An Adaptive Learning System based on Tracking

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Abstract: Success in training is an opportunity that must be offered to each student. However, many universities are experiencing high rates of failure and dropout, especially during the first year of higher studies. We believe that creating a process based on personalization of teaching can contribute to the decrease of failure rate during undergraduate studies. To achieve this goal, we are specifically interested in online learning supported by a Learning Management System (LMS). We have integrated, in a previous works, new tools using traces of learners' activities during collaborative works on an LMS. We therefore propose a system based on intelligent agents. We are designing smart dashboards, automating detection of specific learners' difficulties in order to offer alternatives or solutions to their problems.

1 INTRODUCTION

According to the study published by INSEE[1] (Dardier et al., 2013), learners' failure and professional trajectories consisting of unemployment and limited-term employment are often linked to three main factors: history, educational level and socio-demographic background, orientation during the educational path.

The first factor – history - is linked to the nature of the learning path (difficulties encountered, changes in orientation, absenteeism, etc.). The second factor – educational level and socio-demographic - is dependant of the environment in which the learner operates outside of study hours: parental education, family income, etc. Finally, the third factor – orientation during the educational path - concerns specialties choosen during the school career. This study also notices that "the Baccalauréat holders registered in technological degrees drop out less often than those registered in generalist formation" (27% against 29%). According to the study, individualized follow-up offered in technological formations benefits to students.

Several reforms and actions have been undertaken by the French state and other members of the OECD (eg: Multi-year plan against poverty and for social inclusion launched). A slight drop in the rates mentioned above is observed (ie: -3 points on the rate of leavers without a diploma in 2015, -0.8 points of the rate of young people without a job, or training at the OECD level in 2015) . This progress is due to a more regular and personalized monitoring and to the integration of new technologies in training and education services (interactive platform, MooC for employment for example).

The objective of our work is to design and develop an effective model of adaptive learning. Our model is designed to detect the learner profile and to measure, in real time, the evolution of the learner's skills. The aim is to permanently adapt the flow and form of resources and to offer methods fitting the needs and profile.

Two levels of individualization will therefore be dealt with by the designed model:

1 - Recommendation on resources and disciplinary contents.

2 - Recommendation on the type of support (peer-learning, tutoring, etc.) adequate for the detected profile.

The tool should offer monitoring functionalities for teachers and training managers. These functionalities are necessary to follow evolutions of learners' skills and eventually prevent the risk of dropping out or not completing the training. Alerts

[1]INSEE: Institut National de la Statistique et des Etudes Economiques

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will notify actors (tutor, teacher, training manager, etc.). Detailed situation reports (blocking points, type of assistance needed, risk of dropping out, recommendation for a solution, etc.) will allow regular and individualized monitoring.

2 RELATED WORK

Researchers have been largely interested in adaptation of educational systems. However, most systems are used for specific context such as the ELM-ART system (Brusilovsky et al., 1996). ELM-ART is an adaptive hypermedia system designed to learn the LIPS language.

More recently, we notice that ontologies are largely used, as a basis for modeling in adaptive systems. For example, in (Henze et al., 2004), authors use semantic web to create learning scenarios and to structure the courses. In (Muruganandam et al., 2017), ontology is used to model the learner profile.

A system called Manhali is presented in (El Haddioui, 2015). It allows an adaptation of educational strategies according to the behavior and the learning style of the student. Based on the learner's profile, adaptation is made on three levels: graphic aspect of the platform according to the configuration of the learner's machine, adaptation of scientific content taking into account the skills of the learner and adaptation of teaching strategies according to behavior and style of the learner.

(Chachoua et al., 2016) uses traces left by learners when they are active on an elearning system. Duration of an activity and the number of attempts to solve a problem are the traces that interest the authors. These traces are used for building an evaluation model. This model is integrated in an adaptation model based on ontological rules and an adaptation algorithm. The result is adapted resources and learning strategy.

(Nafea et al., 2017) proposes an adaptive engine that can be integrated into any LMS. It is based on rules written in a rule-based reasoning algorithm.

3 ILLUSTRATION CASE

To illustrate our approach, a case study is presented hereafter. It is adopted from a real situation we encountered: G. is a first-year student at the information Technology department of the IUT. He starts his formation with 80 other students (each one being "unique"). The training manager sends an email to the educative team to inform about the situation of this student. Here is a summary of this email:

G. can only read with the help of his audio device (and very hardly without). He hardly knows how to write and has difficulties memorizing information. He regularly forgets the meaning of simple words and is not able to organize his ideas and to express them. He has trouble doing calculations and he can't focus for long time. He can't stop moving or walking for a long time also. Finally, G. may, under significant stress, be unable to speak and to hear what is said to him.

So far, G. has benefited from a support service. He is worried because he finds it hard to imagine studying without this system that had allowed him to have a certain balance in high school. However, G. is courageous and of good will.

Although it is very complicated to make the necessary adaptations for this student, the training manager recommends that each teacher consider this question and thinks about what to do for this student in his teaching

G. will obtain (among other things) the right to use his computer during exams as well as the right to have the exams adapted (with reading and / or reformulation).

This case perfectly illustrates the specific conditions in which adaptation is needed to offer ways to reduce the risk of failure of a student.

4 PROPOSED SYSTEM

We focus the Moodle LMS. We are working on adaption of scenarios and contents in order to detect specific learning difficulties of the audiences and to best meet their specific needs (offering the adequate learning scenario, the adequate resources in the right form and a correct learning pace).

4.1 System Functionalities

A smart tracking system should then offer:

- Identification of learners who have a risk of learning difficulties;
- Identification of the nature of problem (poor assimilation of knowledge, unsuitable resources - in content and / or format, etc.);
- Adaptation of the learning scenario, the resources offered, the learning pace, the support, etc. to each of these learners having difficulties.

So, the proposed system is based on two steps:

- **Tracking Learners:** creation and real-time updating of a learner model to identify students or learners who have problems or risks. Detection of the nature of these problems;
- **Adaptation:** presentation of alternatives or specific solutions to these problems.

In a previous work (Talon et al., 2013), we have developed a multi-agent system for tracking students' activities and calculating indicators. This system collects various traces on the ILIAS learning platform in the context of collaborative projects. These traces are aggregated in the form of indicators (of different categories). A dashboard allows the teacher to assess activities of the students. It allows, for example, detection of inactive students called "sleeping students". Dashboards form a space where teachers can appreciate activity and participation of each student but also offer to students a way to be aware of their real activity. All the developed indicators are purely informative.

Now, we go further by adding:

- "Traces on demand". The teacher will choose data he wants to collect and combine in order to personalize a learning path.
- "Indicators formulation on demand". The teacher will create his/her own and specific indicators. He/She will select elements in the traces database and will determine the rules that, according to him/her, should be applied to formulate them.

4.2 A Multi-agents Platform

This tracking system uses agents to collect traces, to update the learner model and to develop indicators enabling the personalization of pedagogical scenarios.

Agents are responsible for collecting traces during the training of a student: his success, the number of time he takes the tests to succeed, his presence time on the LMS, the time he needed to resolve a problem, etc. They also generate indicators according to the teacher's will, present them in the teacher's dashboard and they are always looking for the presence of conditions requiring the adaptation of the scenario.

This system implies that the teacher:

- Defines and implements a "standard" scenario in which he offers different resources according to each cognitive ability (level 1 of adaptability). Example: a common process to develop the meta-competence VARIABLE (knowing and understanding the concept of variable, declaring a variable, different type of data, etc.).
- Defines the indicators (on demand) that will allow differentiating between students. For example *abstraction_level*, is an indicator that increases when a student fails in exercises related to the notion of understanding what a variable is. These indicators allow the teacher to define rules. Thus, if the student has an *abstraction_level* indicator less than 8, then he should watch some specific videos before passing the same scenario again.

If the adaptation of scenarios proves to be unsuccessful, the system notifies the teacher who can decide to modify the again or to deactivate them.

4.3 Learner Model

To face the needed adaptation of systems, data are collected about learners and their activities in a specific model called a learner model (Tack et al., 2016).

Indeed, a learner model "*consists of meta-knowledge which includes the instructional decisions about a learner*" (Kaya et al., 2011). As M. A. Tadlaoui and al. said in (Tadlaoui et al., 2016), "*the main objective of learner model is to modify the interaction between the system and the learner in a dynamic way to address the needs of each learner on an individual basis*". So, the learner model is necessary to adapt the learning process to individual learning needs. As it is said in (Gong, 2014), "*the student model is the core component in an ITS"*. In (Tmimi et al., 2017), it is judged to be useful in the phase of learning and adaptation in an adaptive hypermedia.

Y. Gong (Gong, 2014) developed the idea that a learner model should integrate two elements: the learner behavior when using the system and personal properties such as the knowledge of the learner, performance, etc.

To build a learner model, different methods exist: cognitive science method, machine learning method or both at the same time.

The data contained in a learner model are of different types:

- **Learner Data,** which are personal information: identity, gender, age, etc. gathered during the registration process. It is a static view of the learner model.

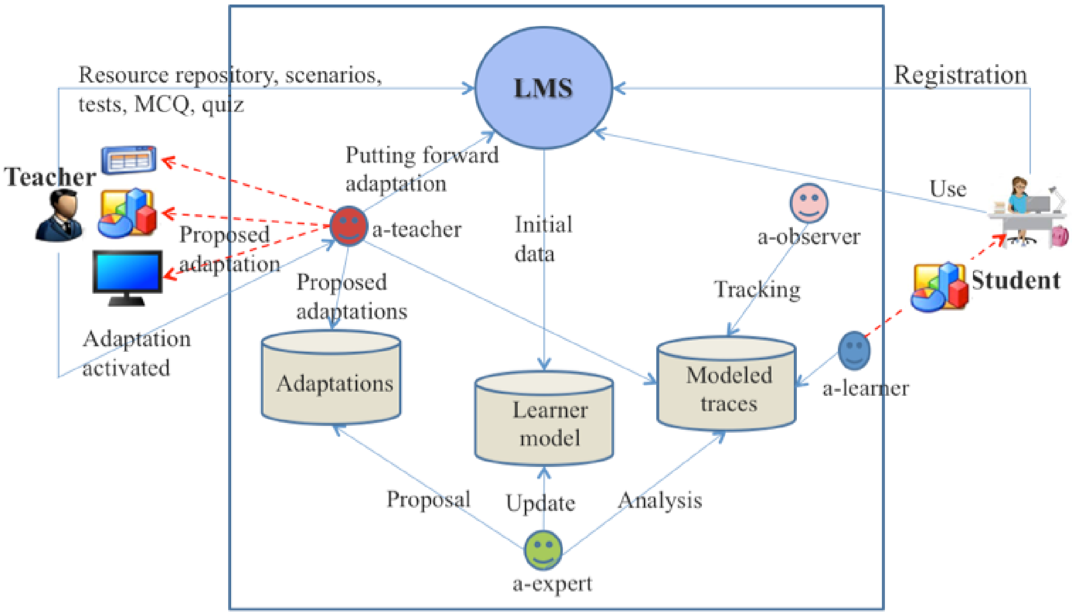

Figure 1: System architecture.

- **Pedagogical Data:** Competency, knowledge, program and subjects sequence.
- **Personality Data:** learning style, learner features and preferences in learning. They can be collected through tests conducted in LMS.
- **LMS Experience:** used to identify whether the learner is familiar with a certain LMS.
- **Cognitive Data:** defines the preferences of the learner. They can be obtained through tests conducted in LMS.

We integrate all these information in the learner model.

4.4 System Architecture

The personalization of learning is now initiated on the multi-agent platform presented in the paragraph 4.2. In such a system, acting in a virtual environment requires that the agents can make a representation of the learning situation.

Agents must be able to have a representation of the environment, the learner's task, the educational actions to be carried out.

A first set of questions concerns the user’s environment. What are the objects that constitute the universe of the learner and where are they located? What are their properties? What are the possibilities of action on these objects? What behaviors can they have? What interactions exist between these objects?

Concerning the representation of the learner's task, it is necessary to know which actions the learner is supposed to perform (and if there are chained constraints) and which actions have been performed (with success or not). An agent must be able to explain what to do, possibly to do for or with the learner. In a context of collective work, where responsibilities are shared and defined by rules, it is moreover necessary to know if it is the right person who carries out an action.

The last type of questions concerns educational interventions. An educational agent must be able to give information on the learning situation (accessible objects, task progress), but it must also to modify the environment for an educational purpose: in order to adapt to the learning, it may be necessary to simplify the problem, by masking some elements or by inhibiting some interactions.

Figure 1 presents the system architecture. The different agents present in the system are the following:

- a-observer: It tracks every action done by the student when using the LMS. The raw traces are cleaned and treated to get modeled traces;
- a-learner: It presents some indicators on the dashboard of the student. These indicators help the student to see his difficulties and to get feedbacks regarding his learning;
- a-expert: It is a smart agent. It analyzes the modeled traces to update the learner model. It suggests adaptations to the teacher. Four adaptation levels can be proposed:
    - Navigational level proposes an order of educational sequences

- Content level proposes adequate resources according to the student's knowledge and in relation with the corresponding sequences
- Presentation level determines the better form and nature of the resources
- Learning process level which defines specific learning methods to adopt during sequences

▪ a-teacher: It presents to the teacher tables and graphs offering a monitoring space and calculate indicators that will be displayed on.

5 CONCLUSIONS AND FUTURE WORK

In this paper, we proposed an agent-based Personalized Learning Architecture. The system is characterized by the following properties:

- A learner model to store and permanently update learner's profile.
- Learning strategies according to the learner's profile.
- Scenarios chosen by the course manager based on prerequisites and learner's profile.

Ontologies play an increasing role in the new generation of information or knowledge-based systems. It is also a keystone of multi-agent systems using high-level communication (Freitas et al., 2017).

Our work is in progress. It consists firstly in finalizing the ontology of the learner model. Secondly agent integration and personalization of scenarios will be dealt in the Moodle environment.

Our challenge is to identify, from traces and questionnaires deployed throughout learning processes on Moodle, the common trajectories leading in achievement of objectives, and in academic and professional success.

REFERENCES

Brusilovsky, P., Schwarz, E., Weber, G., 1996. ELM-ART: An intelligent tutoring system on World Wide Web. In *Intelligent Tutoring Systems, Lectures Notes in Computer Science*, Vol 1086.

Brusilovsky, P., 2001. Adaptive hypermedia, *User Modeling and User Adapted Interaction*, 11(1/2), pp87-110.

Chachoua, S., Tamani, N., Malki, J., Estraillier, P., 2016. Towards a Trace-Based Adaptation Model in e-Learning Systems. In *The 24th International Conference on Computers in Education*, Nov 2016, Mumbai, India. hal-01899912.

Dardier, A., Laïb N., Robert-Bobée I. 2013. Les décrocheurs du système éducatif : de qui parle-t-on ? in *France portrait social*, édition 2013 INSEE Paris

El Haddioui, I., 2015. Manhali : un système de gestion d'apprentissage adaptatif pour la modélisation du comportement et la détection du style d'apprentissage de l'apprenant. In *7ème Conférence sur les Environnements Informatiques pour l'Apprentissage Humain (EIAH 2015)*, Jun 2015, Agadir, Maroc. pp.462-0. hal-01405992.

Freitas, A, Panisson, A., R., Hilgert, L., Meneguzzi, F., 2017. Applying ontologies to the development and execution of Multi-Agent Systems. In *Web Intelligence, vol. 15, no. 4, pp. 291-302,2017.*

Gong,Y., 2014. *Student Modeling in Intelligent Tutoring Systems*, Doctoral dissertation, Worcester Polytechnic Institute.

Henze, N., Dolog, P. Nejdl, W., et al., 2004. Reasoning and ontologies for personalized e-learning in the semantic web. In *Journal of Educational Technology & Society*, 7 (4), 82–97.

Kaya, G., Altun,A., 2011. A Learner Model for Learning Object Based Personalized Learning Environments, Communications. In *Computer and Information Science, October 2011*.

Muruganandam, S., Srininvasan, N., 2017. Personalised e-learning system using learner profile ontology and sequential pattern mining-based recommendation, In *Int. J. Business Intelligence and Data Mining*, Vol. 12, No. 1, pp.78–93.

Nafea, S. M., Siewe, F., He, Y., 2017. An adaptative learning ontological framework based on learning styles and teaching strategies. In *Proceedings of 85th ISERD International Conference, Cairo, Egypt, 11th-12th September 2017.*

Parmentier P. 2018. La réussite des étudiants, objectif de la transformation pédagogique. In *Journées nationales de l'Innovation pédagogique dans l'Enseignement supérieur.* 20 Novembre 2018

Tack, A,François, T., Ligozat, A.-L. Fairon, C., 2016. Modèles adaptatifs pour prédire automatiquement la compétence lexicale d'un apprenant de français langue étrangère. In *JEP-TALNRECITAL 2016*, Jan 2016, Paris, France. Actes de la conférence conjointe JEP-TALN-RECITAL 2016. <hal-01631772>.

Tadlaoui, M. A., Aammou, S., Khaldi,M., Carvalho, R. N., 2016.Learner Modeling in Adaptive Educational Systems: A Comparative Study.In*International Journal of Modern Education and Computer Science, vol. 8, n° 13, p. 1.*

Talon, B., Kerkeni, I., Tliche, S., Belaïd Ajroud, H., 2013.Tracking a collaborative Web 2.0 learning environment. D. In *Hernandez-Leo et al. (Eds): EC-TEL 2013, LNCS 8095, pp 577-583*. Springer-Verlag Berlin Heidelberg.

Tmimi, M.,Benslimane, M., Berrada, M., Ouazzani, K., 2017.A Proposed Conception of the Learner Model for

Adaptive Hypermedia. In *International Journal of Applied Engineering Research ISSN 0973-4562Volume 12, Number 24, pp. 16008-16016.*
Wenger, E., 1987. Artificial intelligence and tutoring systems. Computational and cognitive approaches to the communication of knowledge. San Francisco, *Ed CA: Morgan-Kaufmann.*