Work in Progress - ASAP: an Automatic Student Adapted Learning Path Generator

F. Colace, M. De Santo, M. Iacone
DIIIE-Università degli Studi di Salerno
Via Ponte Don Melillo, 1 84084 Fisciano (Sa)
E-mail: {fcolace, desanto, miacone}@unisa.it

Abstract - Thanks to the technological improvements of recent years, distance education today represents a real and effective tool for integrate (and sometimes substitute!) the traditional formative processes. In literature it is widely recognized that an important component of this success is related with the ability “to customize” the learning process for the specific needs of a given learner. This ability is still far to have been reached and there is a lot of interest in investigating new approaches and tools to adapt the formative process on the specific individual needs. In this paper we present and discuss a model to capture information about learning style and capabilities of students; this information is successively used to select the most suitable learning objects and to arrange them in “adapted” learning paths. We discuss experimental results in using our approach.

Index Terms – Adapted Learning path, E-Learning, Student Model, Metadata.

INTRODUCTION

In the last period, researchers are interesting in the design of value-add services to integrate in E-Learning platforms, such as student activities tracking service. In literature [1] many papers deal with this argument but an interesting approach is proposed in [2]. Starting from this approach in this paper we propose a model for tracking student’s activities during his learning process. Some indexes able to describe the student attitude during the learning process are selected. In particular this approach updates the student’s profile (according to IMS LIP standard) in order to adapt its learning path [3].

1. THE TRACKING PROBLEM

Some of the tasks that an e-learning platform should carry out are to allow people to find adapted learning objects (LO). In this scenario, an ever more detailed description of each training content can be very helpful for the teacher. This process is known in literature as process of creating metadata [4]. Also, it is possible to design and implement “intelligent” services able to help students and teachers during the formative process, such as the student’s tracking: the selection, collection and analysis of a set of parameters of students’ learning process that are essential for an adapted teaching process organization. Therefore, a student model design is needed. In the next section our student model and our adaptation approach by using metadata will be described.

2. THE ASAP APPROACH

An appropriate method for student tracking is necessary to help the docent in an effective evaluation. Starting from the difficulties that the student meets during a didactic unit, the proposed ASAP approach provides to each student the most adapted didactic unit to his actual knowledge and helps the docent to provide the best pedagogical contribution. The hypothesis is to know how time the student spends to study a single LO, \( t_i \), and the mark \( v_k \) obtained in the final test, two parameters that are compared, by using appropriate functions, with other two reference parameters fixed a priori by the docent, \( r_i \) and \( v'_k \) respectively. The ASAP scheme is showed in fig.1. In the next sub-sections we will describe in details the various phases of the ASAP approach.

2.1 Selection of Learning Object

The opportunity of better defining a resource by using its didactic and pedagogical characteristics through the description of standard fields induces us to represent it with a model. A model used to represent as a vector both the resource and the student profile is described in [3]. In this paper an appropriate index is calculated to get the best correspondence between User Resource and Training Resource.

2.2 Study of Learning Object

The student time \( t_k \) of a single LO is evaluated. If the student repeats the same lesson before making the test, the function

\[
T_i(i) = 1/(1 + a(i - 1))
\]

(1)

is evaluated, where \( i \) is the number of items the student studies the same LO and \( a \in ]0,1[ \). So, little by little the student repeats the same LO, his score decreases.
2.3 End Module Test

The learning state of the student is evaluated with a mark \( v_k \). The parameter \( Q_k = v_k L_k / d_k \) (\( L_k \) is the difficulty level of the k-th LO and \( d_k \) the actual training state of the student about the k-th LO) provides information about the punctual performance of the student. \( L_k/d_k \) is an adapting factor between the student state and the selected LO, so that \( Q_k \) relates this term to the student mark, confirming how much \( v_k \) is effectively reliable. Later, the following term is evaluated:

\[
S_p(Q_k) = Q_k \left( 1 / (k - 1) \right) \sum_{q=1}^{k-1} Q_q \quad (2)
\]

2.4 User Profile Updating

Once the student ends the test, his profile is updated and a report on his activity is provided. Then the following student score function is regarded.

\[
Score_k = \mu (\bar{T}_k(i) G_r G_t) + (1 - \mu) (1 + \log(S_p(Q_k))) \quad (3)
\]

where:

\[
G_t = 1 + N + \left( (t_k - t_k')^2 - t^2 \right) / \left( (t_k - t_k')^2 + t^2 / N \right) \quad (4)
\]

compares the time student \( t_k \) with the learning time \( t_k' \) fixed by the docent and \( t_k' \) is such that \( t_k' + t_k \) is the upper limit the student can look through the lesson. Also,

\[
G_v = (v_k - v_k') / (v_k + v_k') \quad (5)
\]

compares the student mark \( v_k \) with the minimum fixed by the docent, \( v_k' = b L_k \) (\( b \in [0,1] \)). It considers, by looking at its sign, if \( v_k \) is satisfactory respect to \( v_k' \), while \( \mu \) weights the first term (the actual performance of the student) and the second term (the historic performance of the student). If \( v_k < v_k' \), an easier LO, defined by \( L_k = L_k - 1 \), is located and provided to the student. Finally, once the student has completed to study the didactic unit, the index

\[
Score = \left( 1 / M \right) \sum_{i=1}^{M} Score_i \quad (6)
\]

about the global evaluation of the student can be evaluated.

3. EXPERIMENTAL RESULTS

The course of “Introduction to Computer Science” at the Foreign Literature and Language Faculty of the University of Salerno, composed in seven modules, is considered in our experimentation. A synthetic dataset composed by five hundred descriptions of LOs (related to the various modules and in according to the ontology model described by the teacher) has been created. The profile of some typical students (clever, average, poor) has been described by the teacher. At the end of every LO a test is simulated. The results of the students are obtained through a Montecarlo method approach based on their profiles. In Table I the obtained results are reported. In particular, the showed values of students’ and contents’ descriptions are the average of contents and students in every module (the first content is random). In the table we can see as our approach is able to follow the user profile offering the fittest contents to the students. Our approach has been simulated on about thirty user profiles and the obtained results confirm that the average difference between students’ and contents’ descriptions is less than 0.8. Our approach is able to provide contents that are, in a very closed range, in comparison with the student description.

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CONCLUSION

In this paper we have showed a student tracking model starting from the concepts, skills and attitudes of the student. A mathematical model is devised to facilitate the course characterization and to provide support for diagnostics. Experimental results confirm the effectiveness of the proposed model to find the most suitable set of contents for each student profile. In the future we will extend this approach to a real classroom.

REFERENCES