Learner Behavior Analysis on an Online Learning Platform

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Abstract—This paper introduces the study of the learners' behavior on e-learning platform to create profiles that regroup learners according to their behavior on the platform. This system can be used by the learner-agent of an intelligent tutoring system (ITS). Thus, this system will allow us to better understand the learner in a virtual learning environment to improve the learning situation by placing the learner at the center of the learning process.

Index Terms—E-Learning, intelligent tutoring system, learner behavior, learner profile.

I. INTRODUCTION

It is clear that human interaction in a classroom is not the same in the particular situation of a user against a machine. His relationship to others and to the discipline is changed. The relationship: Teacher-Discipline-Student is replaced by the relationship: Teacher-Discipline-Media-Student.

For this reason, and to keep the interaction in a virtual learning environment, the receiver should not be a simple student but a learner. The difference is that the student is just a receiver of information. However the learner is an active and social person, is an actor in his own learning. The learner leaves - by using the pedagogical tools of the platform and the achievement of collective work (collaborative and cooperative) - a set of traces on the platform.

Our goal is to create a behavioral analysis system, able to use these traces to create profiles that clustering the learners who have the same behavior. This can facilitate the creation of pedagogical assistances in an intelligent tutoring system.

II. INTELLIGENT TUTORING SYSTEM

An intelligent tutoring system (ITS) is a system that provides direct customized instruction or feedback to students without the intervention of human beings.

Intelligent tutoring systems consist of four different subsystems or modules:

- The interface module: provides the means for the student to interact with the ITS, usually through a graphical user interface and sometimes through a rich simulation of the task domain the student is learning.
- The expert module: references an expert or domain model containing a description of the knowledge or behaviors that represent expertise in the subject-matter domain the ITS is teaching.
- The student module: uses a student model containing descriptions of student knowledge or behaviors, including his misconceptions and knowledge gaps.

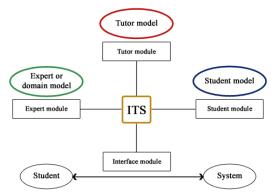


Figure 1. The four modules of the ITS

• The tutor module: takes corrective action, such as providing feedback or remedial instruction. To be able to do this, it needs information about what a human tutor in such situations would do: the tutor model.

III. USING A BEHAVIORAL ANALYSIS SYSTEM INTO AN ITS

In a classical ITS, the pedagogical agent creates pedagogical assistance for learners based on their responses to tests (evaluation method). Our behavioral analysis system will be used by the student module of the ITS, it focuses only on the behavior of learners to assist the pedagogical agent to create more specific pedagogical assistance for all learners, even if the teacher has not yet created a test.

J. Self [12] said that the student model must answer four questions:

- What the learner can do?
- What the learner knows?
- What type of learner is he?
- What the learner has already done?

The most popular intelligent tutoring systems use three basic methods to answer these questions and then build a student model [11]:

- 1. From the rules representing the behavior of the learner;
- 2. From the representation of errors that can be committed by the learner, i.e. a catalog of errors;
- 3. From the direct observation of learner behavior.

Our behavioral analysis system will contain basic profiles. It regularly chooses the appropriate profile for each learner. The pedagogical agent of the ITS chooses a pedagogical assistance for each profile regardless of learners who are present on the platform.

PAPER LEARNER BEHAVIOR ANALYSIS ON AN ONLINE LEARNING PLATFORM

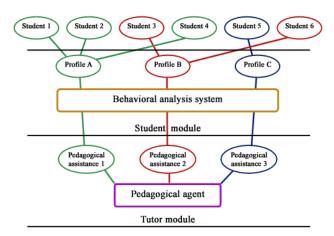


Figure 2. Using a behavioral analysis system into an ITS

IV. BEHAVIORAL ANALYSIS SYSTEM DATA

The behavioral analysis system will be integrated into an online learning platform; this system will use the learner information extracted from the platform, as well as information on learner machine extracted from the web server on which the platform was installed.

A. Data collected from web server

The web server contains environment variables that provide all the information on the learner machine:

TABLE I. Environment variables of a web server

Environ- ment variable	Value	Description	
HTTP_USE R_AGENT	Mozilla/5.0 (Windows; U; Windows NT 5.1; fr; rv:1.9.2.12) Gecko/ 20101026 Firefox/3.6.12	The browser and the operating system of client	
REMOTE _ADDR	81.192.199.13	The client's IP address (e.g. used to find the country of the learner in open platform)	
REMOTE _PORT	7653	The port being used on the user's machine to communicate with the web server	
SCRIPT _NAME	/training/open.php	Contains the current script's path	
REQUEST _URI	/training/open.php? course=1&chapter=3	The URI which was given in order to access this page	
QUERY _STRING	course=1&chapter=3	The query string via which the page was accessed	
HTTP _REFERER	/training/ view.php?action=open	The address of the page which referred the user agent to the current page	
REQUEST _METHOD	GET	Which request method was used to access the page; i.e. GET, HEAD, POST, PUT	
REQUEST_ TIME	1290517719	The timestamp of the start of the request	

B. Data collected from the online learning platform

The learning management systems (LMS) offer more details about learner and some statistics about using the pedagogical tools for each learner on the platform.

We can find a lot of information about learner on an online learning platform:

- Personal information of learner: age, sex, country...
- Statistics of results of self-evaluation.
- Behavioral Information:
 - Number of accesses to the platform;
 - o Access period (morning, afternoon or evening);
 - o Average duration of visits to the platform;
 - Number of visits to each page;
 - o Duration of visits of each page;
 - Page that sent the learner to the current page;
 - o Number of posts on the forum...

C. Eye tracking data

Eye tracking is the process of measuring either the point of gaze ("where we are looking") or the motion of an eye relative to the head. An eye tracker is a device for measuring eye positions and eye movement.

Eye movements provide an indication of learner interest and focus of attention. They provide useful feedback to personalize learning interactions, and this can bring back some of the human functionality of a teacher. With a study of eye movement, learners may be more motivated, and may find learning more fun.

1) Learner's emotion tracking

The data collected from eye-tracking devices indicates the person's interest level and focus of attention. From eye position tracking and indirect measures, such as fixation numbers and duration, gaze position, and blink rate, it is possible to draw information about the user's level of attention, stress, relaxation, problem solving, successfulness in learning, tiredness, and more. Even emotions can be tracked, and based on the data; the eye-tracking system can provide more personalized learning [13].

For example, if the average pupil size has progressively increased within a certain time interval, also user workload may have augmented. A decreased blink rate in the same period would further confirm such a supposition. When detected, such evidences could for example be used to dynamically modify the learning path, proposing a topic related to the main one but less complex (a sort of break). Or, if the user is potentially having problems in understanding something, extra information may be displayed.

Since several external factors may come into play, however, it is practically impossible to be absolutely sure that these signals derive from changes in the user emotional state. Therefore, rather than undertaking direct actions, such as displaying help windows, the system can assist the user indirectly with gradual assistances. For example, when signs of non-understanding or high mental workload are detected, the system simply proposes links to additional material, which progressively enlarge as the signals of stress persist. When eye data suggest that the user may be tired, and the session has been going on for more than a configurable time interval (e.g. one hour), a message advising to take a break is shown [14]. And here are some experimental evidence in psychology / physiology:

- Mental workload depends on the fluctuation of the rhythm of the pupil area.
- Saccade occurrence rate and saccade length decrease with increased complexity of the task.
- Saccadic and blink velocity decrease with increasing tiredness.

2) Learner's interest tracking

We can track learner's interest according to his eye movement on an online learning platform. In this example, we used a free Eye Tracker "Gazetracker 2.0 Beta" to identify areas of interest of a learner on a web page that contains a chapter of an algorithmic course. We have activated the "Eye mouse" option to redirect the mouse cursor to the gaze position. We can use any eye tracker provided that it supports the "Eye mouse".

Figure 3 shows a web page divided into several areas "<div>", each div contains a different type of information of the same chapter and we will calculate the time spent by the learner on each div by tracking the mouse cursor. To do this, we use two Javascript events: onMouseOver and onMouseOut, whenever the cursor enters a div, it starts a timer that calculates the time in milliseconds, and it stops when the cursor leaves the div or when user leaves the entire page, using setInterval() and clearInterval() functions. When the cursor enters again the same div, the timer continues where it stopped last time.

Tracking data will be stored in the database; teachers can find the gaze duration statistics of each area and for each learner. We converted the durations from millisecond to second to make them easier to understand.

The statistics taken from Table 2 and the chart (Figure 4) contain important information that can identify the learning style of each learner. For example, we see that the third learner has spent more time on the text (Div1) than other learners. However, he spent much less time than the others on the Schema and the video. And this means that the text style is the most appropriate style for this learner.

Further analysis on the learner profile such as learning style, tiredness, confusion can also be performed once the data are set. For example a learner with a strong visual memory but weaker verbal processing will spend more time on the picture rather than the text. Once the learner's learning method is identified, the educational content is adapted to provide mainly images and video, rather than text, and thus increasing the efficiency of the learning process.

TABLE II. GAZE DURATION STATISTICS

Course : Algorithms, chapter 3 : Assignment statement						
	Div 1 (Text)	Div 2 (Interactive Flash animation)	Div 3 (Schema)	Div 4 (Video)	Learner Total	
Learner 1	210.22 sec	73.40 sec	43.05 sec	165.25 sec	491.92 sec	
Learner 2	144.12 sec	124.67 sec	29.87 sec	170.45 sec	469.11 sec	
Learner 3	243.49 sec	142.32 sec	12.01 sec	98.71 sec	496.53 sec	
Div Total	597.83 sec	340.39 sec	84.93 sec	434.41 sec		

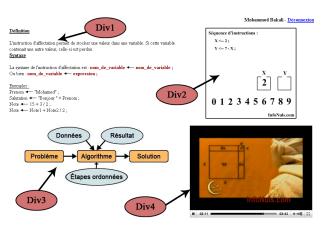


Figure 3. Web page divided into 4 areas to track learner's interest

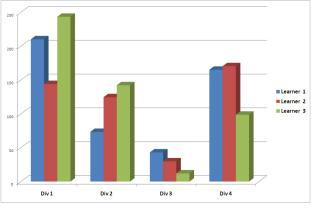


Figure 4. Gaze duration chart

When learner logs in, the results from the parameters analysis block are saved in the database. Every time when the user starts a course, his behavior is recorded in the database. This includes when the course is started, which page the learner had visited and how long she/he spends on each area. This data is combined with eye movement to get a fine-grained user profile.

V. CONCLUSIONS

The work presented in this paper focuses on behavioral analysis system and also the types of information that can be useful in this study and the resources used by the system.

The paper introduced the principle of an intelligent tutoring system, and also the use of our behavioral analysis system in the student module of an ITS, and the interaction between the student module and the tutor module of an ITS.

The next step is to determine the data used by our system and the integration of a data mining system that will be used to extract and organize this information so they are ready for a psychic and pedagogical analysis.

REFERENCES

- Mofreh A. Hogo. (2010). "Evaluation of E-Learners Behaviour using Different Fuzzy Clustering Models: A Comparative Study". International Journal of Computer Science and Information Security, Vol. 7, No. 2.
- [2] C. Buche, R. Querrec, P. De Loor, P. Chevaillier & J. Tisseau. (2009). "PEGASE : un système tutoriel intelligent générique et adaptatif en environnement virtuel". RSTI – TSI, Vol. 28, No. 8/2009, p. 1051-1076.

- [3] Samy S. Abu Naser. (2008). "Developing an Intelligent Tutoring System For Students Learning To Program in C++". Information Technology Journal 7(7), p. 1055-1060. <u>http://dx.doi.org/10.3923/</u> itj.2008.1055.1060
- [4] Komi Sodoké, Gilles Raîche & Roger Nkambou. (2007). "La plateforme d'évaluation adaptative des apprentissages: PersonFit".
- [5] Faouzia Benabbou & Mostafa Hanoune. (2006). "Utilisation des exemples et de la démonstration dans l'Apprentissage de l'Algorithmique".
- [6] Cédric Buche, Pierre De Loor & Ronan Querrec. (2005). "Système tutoriel intelligent pour l'apprentissage de travail procédural et collaboratif".
- [7] Roger Nkambou & Vincent Heritier. (2004). "Reconnaissance émotionnelle par l'analyse des expressions faciales dans un tuteur intelligent affectif".
- [8] Jessica Faivre, Claude Frasson & Roger Nkambou. (2002).
 "Gestion Emotionnelle dans les Systèmes Tuteurs Intelligents".
- [9] Luc Damas, Alain Mille & Rémy Versace. (2002). "Prendre en compte les comportements cognitifs des apprenants dans la conception de systèmes d'assistance à l'apprentissage humain".
- [10] Jean-François Bourdet & Philippe Teutsch. (2000). "Définition d'un profil d'apprenant en situation d'autoévaluation", Apprentissage des Langues et Systèmes d'Information et de Communication, Vol. 3, No 1, juin 2000, p. 125-136.

- [11] Gilberto Lacerda. (1993). "La modélisation cognitive de l'étudiant et les systèmes tutoriels intelligents". Revue des sciences de l'éducation, Vol. 19, No 3, p. 501-509.
- [12] Self, J. (1988). "Artificial intelligence tools in education", Chapter: Student models: What use are they?, p. 73-86. Elsevier Science Publishing.
- [13] Hend S. Al-Khalifa and Remya George (2010). "Eye Tracking and e-Learning: Seeing Through Your Students' Eyes".
- [14] Clara Calvi, Marco Porta & Dario Sacchi (2008). "e5Learning, an E-Learning Environment Based on Eye Tracking". ICALT 2008.

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