COLLABORATIVE TUTORING: A MULTI-TUTOR APPROACH

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ABSTRACT:

An Intelligent Tutorial System (ITS) is a learning computer environment. Many ITSs do not integrate human tutor since they are designed to use in autonomy by the learner. One of the reasons to increase the rate of desertion in a distance training framework compared to that of a face-to-face course is the absence of the human killer. Besides, the existing ITSs are dedicated to a single learning object based on domain-dependent modelling. Our contribution consists in proposing an ITS, independent of the learning domain, capable of initiating learning, of managing an articulation between machine tutoring and human tutoring (teaching and peers) to offer an individualized and personalized follow-up, and ensure certification of the learner’s assessment.

1. INTRODUCTION

The automation of life is always on the rise, exceeding human limits and overproducing especially in the information. Technology and the media invade personal life.
On the other hand, the time spent concentrating and especially the search for useful and necessary information is seeing a decrease. This generates a very high rate of students in great difficulty leading to a high dropout rate. A higher evaporation rate characterizes the first university cycles in the first year compared to other possible courses in higher education.

Recourse to technical and above all, intelligent assistance is necessary. And unlike decision support systems, usually intended for specialists, we are here facing a broad and tremendously varied audience.

Faced with these persistent inequalities, these failures or dropouts, changes in the transmission of knowledge, new learning approaches are emerging and put learners at the center of the learning system, both inside and outside the classrooms, both face-to-face and remote (e-learning).

Experience has shown that it is tough to set up an autonomous or semi-autonomous system that allows good follow-up and practical support for learners. The last global crisis of the Corona pandemic has highlighted this problem and confronted us with the situation where we have to rethink the question of distance education differently.

In this article, we study how the massification of universities, such as the University of Agadir (10,000 students at the Faculty of Sciences), implies the need to rethink the learning process to maintain the quality of teaching in the face of three scales of requirement: versions of their papers.

- To be able to support students and provide them with quality training in the three study cycles. The learner becomes an active actor who participates in the achievement of his learning.
- To be able to help the teacher in supporting students in difficulty. Taking into account the number of students, the particularities of these and the time available to the teacher, it’s often tough for the latter to understand all the difficulties of a student, to identify precisely his strengths and his weak points, and therefore to determine which activities can bring him maximum gain in his learning.
- Be able to offer international training. Students enrol in a system where they can take distance courses, validate certificates and benefit from inter-university communications and collaborations.

For (Hafner, 2004) an Intelligent Tutorial System (ITS) is teaching software containing a part of artificial intelligence. The software tracks the students' work progress and offers them personalized feedback. The analysis of the work of a given learner allows the software to propose avenues to guide him according to his strengths and weaknesses.

First, the specific properties of the problem that are treated with an ITS are identified, followed by choice of structure and data processing. Finally, the modelling of the system kernel is detailed.

2. INTELLIGENT TUTORIAL SYSTEM

Tutoring is a form of teaching that has two main features compared to classroom teaching. The first characteristic concerns the tutor/student ratio, which is generally 1/1 (or 1/2, 1/3). The tutor's attention is, therefore devoted to one student at a time. The second characteristic concerns the role of guide in the lessons exercised by the tutor. Tutoring plays an inverse role in classroom teaching. In the classroom, the teacher asks each student to adapt to a typical lesson for the whole class, while the tutor tries to adjust his intervention to the needs of a student (Nkambou et al., 2010).

Following the various publications on tutoring and its effectiveness (Cohen P., Kulik J., 1982), (BLoom, 1984), (Wenger, 1987), the AIED (Artificial Intelligence in Education / Artificial Intelligence in Education) research community has used the notion of tutoring to develop Intelligent Tutorial Systems (ITS). ITS are computerized learning environments that aim to mimic and simulate the behaviour of a human tutor in his capacities as an expert teacher and expert in the field. As with teaching, the two main functions of tutoring are: (i) to stimulate learning and (ii) to evaluate it. In the ITSs, these two functions are dealt with separately or jointly.

According to Woolf (Woolf, 2009), an ITS is made up of four main parts (Figure 1):

- Domain model: refers to the expert's knowledge of the domain and the subject taught;
- Learner model: represents the skills and actions of the learner;
- Tutor model: makes educational assistance choices based on the two previous models;
- Interface: allows interaction between the learner and the system.

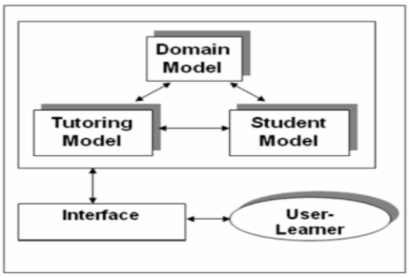

Fig. 1. The components of an ITS (Nkambou et al., 2010)

The real-time adaptation of the educational situation to the learner is one of the major objectives of ITS. For this ITS is based jointly on the learner model and the tutor model. Classically, the "learner model" refers to what the learner knows, what he has done, his learning strategies, etc. The information represented by this model can be the learner's skills, metacognition and his emotional characteristics. This information is generally inductions made by the system on the learner.

These inductions are built by observing the interactions that the learner has had with the system and by measures of learner performance such as the time to complete a task and the errors observed. The learner model does not make any decisions; it only provides information to the tutor's model so that the latter can adapt his interventions to the learner.

Based on the knowledge of the domain model and the learner, the tutor model monitors interactions between the system and the learner on an ongoing basis to ensure that the tutor's strategies are adapted to the learner. The tutor's behaviour must be performed in real-time, and the main challenge of the tutor model is to identify when and how to intervene to help the learner (Razzaq, L., Patvarczki, J., Almeida, S., Vartak, M., Feng, M., Heffernan, N. & Koedinger, 2009).

3. OUR APPROACH

Computer systems for online Learning have traditionally been structured around a single educational module: an artificial tutor. He has expertise in one area of knowledge and applies a teaching strategy to interact with a learner to help him solve a given problem. This principle of operation, in autonomy, of the couple (learner / tutor_machine) can be satisfied until the system reaches its limits; the presence of a human teacher, or even of another learner (a peer) then becomes essential.

Today, the field of distance education is based on digital networks. These networks allow learners to access learning software, whether specific or offered as web applications. The desertion rate is 10 to 20% higher when compared to that of a face-to-face course. How can we minimize this risk in the knowledge acquisition process? Our multidisciplinary approach brings together researchers in computer science, cognitive science, didactics and sociology. The problem is to integrate the analysis of the pedagogical needs of the learners and also the taking into account of the relations between peers within an intelligent tutorial system. This aims to offer the learner, personalized support adapted to their needs and skills.

In this article, our problematic to minimize the risk of learner abandonment, therefore, consists of a theoretical reflection on the process of learning alone or in groups in front of the machine, of the taking into account of this work to detect and prevent at best the difficulties encountered by the learner and the experience of an environment that is both fun and well suited to simulation.

Rethinking learning and taking an orientation towards intelligent tutoring to integrate the learner's profile, anticipate cases of abandonment or failure and help the teacher, requires working on a deep articulation and overall between “machine” tutoring and “human tutoring” (teachers and peers).

“Human” tutoring can come from both teachers and other students who have already integrated advanced concepts and could, therefore, come to the aid of students in difficulty. Their approach could be better because it is different from that of the teacher in charge of the course. It is, therefore, necessary to design a ITS which:

- takes into account the mobility of learners,
- provides individual follow-up to respect their learning pace,
- provides them with a human presence among all available educational resources.

We propose to implement such a system in addition to formal education. It is a question of providing the students with an additional means for their learning and the teachers and device to follow the learners better. The question of the autonomy of the learner in a hybrid situation will be one of the essential issues of educational and computer modelling.

For the learner, the ITS will allow him to have several types/levels of tutoring. Thus, during his learning journey, he will be able to switch between machine tutoring and human tutoring (teacher or peers).

For the teacher, the ITS will offer him the means to devote himself more to the learners who have exceptions (difficulties or excellence) and who require support that machine tutoring or peers cannot provide.

Adapting the learning environment to meet the specific needs of each learner is the expected objective of ITS.

Therefore, the use of this teaching strategy applies to multiple areas. In this sense, there are several ITSs but they are specific to a single subject (algebra, geometry, LISP language, BASIC language…).

The development of tutoring in ITS, whether it is about services, components or functions integrated into another component, expresses the choices that are made in terms of paradigms of cognition.

Software environments are specializing in the development of ITS called author systems. These author systems are also associated with a paradigm. In this sense, sharing and reuse are limited to systems of the same category (Murray, 2007). In addition to authoring systems that aim to develop the entire system, some tools specialize in a component (TCHETAGNI J, NKAMBOU R., 2006). Some simplified, high-level, paradigm-specific authoring tools have been developed to increase accessibility and reduce development costs(Razzaq, L., Patvarczki, J., Almeida, S., Vartak, M., Feng, M., Heffernan, N. & Koedinger, 2009).

In this paper, we propose an original approach to the development of tutoring in ITS. Our approach is made up of three modules (Fig 2):

i) Learning module: use of an exiITSng learning platform, Learning Management System (LMS) to retrieve the tracks of the learner, example Chamilo (ref: https://docs.chamilo.org/fr/).
ii) Intelligent tutoring module: responsible for providing existing LMSs with a module capable of offering personalized tutoring, individualized and independent of the learning subject. Besides, this module offers articulation between “machine” and “human” tutoring.
iii) Certification module: implementation of a certification module for acquired skills so that students can more easily promote their skills with companies and therefore achieve better employability. This module is based on BlockChain technology which can be considered as a "database" with the originality of being open, tamper-proof and distributed. A Blockchain interrogation tool will allow companies to verify the authenticity of certificates presented by job applicants and thus rule out suspicions of forgery. This module is entirely independent of the learning subject.

However, this article focuses on the smart tutoring module.

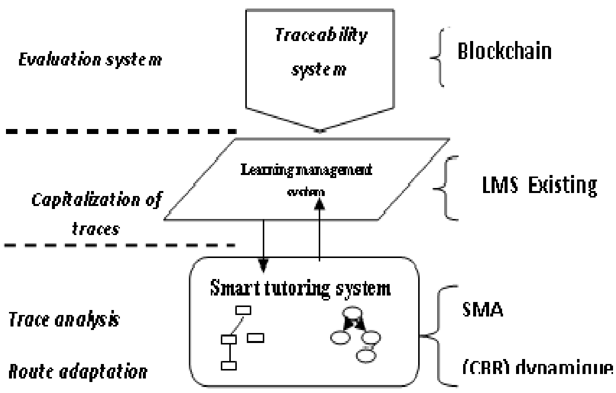

Fig. 2. Generic ITS model

4. ITS ARCHITECTURE

4.1 ITS Architecture

The function of tutoring in ITS is divided into two parts: the diagnosis of the learner's knowledge (for example, the detection of the causes of errors) and the choice of remedial strategies (Nkambou et al., 2010).

There are three categories of methods for performing the tutoring function:

• Methods based on metacognition,

• Methods based on artificial intelligence (AI) and track analysis,

• Methods based on cognitive architectures.

Our method is in the IA and track analysis category. This approach does not seek to model the mechanisms of human learning but aims to identify, based on the actions of the learner, the new knowledge to bring to it. Bayesian networks are one of the techniques that allow this type of tutoring to be carried out (Desmarais & Baker, 2012),(Ramírez-NoriegaA & Al., 2017) and (Mousavinasab & Al., 2018).

For the representation of the tutor, Woolf (Woolf, 2009) and Nkambou et al. (Nkambou et al., 2010) use a breakdown similar to that of Wenger (Wenger, 1987), by presenting architectures taking into account recent technological developments. One of the avenues mentioned is the use of multiagent systems. The dynamic aspect of the situations to be managed during an apprenticeship led us to choose the use of such a system.

In this article, we propose a method that is part of the AI and track analysis approach. Our method is based on Case-Based Reasoning (CBR), multiagent. It is reasoning by analogy based on the following hypothesis. If a situation A resembles a situation B, then the consequences of situation A will be adaptable to those of situation B.

The overall architecture of our ITS takes up the division of Woolf (Woolf, 2009). It consists of the following three components (Fig 3):

i) Domain model. To ensure the genericity and reuse of our system, we use ontologies that offer a solution to manage the heterogeneity of ITS and their paradigms. Ontology makes it possible to explicitly link educational strategies to different cognitive and educational theories (HAYASHI Y., BOURDEAU J., 2009). Our approach separates the representation of knowledge, by nature specific to the field, and its treatment. This provides a system independent of the area to be taught. In other words, our system will apply to different fields such as the teaching of human sciences, languages for engineering sciences.
ii) Learner model and tutor model. We estimate that these two models are strongly linked, and therefore we propose for their modelling to implement reasoning starting from a dynamic case-oriented agent.
iii) Interface. These are the graphical and adaptive interfaces for the different ITS actors/users.

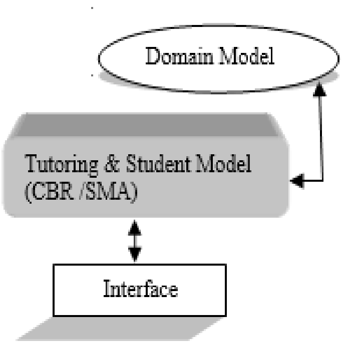

Fig. 3. Model Student Tutoring

4.2 Case-Based Reasoning

The CBR(Kolodner, 1993) presents itself as a reasoning methodology by analogy and also a learning methodology from the field of AI, capable of using specific knowledge from past experiences, formalized in the form of concrete problematic situations called in some cases. This problem-solving technique has its origins in psychological models of memory and human expertise.

A new problem is solved by finding the most similar past case and using it for the resolution of the new problem situation. CBR incorporates an important characteristic, that of learning. It allows to update existing cases, to learn new cases.

The CBR cycle has several phases (Aamodt and E. Plaza, 1994) (Fig 4):

i) elaboration of the target case: the shaping of the problem.
ii) recall: a selection of a source case from the case base similar to the target case.
iii) adaptation: the resolution of the target case based on the recalled case. Reuse the solution from a similar case.
iv) validation: once the target problem is solved, we have a new case (target, solution (target).
v) memorization: memorization, if necessary, of the new case in the case base for the resolution of future problems (learning phase).

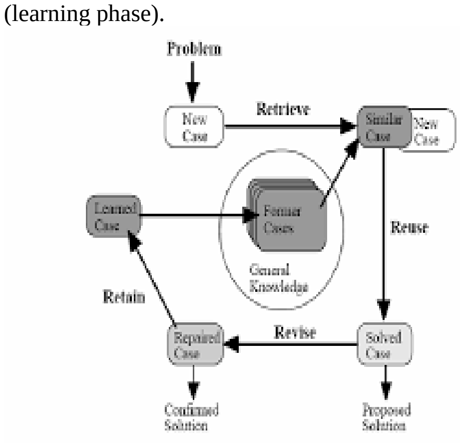

Fig. 4. Case-Based reasoning

4.3 Our system: constraints

The system we are proposing must also take into account the evolving and dynamic nature of the route to be analyzed. The analysis is based on the reconciliation that the system will make, continuously, between the learner's course and past tracks.

The tracks are described by all of the determining aspects in its development. We call here a determining aspect, a fact which played an effective role in the way in which the events unfolded.

The use of a human tutor (peer/teacher) requires detecting that the learner is in a situation such that only the intervention of a human tutor is necessary. It is a question of detecting during the learning activity, the behaviours likely to present pedagogical risks, of identifying them compared to existing cases then of determining if a feedback "machine" or human is the best adapted for providing the necessary feedback.

Knuth (Knuth, 1997) defines a data structure as an array comprising structural relationships and whose processing is done by algorithms for accessing and / or modifying the structure (Murray, 2007). In the field of education, intelligent tutoring systems are complex systems, the main characteristic of which is the number of dynamic data to be modelled and interpreted to provide answers to learners (Clemens, 2005). In agreement with Wooldrigde(Wooldridge, 2009), to take into account the dynamic aspect of learner tracks, we have chosen a multiagent System (SMA) for the organization of the data.

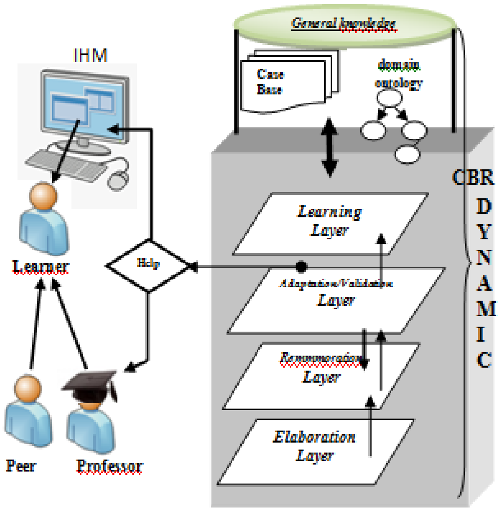

Fig. 5. Multiagent Multi-level architecture

5. CBR AGENT ORIENTED

5.1 CBR and dynamic system

We are interested in the problem presented by the development of dynamic and reactive systems, capable of adapting quickly and gradually to changes in the needs and uses of their users. The development of such applications requires taking into account the fact that the needs and changes in uses cannot be anticipated. To meet this requirement, we propose the implementation of such reasoning to make these systems adaptable. Within the framework of classic CBR, the system's ability to adapt is limited by the fact that knowledge models and reasoning mechanisms are defined during the design stage and are therefore very difficult to evolve.

This article deals with reasoning based on multiagent cases (Agent-oriented), reasoning which exploits the tracks of interaction left by the learner. Interaction tracks are used to memorize the learner's problem-solving experiences, and thus to reuse them. Interaction tracks are also used as sources of knowledge to generate other knowledge useful for the reasoning process.

This paper describes the principles of this multiagent CBR and proposes a general architecture for the development of tracks - based applications**.**

5.2 The Tracks

This multiagent CBR aims to bring more dynamic and flexible solutions to the problem of experience reuse. This reasoning is based on the exploitation of interaction traces. By interacting with a system, the user produces traces that constitute digital borrowings of his own experiences.

The trace is the central object of our approach. A trace represents the result of the tracing of the user's interactions with the system. Past experiences, which we will call "sequences", are remembered in case of similarity. This mechanism guarantees the flexibility and adaptability of the reasoning process.
Sequences are always linked to the traces that contain them. Therefore, at any moment, it is possible to find indicators related to the current sequence and use them to feed the reasoning process. In this way, multiagent CBR makes it possible to manipulate and reuse experiments in a much less constraining way than if they were represented as structured and static cases.

5.3 Multi-agent CPR: cycle

Compared to the classical CBR (Aamodt and E. Plaza, 1994), the multiagent CBR we propose, aims at the same principle: to find a past experience, then adapt it to bring a solution to the current problem. But in practice, the mechanisms implemented are different.

In our context, we can no longer consider reasoning as a cycle made up of five successive and identifiable stages. On the contrary, the steps are intertwined and the back and forth between the steps multiply to clarify the description of the problem as well as its resolution.

The implementation of our solution requires a scientific approach involving three steps:

- The first stage called the stage of construction of the learning base. It describes the learner's behaviour in the form of empirical knowledge represented as a case. This set of cases forms the learning base.
- The second stage called the target case construction stage. The set of traces, coming from the LMS, forms the target case. This target case has two properties: it is dynamic and incremental.
- The third stage of reasoning and learning allows, on the one hand, the personalized follow-up, machine or human, of the learner and, on the other hand, the updating of the case base following the appearance of new unknown behaviors.

We focus on a very close interaction between the machine and the user (tutor/learner) because the system is very dynamic and interactive. This dynamicity makes classical learning, which is based on a simple update of the knowledge base, difficult. Collaborative learning is therefore necessary. This has led us to rethink the system or the reasoning mechanism.

We have implemented an "agent-oriented" CBR. It is moreover reasoning based on dynamic cases. The target case is an evolving set of traces, so our new CBR must take this evolution into account incrementally. In other words, we should not consider each evolution as a new target case.

The architecture is based on 4 levels of agents leading to a pyramidal relationship (Fig 5).

i) The lowest level allows the dynamic and incremental elaboration of the target case (current situation). The aim is to clearly identify the problem and then to build a set of indicators that will allow to dynamically find a similar sequence in the trace.
ii) The second level implements a dynamic and incremental recalling process allowing the search for past situations similar to the current situation. Recall consists of finding this sequence. It is a matter of constructing the right sequence, by selecting the right indicators in the trace.
iii) The third level is in charge of giving feedback. Adaptation is also different, since the adaptation strategy no longer depends only on the problem to be solved, but also on the type of sequence remembered.
iv) The last level is in charge of feeding the case base. The entire architecture allows the scenarios found to be evaluated as changes occur in the observed situation.

6. CONCLUSION AND PERSPECTIVE

The proposed approach aims to rethink the e-learning system to create a real support and monitoring system. Within the Faculty of Sciences of Agadir, 19% of students obtain their bachelor's degree in 4 years, 7% in 3 years, and 37% whose situation is almost unknown. It is, therefore, necessary to support students entering university differently, as the transition from high school to university remains difficult for the majority of new students.

Our intelligent tutorial system will allow teachers to follow students in difficulty better and efficiently. It will facilitate the detection of difficulty points in a personalized way for each student. The "machine" tutor will help the student in essential learning that does not require human intervention. The teacher will be able to find his rightful place in the learning process.

The proposed model is generic and adaptive: it will apply to any object and type of learning and will adapt to the different students' learning paths. Through this system, we will provide, in a configurable way, two types of deliverables. The first will be intended for university training to deal with the problems of massification and inter-university collaboration. The second will concern a restricted public to obtain professional certifications.

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