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Seeking Adaptation in Intelligent Tutoring Systems: A Learning Classifier Systems Proposal [1]

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Abstract: This work describes the use of personality and learning styles aspects for modeling of users and how, in a second step, to use these models with a Learning Classifier System (LCS) approach to adapt interfaces within an intelligent tutoring system. The final objective of this work is to provide mechanisms for the design and development of system interfaces for tutoring/training, that are effective and at the same time modular, flexible and adaptable finding the optimal taching strategy for an individual student.

Keywords: User Modeling, Intelligent Tutoring Systems, Web-based Adaptive Systems, Adaptive User Interfaces, Genetic Algorithms, Learning Classifier Systems

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1 Introduction

The growing of Internet services, has favoured the development of systems that support web-based education. These systems overcome the students and teachers isolation with communication and collaboration services. In this situation, the courses based on cooperative learning has been taking advantage of the improvement of these types of services. This is specially useful in distance learning since it allows the students and teachers to collaborate in distance courses. In this way, it has been improved the traditional distance educational model, by giving the students the chance to interact with his/her partners and to participate in shared workspaces. These new technological opportunities demand a revision of the web-based educational systems and the educational models on which these systems are based on.

In addition, due to the diversity of users and information sources in web-based courses, it is advisable that the web-based educational systems adapt the responses given to the students according to their characteristics such us background knowledge, preferences or interests. These adaptive systems are called Web-based adaptive educational systems.

There are systems related to the above mentioned, that involve machine learning to improve their interaction with humans. To reach our purpose, we are trying use learning styles and personality theories ([3],[9]) related to the user modelling aspect. We want to take advantage of these models with an evolutionary algorithm approach [1].

The paper is organized in the following way: we start we begin doing mention of the related theories to personality ans learning styles. The second section illustrates the Learning Classifier System approach. In the third section we describe our Tutoring Model, and in the end we provide some final comments.

2 Personality And Learning Styles Theories

The expression “learning style” is related to the situation when we want to learn something, each one using their own method or strategy. Although the concrete strategies to utilize vary according to what we want to learn, each one tends to develop some global preferences. These preferences or tendencies, in addition to specific ways to learn, constitute our learning style. In any group in which more than two persons begin to study a subject (together) and starting from the same level, we will find in very little time with large differences in the knowledge of each member of the group. Each member of the group will learn in a different way, will have different doubts and will advance more in some areas that in others. The different models and existing theories on learning styles offer a conceptual framework that help us to understand the behaviours that we observe daily in the classroom, and how those behaviours are related with the way in which our students are learning, and the type of actions that can turn out to be more efficient at specific times.

There are many theories that define learning styles; in our research we take as reference the learning styles proposed by [3]and [9]. Kolb´s model is a descriptive model for learning in adults. This model starts with the Lewin´s Cycle [5], and suggests four consecutive states in the learning process: Concrete Experiences, Reflection, Abstract Conceptualization and Active Experimentation. [2] built a typology identifying preferences for each state in Lewin´s cycle: Activist, Reflector, Theorist and Pragmatist. Finally Kolb´s work relates themes and sub- themes of the areas within the Lewin´s cycle (Fig. 1).

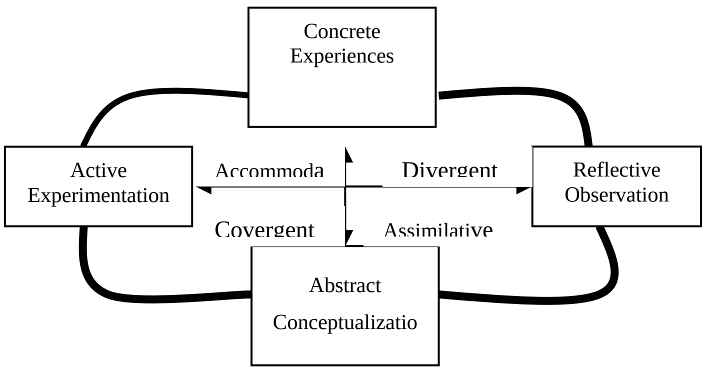

Fig. 1. Kolb´s Learning Model

In [9] we find two different learning styles:

- *analytical*, which are objective students, very reflexive, that try to develop correct strategies for problem solving. They use heuristics for the solution and it is not necessary too much intervention by the teacher, because these students prefer to learn by discovery.
- *holistic*, which are impulsive students that have good performance in the short term memory, they work better in group and have difficulties for problem solving with extra information.

In our research we are proposing a mixture of the two works before mentioned, with which we obtain a total of 8 different models of apprentices (Fig. 2).

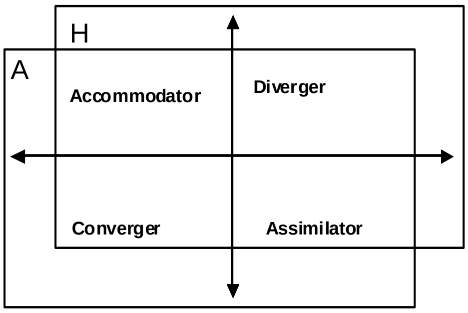

Fig. 2. The Kolb-Witkin Joint Model

- Convergent Analytic: They establish goals and action plans, focused on specific problems. They analyze the information structurally using deductive hypothetical reasoning and trust in their own cognitive structures.
- Convergent Holistic: They can follow an order structured in pursuit to perform a task, and feel comfortable with the text – graphic type of information.
- Divergent Analytic: They look at the situations from many perspectives, analyze the information observed structurally, select it and determine its functionality, see and analyze the relations among the things structurally to deduce the information that it carries to reach concepts.
- Divergent Holistic: Due to their social orientation they desire to see the world as a complete figure, before examining the parts, present sketches or graphic organizations of the contents, are pleased to be involved in the experience.
- Assimilator Analytic: They analyze in a systematic method, are involved in something that awakes their interests and concentrate on it.
- Assimilator Holistic: They trust in external references, tend to approach things in a global way, and desire to see the whole before the parts, do many questions.
- Accommodator Analytic: They are characterized for being analytic, logical and deductive, utilize the theoretical models, and select the information in a clear way.
- Accommodator Holistic: They identify the relations among the ideas, are characterized for trusting in external references for their learning, it is complicated for them to summarize the information.

3 Learning Classifier System Proposal

The initial point for our approach is the assumption that Evolutionary Computation techniques are especially adequate for the adaptation and learning of Intelligent Interface Agents [7] because they are inherently based on a distributed paradigm (the natural evolution), we are taking as initial point of our Learning Classifier System proposal the work presented in [6]

3.1 Introduction to Learning Classifier Systems

Learning Classifier Systems (LCS) were proposed by Holland [1], as a evolutionary technique for machine learning. It is also often described as a production system framework with a Genetic Algorithm as the primary rule discovery method. The architecture is formed by three sub-systems: Rule System, Credit Assignment System (CAS), and Genetic Algorithm (GA).

The structure of a typical LCS is shown in Fig. 3. This is known as a stimulus-response LCS, since no internal messages are used as memory.

Every rule has the following syntax: *<classifier>::=<condition>:<message>* where <condition> and <message> are strings of characters from alphabet {0, 1, #}, # is an unspecified character (replaces so much to the 0 as to the 1). The condition is the part that is registered for the LCS while the message corresponds to the outputs that activate internal or external actions.

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The Credit Assignment System (*bucket brigade*, first introduced in [8]) is the responsible for distributing among the classifiers the profit received in compensation to their actions. It is an algorithm that simulates a market economy where the privilege to trade information is bought and sold by the classifiers. The algorithm is based on two procedures: an auction in which each classifier bets by sending their message in answer upon stimuli received by the system; and a house of payments that returns the investment of those classifiers that did well their task.

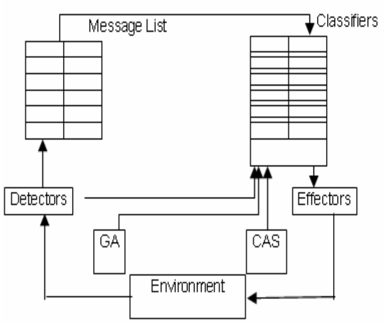

Fig. 4. Basic Approach for Learning Classifier Systems

3.2 Codification of the User Model

The User Model should (according to the illustrated in the previous section) be inserted into the LCS. Depending on this, the system will be able to find an adequate pedagogical strategy for each apprentice, and besides feedback diagnosis on the student. The sensors of the LCS will take charge of detecting the following user characteristics (detectors) that should be codified in the <*condition*> part of each rule:

Level of Exercise (d1)	Real Situations (d2)
Use of the help system (d3)	Procedure Solutions (d4)
Visit Interest Level (d5)	Tools Employment (d6)
Conceptualization level (d7)	Navigation (Sequential or personalized) (d8)
Performance of short time memory (d9)	Perceptual representation (d10)
Incoherent information management (d11)	Counting Errors (d12)
Reflexivity or Impulsiveness (d13)	

Table 1 shows a more concrete description of the codification of the detectors into the condition part in the classifier:

Detector	**Bits**	**Description**
d1	4	Between 0-10 (from 0000 to 1010 in binary) where 0 is 0% and 10 is 100%
d2	4	Is a percentage
d3	4	Is a percentage
d4	4	Numbers of errors for problems
d5	4	Is a percentage
d6	4	Number of used tools
d7	4	Is a percentage
d8	1	Boolean value
d9	1	Boolean value
d10	1	Boolean value
d11	4	Is a percentage
d12	4	Is a percentage
d13	1	Boolean value
Total	40	Total length

Table 1: Description of each detector in the classifier conditions

In concordance with our previous user model proposal, the message (output) of our classifier will be related with the possible model of the current user:

- Convergent Analytic: 000
- Convergent Analytic: 001
- Divergent Analytic: 010
- Divergent Holistic: 011
- Assimilator Holistic: 100
- Assimilator Holistic: 101
- Accommodator Analytic: 110
- Accommodator Holistic: 111

The fitness scheme for any classifier is related with the bucket brigade algorithm before mentioned; we have a profit distribution in the following way:

$$S(t+1) = S(t) - BiS(t) - CtaxS(t) + R(t) - TaxbidS(T) \quad \textbf{(1)}$$

Table 2 explains the components for the profit mechanism.

S(t+1)	Profit in t+1
S(t)	Current profit
BiS(t)	(Cbid +BidRatio)S(t) + N
Cbid	Rate of bet (betwen 0 and 1)
BidRatio	Level of specificity. More wild cards is less specific
N	Gaussian noise (normal distribution)
Ctax	Rate of tax that charges to those that never wager (betwen 0 and 1)
R(t)	Reinforcement signal
Taxbid	Tax that charges to the squanderer classifiers (they wager always and never gain)

Table 2: Assignment of Profits

The reinforcement mechanism signal (R(t)) originates from the score obtained by the student in two successive evaluations as we can see in the Figure 4.

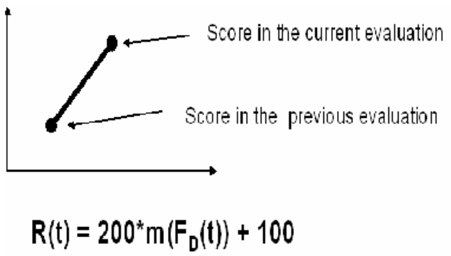

Fig. 4. Reinforcement Mechanism based on the evaluation of users

4 Tutorial Model

When we are trying personalizing any system, firstly we should have clearly, the user model, but also one must keep in mind that for a system as the proposed, another crucial aspect is the tutorial model, in this model, the pedagogical strategies are established and the type of instruction that the system will use, as well as also the guiding way to the student along the learning process.

Our tutoring model is composed for two main elements: Contents and pedagogical models

4.1 Contents Model

Is the formal repersentation of the course contents, reflecteds in the conceptual map that enters the teacher. In this mapany node is any concept (or information unit) that the student must to learn, while the conectors are the relations between these concepts and the way in the which the concepts evolve in others, according to the student interests. In this is established the general structure of the course, kernels (units) and sub-kernels (topics) descriptions of the area.

For the purpose of model explicitly, the course contents and its associated learning activities, we have choiced one into many proposals that exists for course descriptions and that can be easily applicable in diverse systems, this is the EML Model [4]

Related to EML, we have adopted the following representatives activities:

- Instruction Model: Specifies the type of instruction that will give the system to each student, depending on his learning and personality style.
- Learning Model: Contains the information about the way in which the student learns the concepts, for example see the Table 3
- Domain Model: In this model is immersed the course organization and actors and objects involved in the learning process.

4.2 Pedagogical Model

Contains the related information to the way in the which the system will guide to the student in the learning process, leaving from the general conceptual map, the system will extract rules of traveling through the sequence of contents that should continue the student at any moment.

The teacher establishes the Conceptual Map of the subject differentiating the concepts
through sub-kernels, in agreement tom the domain, will have concepts that will be in various sub-kernels at time, for this and depending on the results of one evaluation about previous knowledge the system will design the navigation with those contents that the student does not know.

Components / Styles	Objectives	Study Cases	Lectures	Conceptual Maps
Convergent Analytic	X	X		
Convergent Holistic	X	X	X	
Divergent Analytic		X	X	X
Divergent Holistic		X	X	X
Assimilator Analytic	X	X	X	X
Assimilator Holistic	X	X	X	X
Accommodator Analytic	X	X		
Accommodator Holistic	X	X		

Table 3: Matrix of Instructional Strategies Components

5 Final Comments

With the proposal system we are incorporating adaptive capabilities to Web-based tutoring system that tkake in account leaning styles and personality models, this adaptive capability is based in LCS approach. We expect to be able to incorporate another learning sheme in conjunction with the LCS for accelerating the convergence of learning process and for to predict the most closely fitting student model.

6 References

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