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Architecture for the adaptation of learning paths based on ontologies and Bayesian networks

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Several researches in the field of education have shown that taking into account learning styles has drastically improved the quality of teaching / learning. The adaptation of the course into the profiles and preferences of learners requires the collection of more information on learners, learning styles and educational resources.
To identify the learning style of each learner, the architecture is designed to require the learner to pass the test of Felder and Silverman in his first connection. This test provides information about the preferences of learning styles of the learner.

Our contribution in this paper consists of an adaptive approach based on the semantic web and Bayesian networks (BN), to provide learners with personalized courses according to their profiles and learning objectives. In addition, the system allows to make a diagnosis and classification of errors made by learners to generate relevant remedial course. Indeed, this model allows learners, teachers and instructional designers to work with software agents to automatically and effectively build custom routes oriented educational goals.

Key words : Adaptive Learning Paths, Bayesian Network, Learning Object, Multi-agent System.

1. INTRODUCTION

The adaptation of learning paths to learners' profiles requires the collection of more information about learners and learning resources. This article aims to develop a model of E-Learning to generate personalized learning paths for a group of learners with similar characteristics and common goals. The proposed model is designed based on a multi-agent paradigm, the semantic web and Bayesian networks. A phase which is essential to ensure that adaptation of course, is the classification of learners. It is done by the system based on a multi-agent architecture [1]. These agents are in constant communication and cooperation between them in order to promote the recognition of the learner profile (preferences, learning style, knowledge and skills, etc..) And assign it to a class. The classification is imposed on the learner during his first connection and can be requested by a student to change its class membership already registered who wants to manually update your profile or required by the system in case the learner performance is modest.
To this classification, we chose the naïve Bayesian classifiers because they have demonstrated an efficiency more than enough in many real and complex situations. The advantage of naive Bayes classifier is that it requires relatively little training data to estimate the parameters needed to classify.
In other words, we modeled three ontologies: ontology learning resources to represent teaching materials, ontology learning objectives according to Bloom's taxonomy and ontology to model the learner's profile.
In addition, we kindly use the classification results at multiple levels in addition to creating customized learning paths will also create routes remediation for learners who have not been successful goal. For this, the system will make a diagnosis and classification errors made by learners to generate these routes that attempt to correct errors and fill gaps learners. This method will allow us to reuse already created remedial courses, optimizing their creation time and to target the difficulties learners.

2. REPRESENTATION OF RESOURCES

In our approach, we use ontologies for describing the features of domains. The contribution of ontologies for understanding, sharing and integration of information is demonstrated. Indeed, research and practice in this area begin to bear fruit, especially for the Semantic Web. Three ontologies were designed: Ontology of pedagogical resources, Objectives Ontology, Ontology of learners’ profiles.

2.1 Learning Object

Learning objects (or Unit of Learning) are smaller units of learning and is currently at the heart of many applications of instructional design. Current work on learning objects interested in the standardization of these based on metadata describing their content to ensure case pedagogical productions in what is called the education market. Generally, this standardization is based on different research directions or describe learning objects as entities that the system has and which manipulations are based on the metadata specification, either towards the educational modeling languages for represent Hypermedia Units of Learning. Three approaches have emerged and led successively on each of the standards or proposed standards: LOM, SCORM and IMS Learning Design. The term "learning object" emerged in the mid 1990s in international consortia such as IMS and ARIADNE - which led him to propose a standard. In this paper we use the LOM [2] standard for the representation of educational resources LOM (Learning Object Metadata) in the early 2000s. The goal is then profitable production and develop reuse (economic perspective). Several standardization of metadata for educational resources have been conducted, [4, 5].

2.2 Structure of the Training Modules

Our architecture is based on the pedagogy by goals to structure the material to teach (i.e. the learning module), we use a three-level hierarchy of educational objectives as defined in [6, 7]:

1. The General Objectives or abstract (GO);
2. The Specific Objectives or composite (SO);
3. The Operational Objectives or atomic (OO);

To classify these objectives, we opted for the taxonomy of cognitive domain by Benjamin BLOOM, who is the father of the first hierarchical classification of educational objectives. The taxonomy of educational objectives BLOOM [8],is composed of six levels, including: knowledge, comprehension, application, analysis, synthesis and evaluation. For each class, there is a set of verbs that can be used to express the objectives of educational services.

This hierarchy has allowed us to consider three levels of abstraction module of instruction:

1. Parts (meeting the General Objectives);
2. Chapters (that meets the Specific Objectives);
3. Hypermedia Learning Units (Object Learning) (meeting the operational objectives).

These are transfer credits evaluated. The system, then, organizes the process of education around these components hypermedia (the L.O). The LOs are supposed to receive, by instantiation, all kinds of domain knowledge in all forms of media permitted by HTML (text, image, sound, video, script, applet), Figure 1 shows the structure of a module into simple elements.

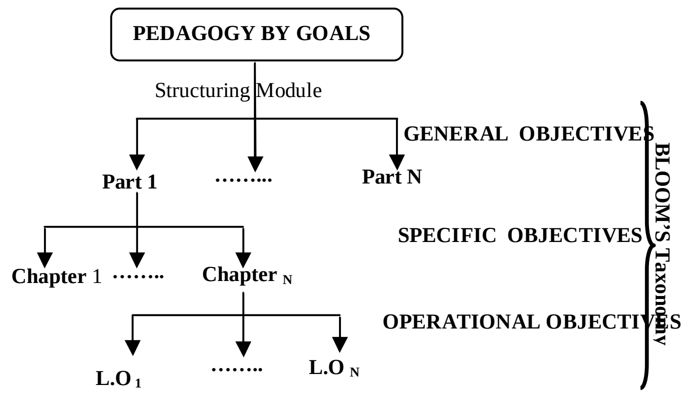

Figure 1: Hierarchical representation of a module

The sequence of learning objectives (LOs) by the system is made on the basis of a "network of pre-requisites" proposed by the author of the teaching module. A prerequisite link between two objectives LO1 and LO2 (from LO1 to LO2) defines on the one hand a precedence desired by the author between the two objectives, proposing that learning the second objective cannot be completed until LO2 achievement (or success) of the first goal LO1, on the other hand, a link indicative of progression or a remediation of a potential link. This latter feature means that the system can choose a LO that is a pre-requisite to a LO on which the learner has failed in order to offer him a contribution of knowledge that relates to the LO prerequisites.

3. LEARNER MODEL

The learner model is a model for representing the information of the student come into play when building a suitable learning path. It also allows the system to adapt to the learner who interacts with him. That is to say, it has the knowledge to understand and use what the learner already knows.
This can be achieved through knowledge of the learner profile. This profile must integrate the knowledge of the learner on the field, but also can add features to the learner as its educational objectives, preferences ....etc.

To design the model of learning there are two major standards that can be adopted. This is the PAPI (IEEE / PAPI "Public and Private Information for Learners" - "Information on public and private learners") and IMS LIP (IMS / LIP "Instructional Management Systems Global Learning Consortium for Learner Information Package"). Both standards specify several categories of information about the learner.

In this paper we adopt the standard IMS-LIP[3,8, 9,10] it is based on a data model that describes the basic categories to record and manage the academic background, training objectives, and outcomes of learners. These categories are described in Figure 2.

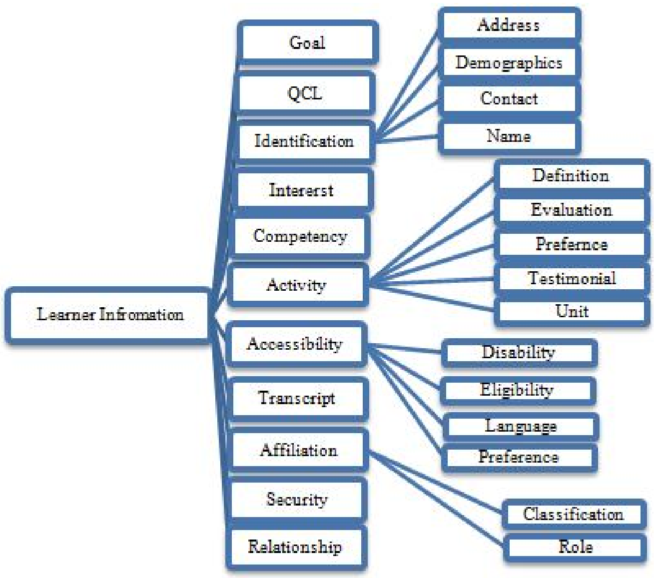

Figure 2: Hierarchy of concepts of the IMS- Learner Information Package (LIP).

The elements of the LIP specification are: the identification that represents the data on the demographic and biographical studies. Goal representing the study objectives and aspirations of the learner. The QCL (Qualifications, Certificates & Licenses) which as its name implies is the qualifications, certifications and permits granted by competent authorities to the learner.

Activity that represents all learning activities regardless of their state of completion, including formal and informal education, training and work experience.

The element transcript is a record for a summary of activities based on academic achievement. The interest element that represents the information on recreation and activities outside of work and school. The element that represents competency skills, knowledge and skills acquired in the cognitive, affective, or psychomotor. The affiliation is part of the student memberships in professional organizations. The element that characterizes the accessibility information accessibility to the learner as defined by the possibilities of language, disabilities, acceptability and preference studies including cognitive preferences (c to d learning style), physical preferences (c to d a preference for large page), and technological preferences (c to d preference for a particular computer platform). The security element key is the set of passwords and security keys assigned to the learner for transactions with the systems and information services for learners. Finally the element relationship for all relations between components of the nucleus.

4. THE LEARNING STYLE MODEL

Learning Style (LS) can be defined as the way a person collects, processes and organizes information. Among the different proposals for modeling LS, we choose the FSLS since it is one of the more successful models and has been implemented in many e-learning systems. FSLS classifies students in four dimensions [12]:

Active / Reflective (Processing). Active people consider having understood a piece of information only if they have discussed it, applied it or tried to explain it to other people. Reflexive people, on the other hand, prefer reflecting about the issue before assuming any practical posture.

Sensing / Intuitive (Perception). Sensing people are meant to learn from tasks related to problems and facts that could be solved by well-behaved methods, with no surprises or unexpected effects. Besides, this style usually refers to students that are fond of details and very good memorizers of facts and practical applications. Conversely, intuitive students are meant to discover alternate possibilities and relationships by themselves, working with abstractions and formula, which allows them to understand new concepts and to quickly and innovatively perform new tasks.

Visual / Verbal (Input). Visual-driven people find no difficulties in interpreting, for an example, pictures, diagrams, timelines or movies. Distinctly, verbal students' personal learning processes are driven by written or spoken explanation.

Sequential / Global (Understanding). Sequential people structure their learning process by logically, successively chained steps, each one of them related to the search for solutions. On the other hand, global students learning processes are distinguished by random jumps: they often are able to solve a complex problem, although they do not know how they arrived at the solution.

Felder and Silverman proposed a psychometric instrument, the Index of Learning Style Questionnaire (ILSQ), that classifies the preferences for one or the other category as mild, moderate or strong. In the majority of traditional AEHS that make use of a learning style model for adaptive purposes, the assumptions about the student's learning style are usually acquired by a psychometric instrument like ILSQ. Nevertheless, the use of such a test has some drawbacks. First, students tend to choose answers arbitrarily. Second, it is really difficult to design tests capable of exactly measuring "how people learn". Therefore, the information gathered trough these instruments encloses some grade of uncertainty. Moreover, this information, as a rule, is no longer updated in the light of new evidences from the student's interactions with the system. An alternative approach that uses a Bayesian Network (BN) to model the student's LS, instead of acquiring it by a psychometric test. Using a BN as a LS model allows that observations about the user's behaviour can be used to discover each user's LS automatically using the inference mechanisms.

5. THECLASSIFICATION OF LEARNERS

Several ideas have emerged over the years on how to obtain relevant results for classification, so there are different approaches that can be used to a degree such as: clustering, Bayesian Networks, Neural Networks, Support Vector Machines (SVM), etc. In this paper, we used Bayesian networks to classify the learners, the classification of students is done in two phases: first when a student logs into the system for the first time, the system requests information on their profile. These will be stored in a file OWL, which will be used by the classifier agent. It affects the learner at first level of a given class based on cognitive preferences, preferences, physical and technological preferences. Then, when a student makes a goal to apply for a learning path, and if the course has prerequisites, the system generates a pre-test to verify these prerequisites, the results of this test are used to assign the learner at a particular level of the class itself. In addition, at the end of each course, the learner passes a test to pass the goal. The system decides the outcome of the following tests to create a remedial course or not. We will explain later in detail the principle of creating a course of remediation while classifying the errors made by the learner.

5.1 Bayesian Classifiers

Bayesian classifiers are statistical classifiers. They can predict classmembership probabilities, such as the probability that a given sample belongs to a particular class.

Bayesian classifier is based on Bayes's theorem. Naive Bayesian classifiers assume that the effect of an attribute value on a given class is independent of the values of the other attributes. This assumption is called class conditional Independence. It is made to simplify the computation involved and, in this sense, is considered "naive".

Depending on the nature of each probabilistic model, the naive Bayesian classifier can be trained effectively in the context of supervised learning. In many practical applications, parameter estimation for naive Bayesian models based on maximum likelihood. In other words, it is possible to work with the naive Bayesian model without worrying about Bayesian probability or using Bayesian methods.

The naive Bayesian classifier showed an efficiency more than adequate in many complex real situations. The advantage of the naive Bayesian classifier is that it requires relatively little training data to estimate the parameters required for classification, ie means and variances of different variables. Indeed, the assumption of independent variables can be satisfied with the variance of each of them for each class, without having to calculate covariance matrix. The probabilistic model for a classifier is the conditional model :

$p(C|F_1,F_2,\ldots,F_n)$

where C is a variable dependent class or classes whose instances are few, determined by several characteristic variables $F_1,\ldots,F_n$

When the number of features n is large, or when these features can take many values, this model based on probability tables is impossible. Therefore, we derive to be more easily soluble. Our classification algorithm is based on the NB approach. The standard Bayes rule is defined as follows:

$$arg\max\{P(Cn|w)\} = \frac{p(W|Cn)*P(Cn)}{p(w)} \quad (1)$$

Where;

$P(C_n)$= the prior probability of category n,

W = the new profile to be classified,

$P(w|C_n)$= the conditional probability of test profile, given category n.

The P(w) can be disregarded, because it has the same value regardless of the category for which the calculation is carried out, and as such it will scale the end probabilities by the exact same amount, thus making no difference to the overall calculation. Also, the results of this calculation are going to be used in comparison with each other, rather than as stand-alone probabilities, thus calculating P(w) would be unnecessary effort. The Bayes Theorem in (eq. 1) [13] is therefore simplified to:

$$\arg\max\{P(Cn|w)\}\infty P(w|Cn) * P(Cn)$$

5.2 Creating an optimal course of remediation.

The course of remediation is a course that meets and specific business objectives, goals unsuccessful by a learner. This path is generated according to the result obtained by a learner after training. If the learner could not achieve its goal of learning a course of remediation will be issued before moving on to another target.

In this section we describe a simple example how to optimize the development of remediation courses. The proposed method is to make a classification of errors made by the learner. Always using Naive Bayesian algorithm can detect concepts not mastered by a learner.

This will optimize the creation of remedial courses by reusing those already created and minimize search time, concepts already mastered, in a large database of educational resources. Figure 3 shows the process of classification errors of learners.

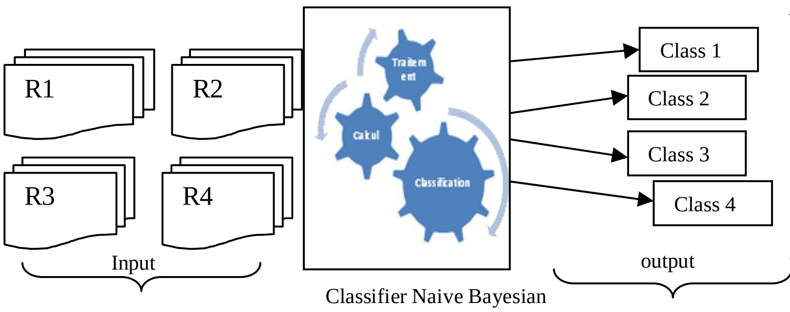

Figure 3: classification of learner's errors.

The reports generated by the assessment system [1], (R1, R2, R3 ...) are the inputs for the agent Classifier. The latter performs processing on errors of learning to determine the most appropriate class. Class 1, Class2, Class3 is predefined classes. For example, if a learner makes a goal to learn the repetitive structures in Pascal, at the end of his training the student must pass a test to move to the next objective, the agent detector generates a difference report similarity between the responses of the learner and those expected. The course of remediation may relate to the variable declaration and assignment (class1), conditional structures if-then else (Class2), repetitive structures, for-do, while-do, repat-until (class3), conditional structures inside loops (Class4). Aini can dissect each objective formulated by a multi-faceted learning where each component belongs to a class.

6. CONCLUSION

In this paper we proposed a personalized model in e-learning to categorize students according to their profiles and learning styles to create suitable learning paths and optimize remediation while those based on the approach to teaching by objectives, techniques semantic Web and Artificial Intelligence(i.e ontologies, Bayesian Networks and multi-agent paradigm) .

First create a learning path suited to the profile of a group of learners, inevitably a classification phase, which involves gathering information on learners and extract key elements to classify. As for the profile of the learner, it is modeled according to the standard IMS-LIP is represented by ontology of learning.

As perspective, it aims to increase the sample of learners to encourage the creation of customized courses for a group of learners and increase the number of classes.

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