner/learner and learner/system interactions. From these traces the system will build the model of the learner. The latter will be modeled by the quadruplet (CP, AP, BP, TP) where CP designates the cognitive profile, AP denotes the attendance profile, BP is the behavioral profile and finally TP designates the tutorial profile.

3.1.1. Learner Model

As already mentioned, our learning model consists of the cognitive profile, the attendance profile, the behavioral profile and finally the tutorial profile. Evidently, these names of profiles do exist and are cited by several researchers, even in our previous research works, except that in this work is the way to represent these profiles and the formulas used to calculate them are different. Indeed, we have proposed a model of the learner that contains: the cognitive profile that is modeled by tokens, the behavioral profile that is modeled by stars and the tutorial profile that is represented by sticks. We have associated with each interval a color to indicate the situation where the learner is.

Table 1 shows the proposed color classification.

Table 1. Classification of colors associated with the intervention zones

Profile	Number of	Representation	Red Zone	Orange Zone	Yellow Zone	Green Zone	Blue Zone
Cognitive	Tokens	●	0...25	25...45	45...60	60..85	85..100
Behavioral	Stars	☼	0..25	25..45	45..60	60..85	85..100
Tutorial	Sticks	|||||||	0..20	20..40	40..60	60..80	80..100

3.1.1.1. Cognitive profile

A. Level of knowledge:

This profile refers to the level of knowledge of the learner. It is calculated according to the learner's answers on a questionnaire designed for this purpose. Depending on the obtained responses, this profile can be: Very good, good, average, weak or very weak. We used the same formulas adopted in our previous research. Therefore, according to the final obtained grade (i.e. score); we obtain the associated cognitive level. Therefore, we propose the following levels:

- if (score <25%) then the cognitive_level := "very low".
- if (25 % <= score <45%) then the cognitive_level := "low".
- if (45% <= score <60%) then cognitive_level := "average".
- if (60% <= score <85%) then the cognitive_level := "good".
- if (85% <= score <= 100%) then the cognitive_level := "very good".

After the enrollment of a learner, he must pass a test in the form of multiple choices questions to know his initial level; once his level is upgraded the learner makes other tests. In our proposal, we used tokens to represent this level.

B. Attendance:

It indicates the learner's attendance towards the evaluation activities proposed by the teaching staff in the system or the MOOC. These activities may include homework, quizzes, questionnaires or any other type of assessment.

In any e-learning system or a MOOC, the teachers' staff proposes activities to be carried out by the learners to test their knowledge. In our proposal, we associate a coefficient of importance to each activity. This coefficient is designated by the staff when designing the evaluation activity. This coefficient can take an integer value between 1 and 3 (3: Very Important, 2: Important and 1: Not important). For example, "the exam" is a very important activity whereas "the assignment can be either small or important according to the staff.

Table 2. Coefficients of importance associated with some pedagogical activities

Type of activity	Degree of importance	Coefficient
Examination	Very important	3
Quiz	Important	2
Duty	Not important	1

This work shows the importance of the individual effort of each learner. Willingness and serious work can guide the learner to develop his level.

We propose a simple mathematical equation to calculate the attendance as follows (it is noted by A).

A = (number of completed activities) / (total number of scheduled activities) (1)

According to the value of A, we deduce if a learner is serious (when A is close to 1) or not (when the value of A is close to 0).

To update the cognitive profile of the learner, we use the following formula:

$$CP(Aj) = \frac{\sum_{i=1}^{n} Coefi * Mark\ (Activityi)}{\sum_{i=1}^{n} Coefi * Max - Mark(Activityi)}$$

With :

- ***Mark (activityi)*** is the grade associated with the pedagogical activity **i**. This grade is between 0 and 20 as in the notation adopted by institutions of higher education in Algeria.

- ***Coefi***: is the coefficient of the activity i.

- ***n***: total number of the activities.

3.1.1.2. Behavioral profile

It represents the behavior of the learner in the system. Notably, this profile indicates the degree of the interactions made by the learner. In other words, the learner's contributions using different communication tools offered determine his behavior. This profile is calculated using a set of indicators such as the number of questions posted on the forum, the number of messages sent, etc. To model this profile, we used "the stars" that indicate the degree of behavior of the learner. Each action performed by the learner is associated with a certain number of stars. We propose to use the following indicators:

Table 3. Indicators associated with the behavioral profile of the learner

Action / indicator	Number of proposed stars	Maximum number of stars
Number of system access (access)	1	20
Message sent via email (message-email)	1	20
Number of words "I like"(I-like)	1	20
Number of topics posted on the forum(subjects)	1	20
Public comment posted on the course(comments)	1	20

To enhance this social tutoring to work more in favor of the learners, we asked for their opinions and eventually the comments ranged from being positive to negative. According to the number of positive opinions (by quota of 10 in our case), the number of stars increases to reach a maximum (20 stars for our case). Similarly, depending on the number of negative reviews, the number of stars decreases to a minimum.

Finally, we can calculate the number of stars for a learner **j** using the following formula. This number is written as **Bj** as follows:

Bj=nb(accesj) + nb(commentsj) + nb(message_emailj) + nb(I-likej) + nb(subjectj)

Depending on the number of obtained stars, the associated zone and the corresponding color are obtained. We used the following rules to obtain the behavioral profile of a learner j (BPj) and the intervention zone:

- if (Bj <25) then BP_j: = “Isolated” and zone: = “red”.
- if (25 <= Bj <45) then BP_j: = “not very dynamic” and zone: = “orange”.
- if (45 <= Bj <60) then BP_j: = “moderately dynamic” and zone: = “yellow”.
- if (60 <= Bj <85) then BP_j: = “dynamic” and zone: = “green”.
- if (85 <= Bj <= 100) then BP_j: = “strongly dynamic” and zone: = “blue”.

3.1.1.3. Tutorial profile

It defines the learner’s ability to perform assistance tasks for other learners. In other words, it shows whether or not the learner can act as a tutor and, if so, what are his or her roles. All this information is then stored in his tutorial profile. This last one includes two types of information: the role of the tutor and the number of sticks acquired.

Of course, the learner-tutor with more skills and knowledge is expected to help and answer other learner’s (his or her peers) requests for help, known as peer tutoring. During their time in the system, learners can support other learners by helping them to find appropriate learning resources, perform suitable tasks correctly, as well as motivate and encourage them. In our approach, we propose to adopt a stick-based approach.

Every request for help (tutoring) is rewarded with a number of sticks. In other words, each learner is assigned a number of sticks (nb = 100 in our case). This number will be updated according to the requests for assistance addressed to other learners and the replies given by the learner-tutor to the requests for assistance issued by the other learners.

If the answer sent by a tutor-learner is appreciated by the learner requesting the tutoring, the number of corresponding sticks is subtracted from the learner’s account and added to the participant’s account (number_sticks_response = 4 in our case). In the opposite scenario, i.e. if the tutor learner’s answer was not appreciated by the learner, the number of sticks allocated is divided on both (i.e. 2 sticks in our case of application).

Within our system, any learner can be considered as a tutor as long as he/she answers at least one request for assistance and this answer is satisfied. In other words, a learner can be a tutor if he or she possesses a number of sticks that is greater or equal to 104 (100 sticks at the beginning plus 4 sticks acquired after a satisfying answer). We have also proposed a ranking system for tutor-learners so that they can be promoted to senior tutors. This ranking is based on the number of sticks belonging to each of them. We have followed this ranking with regarding the number of sticks acquired.

- If number_sticks >= 104 then Tutor_Type: = “Beginner”.
- If number_sticks >= 200 then Tutor_Type: = “Experienced”.
- If number_sticks >= 300 then Tutor_Type: = “Senior”.

Figure 3 bellow shows a screenshot from by TutMOOC system that indicates the tutorial profile of a learner, where his zone is blue.

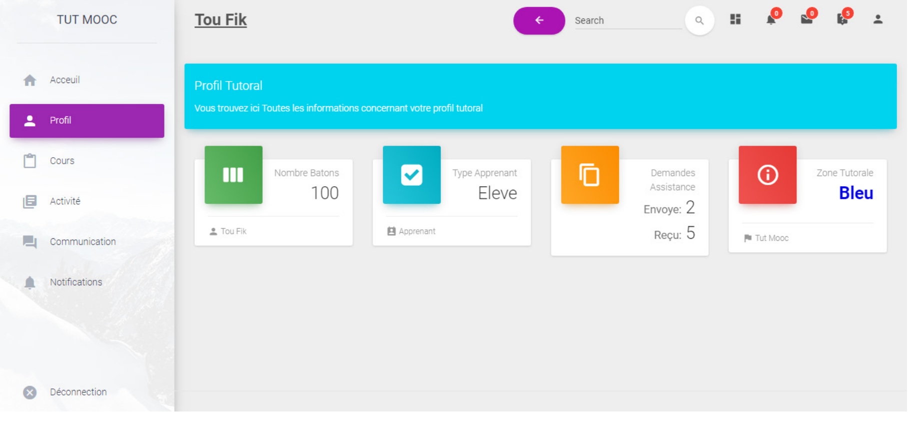

Figure 3. Tutorial profile of a learner in TutMOOC system

3.2. Detection of the critical intervention zone

This phase makes it possible to detect if the learner needs a tutorial intervention through the detection of a tutorial intervention zone. These areas are detected from the traces left by the learners by carrying out the different pedagogical activities (learning, assessment, tutoring ...) as well as the interactions done between them. These areas indicate the degree of need for the assistance of the concerned learner. Thus, this stage designates an entry state which represents the traces of the learner and an output (or the exit) one that demonstrates its exact situation or the zone of tutorial intervention.

Nevertheless, in a difficult situation, these profiles (cognitive, behavioral or tutorial) do not have the same importance. We assume that learners who have difficulties in their learning have priority over learners who have a weak tutorial profile (because of the lack of sticks for example). For this reason, we have identified two types of zones: **a primary zone and a secondary zone**. The first zone contains both Cognitive and Behavioral profiles (total activities performed on the platform), while the second one is called the secondary zone and contains the tutorial profile.

Each zone has a coefficient, which can be modified by the staff (administrator, teachers and tutors). In our case, we assigned the value “3” as a coefficient for the primary zone since this part is more important for the learner because it represents his dynamism and his learning activities, and the value “1” for the secondary zone. We used a set of mathematical formulas to calculate the zone of each learner (they will be the subject of another research paper).

For example, from the value of the cognitive profile (CP), we detect the zone and its color as follows:

- If (Cognitive_ Profile <25%) then zone: = “red”.
- If (25 % <= Cognitive_ Profile <45%) then zone: = “orange”.
- If (45% <= Cognitive_ Profile <60%) then zone: = “yellow”.
- If (60% <= Cognitive_ Profile <85%) then zone: = “green”.
- If (85% <= Cognitive_ Profile <= 100%) then zone: = “blue”.

3.3. Intelligent tutorial intervention

After determining the learner’s situation (the critical intervention area), we apply a series of tutoring rules to identify the means or tools to be adopted for social tutoring.

3.3.1. Proposed tutoring type

There are several types of tutoring, which vary according to the level of the tutor.

A. Human tutoring: it can be split up in two categories:

- **Tutoring by a teacher**: for this category, tutors are teachers. They have more knowledge with more experience than learners who are seeking tutoring. The concept of this type of tutoring is simple: we assign a teacher to each learner or group of learners who will act as their tutor. He only deals with pedagogical problems, so he cannot reach all the objectives of the tutoring.
- **Tutoring by a specialist**: Since the previous category is not enough to achieve all tutoring goals, experts suggested the creation of a special job called “specialized tutor for learner follow-up “. As a result, the tutor has a specific job (role). In this case, the tutor must undergo a training in order to be able to carry out this activity.

B. Peer Tutoring: In some cases, learners can help their peers (i.e. the tutor is another learner). This tutoring is called peer tutoring. Thus, the tutoring requester (who requests tutoring) and the tutor are both learners.

C. Semi-Collaborative Tutoring: The system assigns a main primary tutor for the learner in question. This tutor will then create a group of tutors who will work together to help the learner requesting tutoring or help. The appointed tutor (lead tutor) may contact other tutors to assist him/her with specific requests. When selecting the main tutor, the system computes a degree of freedom for each tutor and takes the tutor with the highest degree of freedom.

D. Tutoring by an Animated Conversational Agent (Automatic tutoring):

This type of tutoring is intended for learners who are not in a critical situation. It consists of selecting a set of questions predefined by the administrative staff of the system/MOOC. The answer to the question is also predefined by the same staff. It is the same principle as the FAQ (Frequently Asked Questions). In our system, we proposed reading the associated response by a lively animated conversational agent. We have offered another option to the learners in our system, which is to add the most popular questions to the database of questions that are predefined by the staff. In other words, learners can ask questions or ask for help. If the answers sent to these learners are appreciated by other learners using the statement "I like", this question can be added to the questions database so that it can be used by the animated conversational agent or the artificial tutor.

3.3.2. Tutorial rules:

In this section, we give a set of tutoring rules that can be applied depending on the critical area of intervention detected for each learner. Rules can be of the form: **If zone then tutoring_Type**. In what follows, we provide the appropriate type of tutoring detection algorithm based on the intervention zone associated with each learner seeking help (Algorithm1).

Algorithm1: Algorithm of the social adapter;

Entry: learner's-zone

Output: Type of tutoring (Type_Tut)

begin

If learner's-zone = "red" then Type_Tut: = "Semi-collaborative tutoring"

Otherwise if learner's-zone = "orange" then Type_Tut: = "Human tutoring"

Otherwise if learner's-zone = "yellow" then Type_Tut: = "Peer Tutoring"

Otherwise if learner's-zone = "green" then Type_Tut: = "Tutoring by animated conversational agents"

End.

4. Conclusion and future works

The field of learning kept evolving to include different types of supporting the learners. This evolution was highly demonstrated by MOOCs. The latter is one of the most significant systems that has seen such an interest and been the main focus of many researchers in recent years. These MOOCs seek to look for tools and techniques to improve the skills of learners and facilitate their different teaching tasks. Although it has attracted many learners' interest who considered their enrollment in these spaces highly beneficial, the system has recorded high rates of the participants' withdrawals for some unknown reasons at the beginning.

Such quitting was very disappointing for MOOC advocates. This situation has led many researchers to come up with immediate solutions or simply to try to adopt approaches already implemented in human learning environments. Indeed, some researchers have proposed techniques such as the personalization of MOOCs (Lefevre et al., 2016; Clerc et al., 2015), the adaptation of educational pathways (Sun et al., 2015; Bakki et al., 2015), motivation of learners in MOOCs (Mangenot, 2014; Hew and Cheung, 2014; Bakki et al., 2015) or in other e-learning systems, etc.

Therefore, the purpose of this research was to provide learner's support functions in such environments (i.e. tutoring), that is made throughout the learning process and based on the needs of learners and their skills and behaviors. These are represented by a learner model that encompasses a number of profiles. It is from his profiles that the degree of a learner's need for assistance is detected. This degree makes it possible to identify a tutorial intervention zone that will be used to designate the type of tutoring offered to the concerned learner. In our proposal, we identified four zones of tutorial intervention. Each zone is associated with a different color and a type of tutoring. For example, if the detected situation of the learner is very serious (close to quitting), tutoring by a senior tutor (experienced) is recommended. Therefore, depending on the situation of the learner (i.e. his tutorial zone), a type of tutoring is proposed. Special emphasis has been placed on a special type of tutoring, which is the peer-tutoring. This activity can be done by the learners themselves under certain conditions.

Another type of offered tutoring is the artificial tutoring. It is dedicated to situations that are not serious. It holds a set of pre-set questions with their answers. In such cases, the nature of the questions differs, and most of the times according to the learners' opinions. They can be added with their best answers to the database of the questions used by the artificial tutor.

All these ideas have been implemented in a system dedicated to learning the concepts of the "algorithmic" subject. This system offers several services facilitating the tasks of the various human actors namely: teachers, tutors and learners. In addition, it has several features related to the management of different learner's profiles, the safeguarding of tutorial zones, the management of various educational resources, the follow-up of tutorial assistance requests, etc. Special attention has been given to the peer-tutoring process. Indeed, a particular management is associated with the requests for assistance issued by the learners to the learners-tutors as well as the answers and the announced appreciations.

Finally, through the carried out experimentation on the implemented system, several remarks and suggestions were made. We further seek to improve this system, and we suggest adding a learner annotations tracking tool, customizing and proposing an alternative algorithmic tool to predict at least the learners' withdrawal from their tracks just before completing their training.

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