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Evolutive Platform – A Genetic E-Learning Environment

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1. Introduction

It is now a widely accepted fact that IT can radically change educational practices and learning processes. The technological revolution requires better cognitive skills, either through the innovation or creativity, cognitive attributes par excellence. These attributes are not stratified by class or social status. A low cognitive functioning, with implications in poor school performance, are not indicators of lower classes or marginalized ethnic groups, i.e., their intelligence is not limited to the models of society. There will be one cognitive dysfunction ("Input," preparation, "Output") that in most cases, those responsible for education are not formed to overcome it, or do not make use of strategic resources to avoid waste of the cognitive potential of individuals (Fonseca, 1999).

Therefore the objective to be achieved is to build a self-regulating system that enables the improvement of different cognitive factors, allowing the student to fill certain gaps in their learning process by using genetic algorithms combined with statistical functions and evaluation learning models properly defined.

1.1 The cognitive approach

Cognition, as an act of assimilation, integration and ability to express and develop information, prepares us as a species to understand our past and build our future. Surroundings of an evolutionary process as a species stems from the informational and communication between plurineuronal sensory systems (Input) and motors (output) and is unavoidably in the genesis of adaptability and learning (Fonseca, 1999). A motivated individual be automatically a better skills receiver; a genius is 1% talent and 99% work (Edison 1902).

Cognition has grown as a doctrine based on the various time-empirical observations, and hard data of field research evidence proof, that are mental structures underlying not only thought, but also emotion, as well as the very perception and interpretation of both, inner/internal and outer/external source information (Lazarus, 1999, as cited in Kerkiri et al., 2010). (Gardner, 1993, as cited in Kerkiri et al., 2010), whose multiple intelligence theory is based on cognitivism, asserts that mind consists of numerous fairly specific and independent computational mechanisms, and it is in this context that research on learning styles has also been promoted. Based on cognitive learning theory, the structure of content

of the cognitive matter should be organized hierarchically. Relevant research (Deshler, 1986, as cited in Kerkiri et al., 2010) has surely led to the conclusion that students learn mainly from the progressive and relation-linked construction of knowledge. This approach may well find applications in a Learning Management System (LMS) with a psycho-pedagogically driven learning path creation module (Kerkiri et al., 2010).

1.2 The co-constructivism approach

From constructivist point of view, the knowledge "built" by an individual and not broadcasted, is itself both a reflective and active process. The interpretation that the individual performs of the new experience is influenced by their prior knowledge introducing in social interaction, multiple perspectives of learning. Learning requires understanding of the whole and the parts, and should be understood in a global context. In this perspective, Reuven Feuerstein introduces one new dynamic, co-constructivism (Feuerstein, 1990).

The theory of Structural Cognitive Modifiability – (SCM), far transcends the purely cognitivist approach, and advocates that every individual is modifiable, a process that is inherent to the human species (Feuerstein, 1990).

1.3 Conditioning the learning process

Considering that in terms of learning, we retain 20% of what we see and 90% of what we practice and that the two stages of learning are supported on know how to make and know evolve, and that three of the most important processes of learning are learning studying, learning reflecting and learning by doing, we must reflect on the dangers of abandonment or the demotivation on the incentive on the learning process, that result on an extinction of the knowledge acquired. Extinction occurs, when one previously conditioned response becomes less frequent and finally disappears (Feldman, 2001).

The conditioning in the learning process can be obtained through an educational incentive structure built extremely well, so that the individual is identified with the learning process. The positive and negative reinforcements in weighted measures are also two instruments for consolidating the learning model, helping to maintain the incentive, because the behavior can be modeled by the administration of positive and negative reinforcements, which also implies a causal relationship of reinforcement (cause) and behavior (effect). As mentioned, these stimuli must be used carefully, since the short / medium term may create a dependency on the user, if eventually ceased to exist. This is because human beings however much they want or wish, to shape their humility, are always waiting for a feedback regarding their performance.

In this study, these reinforcements may result from the machine itself through the use of happy smiles or pleasing sounds - for positive reinforcement, or sad smiles and unpleasant sounds - for negative reinforcement. In both cases, we can use more advanced techniques as the use of subliminal messages.

For these reasons, we conclude that individuals follow standards and models imposed by society; however, the reality is quite different, since the profiles of learning and speed of acquisition of knowledge in each of us are different. This is the purpose of this investigation; prove that we can improve our multiple intelligences/ cognitive profiles.

2. Targets

2.1 The outlook

When moving from traditional learning to educational e-systems, students get increasingly involved in their learning process. Technological systems are the new vectors used to disseminate knowledge between and provide feedback amongst the learning process (actors, pedagogues, the tutors and the learners). The use of IT in education covers a wide range of very different activities; e.g. learning environments, course management, and much more. Because the *one-size-fits-all* paradigm cannot be applied to individual learning, adaptability is a must. Hence, courseware is meant to be tailored according to the learner's needs. Two main families of computerized applications aspire to offer this adaptability: Intelligent Tutoring Systems (ITS) (Brusilovsky, 1992, as cited in Madhour & Forte, 2010) and Adaptive Hypermedia Systems (AHS) (Brusilovsky, 1996, as cited in Madhour & Forte, 2010).

Intelligent Tutoring Systems (Brusilovsky, 1992, as cited in Madhour & Forte, 2010) rely on curriculum sequencing mechanisms to provide the student with a path through the learning material. An adaptability algorithm computes this so-called personalized path, corresponding to the course construction and curriculum sequencing (Shang et al., 2001, as cited in Madhour & Forte, 2010). The process is twofold:

- Find the relevant topics and select the most satisfactory one;
- Construct dynamically page contents based on the tutor decision for what the learner should study next

ITS usually provide an evaluation of the learner's level of mastery of the domain concepts through an answer analysis and error feedback process that eventually allows the system to update the user's model. This process is called intelligent solution analysis (Serengul & Smith-Atakan, 1998, as cited in Madhour & Forte, 2010).

Adaptive Hypermedia (AH) (Brusilovsky, 1992, as cited in Madhour & Forte, 2010) was born as a trial to combine ITS and AH. As in ITS, adaptive education hypermedia focus on the learner, while at the same time it has been greatly influenced by adaptive navigation support in educational hypermedia (Brusilovsky, 1996, as cited in Madhour & Forte, 2010). In fact, adaptability implies the integration of a student model in the system in the framework of a curriculum, which sequence depends on pedagogical objectives, user's needs and motivation.

Hence, the use of adaptive and/or interactive hypermedia systems was proposed as a promising solution (Brusilovsky, 1996; Prentzas & Hatziligeroudis, 2001, as cited in Kazanidis & Satratzemi, 2009). Adaptivity in e-learning is a new research trend that personalizes the educational process through the use of Adaptive Educational Hypermedia Systems (AEHS). These systems attempt to create an individualized course according to the user's personal characteristics, such as language, learning style, preferences, educational goals and progress. In this way, instructors expect to solve some of the main problems of web courses and hope to succeed in achieving a better learning outcome (Kazanidis & Stratzemi, 2009)

However, there is still a problem in the presented families; information comes from different sources embedded with diverse formats into the form of metadata making it troublesome

for the computerized programming to create professional materials (Shih et al., 2007, as cited in Liu & Shih, 2010). The major identified problems are (Liu & Shih, 2010):

- Difficulty of learning resource sharing;
- Even if all e-Learning systems follow the common standard, users still have to visit individual platforms to gain appropriate course materials contents. It is comparatively inconvenient;
- High redundancy of learning material;
- Due to difficulty of resource-sharing, it is hard for teachers to figure out the redundancy of course materials and therefore results in the waste of resources, physically and virtually;
- Even worse, the consistency of course content is endangered which might eventually slow down the innovation momentum of course materials;
- Deficiency of the course brief;
- It is hard to abstract course summary or brief automatically in efficient way. So, most courseware systems only list the course names or the unit titles. Information is insufficient for learners to judge quality of course content before they enroll certain courses;

2.2 The new environment paradigm

Web courses and hypermedia systems deliver knowledge to a wide number of users with different characteristics, preferences and knowledge of the domain, irrespective of where they live, their age or their study credentials. However, these systems do appear to have some quite major problems which have been identified and documented through research studies and have differentiated into three distinct categories (Kazanidis & Stratzemi, 2009). The first deals with problems related to disorientation, cognitive overload, discontinuous flow (Murray et al., 2000, as cited in Kazanidis & Stratzemi, 2009), content readiness and distraction. The main solution that research proposes is the use of adaptive and or interactive systems. The second category of problems is those that arise from the absence of a common development framework for course construction. Course content, thus, lacks reusability, durability and interoperability. A suggested solution is the adoption of common educational standards for course construction and delivery. The third category involves instructors who come up against difficulties during course construction as most of the time course development requires not only specific programming capabilities but also deep knowledge of adaptive strategies and educational standard specifications (Kazanidis & Stratzemi, 2009).

This research is based on work of a PhD thesis. The idea has emerged because the authors - that are teachers in various education institutions in Spain and Portugal, feel that the students /learners needed a new way of acquiring knowledge. The need for a new paradigm with regard to learning processes and educational practices, led authors to begin the process of research on the state of the art and later, the investigation of a unique process that would use a single tool / environment that would allow the concentration of the student / learners exclusively in the acquisition of knowledge. Personalization consists in adapting the behavior of the system according to some specific information related to an individual user (Madhour & Forte, 2010).

Creating this new paradigm implies that both a new industry, that will emerge, as the creators content, for example, teachers or trainers are the responsible for creating content and the implied level of difficulty. The difficulty inherent to each block of knowledge, is set in a consciously way by the creators, and the "market", will be the quality evaluator of each. Teachers and Trainers can also adapt old methods, such as the traditional manuals, or Power Point presentations, to the new paradigm, since this follows the Sharable Content Object Reference Model (SCORM) standard, and can be accepted in virtually any kind of (LMS), although initially be developed using the Moodle. The use of universal normative and free software - such as Extensible Markup Language (XML), JAVA, Hot Potatoes or Reload Editor, among others, will be an additional advantage of this paradigm.

Thus, this structure addresses in a single way, the problems identified by (Shih et al., 2007) and (Liu & Shih, 2010) have exposed. Regarding what (Murray et al., 2009, as cited in Kazanidis & Stratzemi, 2009) and (Kazanidis & Stratzemi, 2009), claimed, adaptability, interactivity, lack of reusability, the durability, the interoperability and the difficulties in the construction of materials, are guaranteed by the use of the Knowledge Block (KB) and by the inherent structure.

Sharable Content Object Reference Model

On the other hand, students have greater flexibility in learning, since there will be an exclusively – if it is so desired – man-machine interaction, with no third party involved, thus reducing certain constraints to progress, that might occur with traditional methods.

Another advantage is that the solution delivers in a single structure – the KB, several sources of information (Fig. 4), thus solving the problem of diversity in content origin.

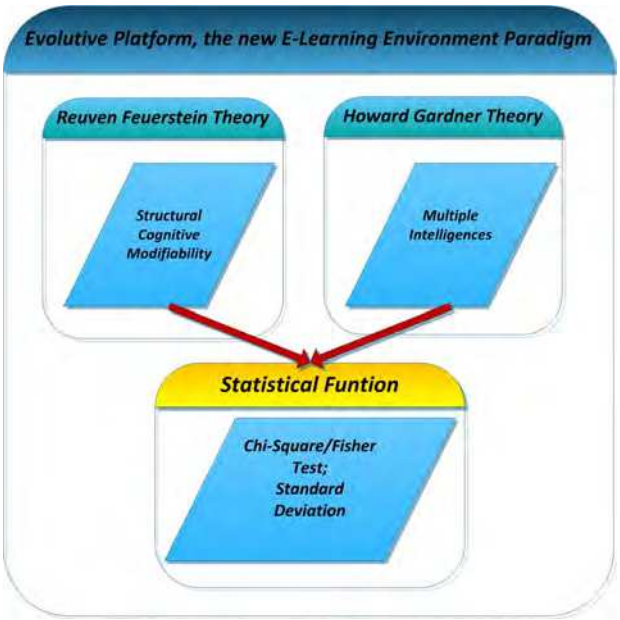


Fig. 1. Global Block Diagram

3. Method

A host of research has been devoted to the way individuals acquire and perceive educational material in relation to their personality (Wallace et al., 2007, as cited in Kerkiri et al., 2010). Early efforts that approached provision of personalized learning paths were either based on the performance of the learner (Carchiolo et al., 2007, as cited in Kerkiri et al., 2010), or on indicators of her/his preferences (Graf et al., 2008, as cited in Kerkiri et al., 2010).

Individuals present distinct ways of learning, different background, and diverse preferences. By composing these characteristics, aspects of the student learning process and knowledge, construction process can be inferred by computational systems and registered in a profile (Stiubiener et al., 2010).

Each individual has her/his unique way of learning. Thus, learning style greatly affects both the learning process and the outcome (Carver and Howard, 1999, as cited in Kazanidis & Satratzemi, 2009). In order to achieve better learning outcomes, several research streams are attempting to provide adaptivity of the learning process. One of these streams exploits educational theories about student learning styles in order to gain a better learning outcome. Some of the most well known learning styles are (Kazanidis & Satratzemi, 2009):

- Kolb's learning style theory (Kolb, 1984).
- Honey and Mumford (1992)
- Felder & Silverman (1988) Learning Style Model (FSLSM)..
- Witkin's Field Dependent- Field Independent Model (Witkin et al., 1977).
- Dunn & Dunn (1978) Model.
- Grasha-Riechmann Student Leaming Styles Scale (GRSLSS) (Riechmann & Crasha 1974).
- Gardner's theory of multiple intelligences (Gardner, 1993).

Various studies have been done that have applied several techniques in e-Learning:

- Becker and Vanzin (2003) tried to detect meaningful patterns of learning activities in e-Learning using the association rule.
- Minaei-Bidgoli, Kashy, Kortemeyer, and Punch (2003) proposed a method of predicting a learner's final test score by using a combination of multiple classifiers (CMC) constructed from learning-history data in e-Learning, and they reported that a modified method using a Genetic Algorithm (GA) could improve the accuracy of prediction.
- Talavera and Gaudioso (2004) and Hamalainen, Laine, and Sutien (2006) proposed a method to prediction final test scores using the native Bayes model obtained from learning-history data in e-Learning.
- Ueno (2010) does not simply propose a system of predicting a learner's final status using a data-mining technique, but an agent that acquires domain knowledge related to the content from a learning-history-log database that automatically generates adaptive instructional messages to guide the learners.

3.1 The adaptive system structure

Adaptive systems (Kobsa, 1996 & Kobsa, 2001, as cited in Stiubiener et al., 2010) include a user model that represents student's knowledge, objectives, interests, and other characteristics that enable a system to differentiate among its users. The system gathers information, models users, and uses that information to provide adaptation. This enables

the system to interact with several users, in the same context, but in different ways. The sources of information on which the adaptation is based might range from user's interaction to a direct request for information (Stiubiener et al., 2010).

The proposed system adapts itself and guides the user through the available KB, individualizing student outcomes through identifiers in the database. This information is used to determine what lessons should be selected to achieve the objectives.

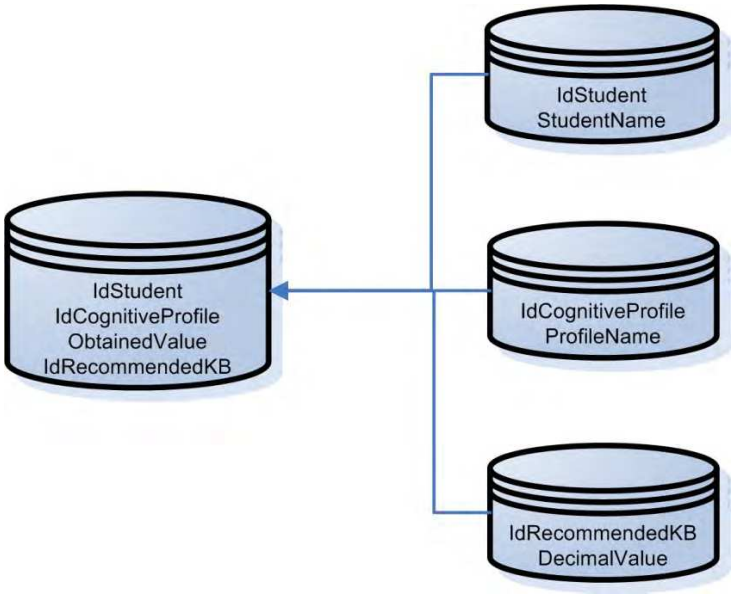


Fig. 2. Database Structure

The user's knowledge level is a crucial parameter for adaptive systems (Kazanidis & Satratzemi, 2009). The proposal agent uses learner's history data, which is stored in a database to individualize learners.

A computational agent that learns using machine learning or data-mining technologies from data is called a "learning agent". This article proposes a learning agent for e-Learning (Ueno, 2010).

In the social context, artificial intelligence can take advantage of biological observations of certain species to imitate their experiences. This trend, called evolutionary computation, uses genetic algorithms (GAs) on one hand and swarm intelligent techniques on the other hand (Madhour & Forte, 2010). This learning agent, in particular, uses a GA that enables extraction of the necessary values to choose the most appropriate KB, based on two statistic functions.

The learning model (LM) (fig. 4), defines the learning activities in which the individuals learn. The content is structured information, consisting of multimedia resources, texts, lectures and other materials. The content is a set of circumstances that are relevant to the student to build knowledge through its connection with it.

In this model the teacher, has a bipartite role in the presentation of content and creation the learning context. The context can be a classroom or a virtual learning activity, in which the role of teacher is more focused on content in the case of a classroom, and the context in the case of a virtual learning activity. In this study the LM is transformed in the KB with the following structure (Fig. 5).

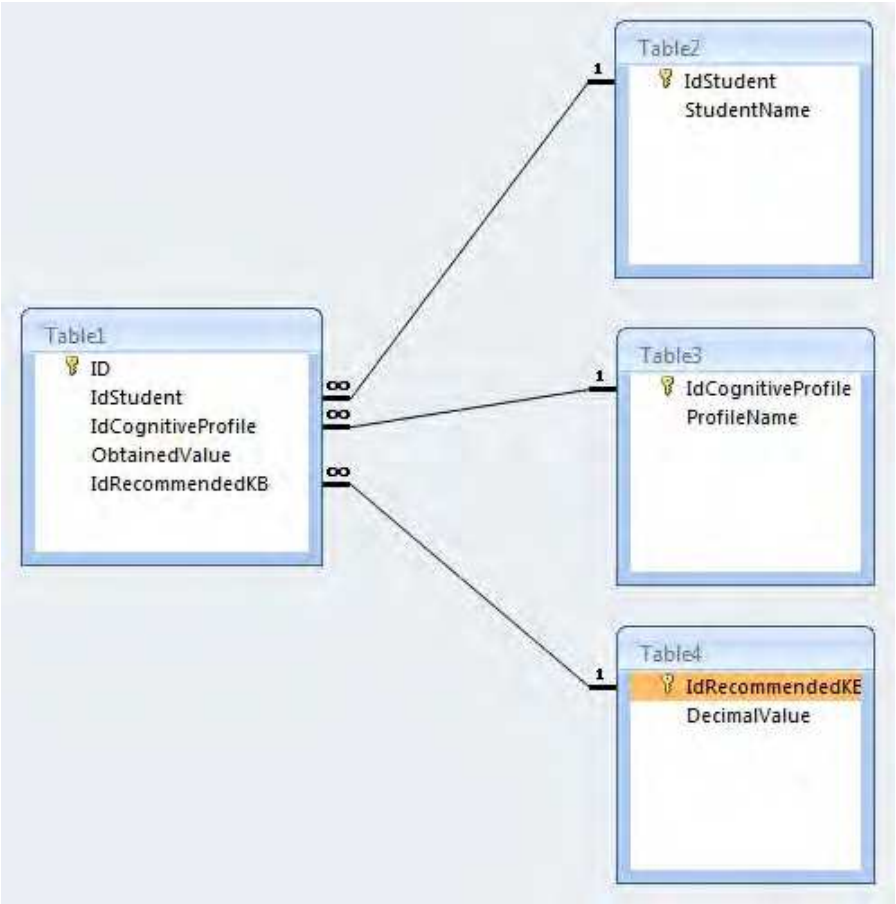


Fig. 3. Database Relations

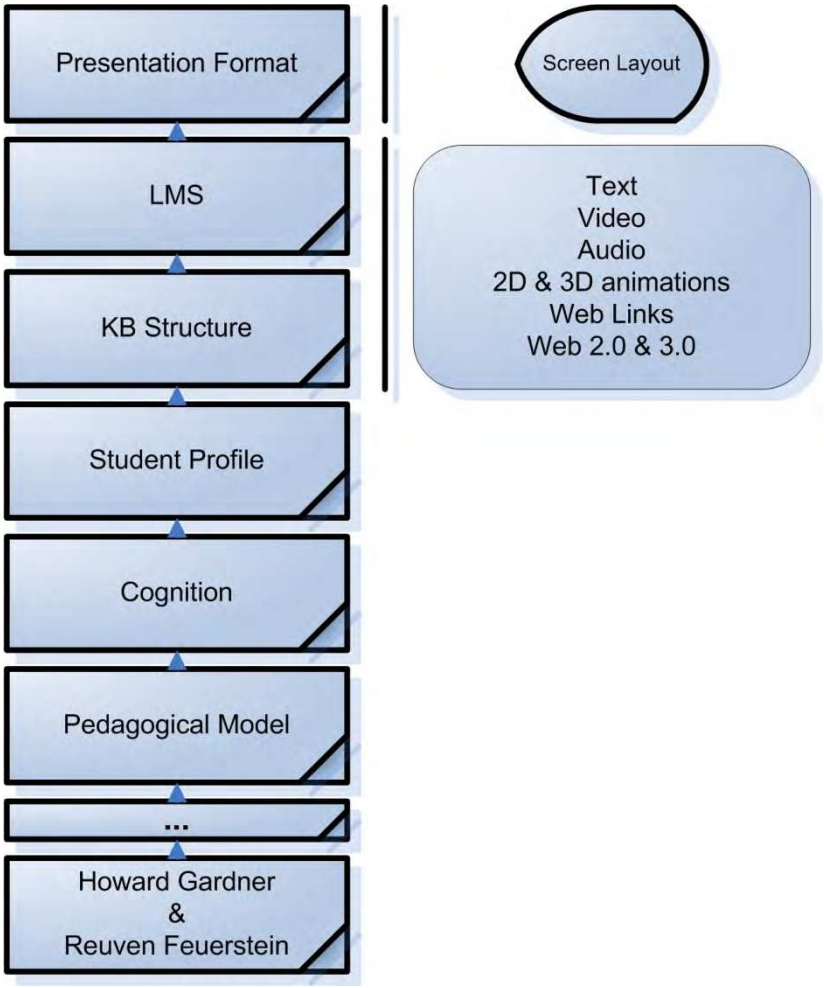


Fig. 4. Learning Model Orientation Layer Structure

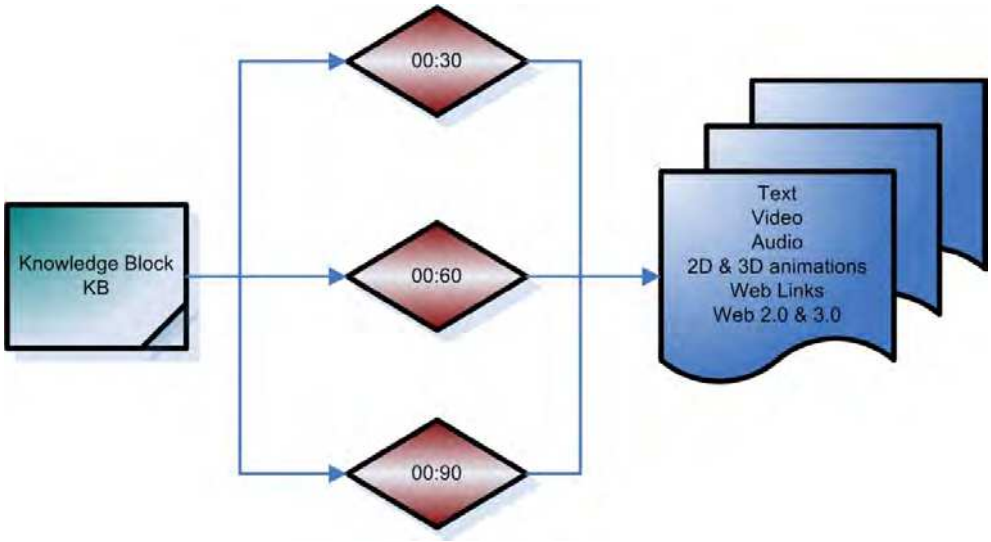


Fig. 5. Knowledge Block Structure

The KB represent 30, 60 or 90 minutes lessons, covering all aspects of Gardner's multiple intelligences (Gardner, 1993) using a variety of content that go from text to images, sounds, video and web links. This structure can be prepared by the teacher or by multidisciplinary teams or companies that want to develop contents.

4. The core

Student centered learning is an educational paradigm that gives students greater autonomy and approach is very similar to the Bologna Process goals in terms of student centered model based on learning outcomes and competences (Alves, 2010). Some of the characteristics of effective learners in the student centered learning paradigm are (de la Harpe et al., 1999, as cited in Alves, 2010):

- Have clear learning goals;
- Have a wide repertoire of learning strategies and know when to use them;
- Use available resources effectively;
- Know about their strengths and weaknesses;
- Understand the learning process;
- Deal appropriately with their feelings;
- Take responsibility for their own learning;
- Plan, monitor, evaluate and adapt their learning process;

The majority of virtual learning environments (VLE) are used as mere repositories of content, based on the classroom paradigm and don't support the individualization of the learning process (Alves, 2010). According to Dias (Dias, 2004), building spaces for online learning is a challenge that goes beyond the simple transfer of content to the Web. This approach tends to transform the environments in online repositories of information rather than in the desired spaces of interaction and experimentation (Alves, 2010).

The integration of the intelligent systems in the learning process support, allows an adaptation of content and contexts to the learning style of each student, providing adaptive tools to support collaboration (Lesgold et al., 1992; Goodman et al., 2003, as cited in Alves, 2010).

To allow a greater adaptation of the learning environment based on the student's profile the adoption of theories of artificial intelligence in education is proposed, based on the learning experience, adapting contents and contexts to the student needs (Alves, 2010).

In the last three decades, artificial intelligence has been adopted in various forms of education. One of the most important issues in the adaptation of an intelligent tutoring system is the modulation of student behavior in order to adapt the pedagogical model to the student model. For this adaptation to be more effective the student profile must be identified. In this context, the development of adaptive learning environments based on the student profile is one of the most important challenges in the adoption of artificial intelligence systems in education, in order to improve the educational process. This approach is based on new pedagogical methodologies to provide learning environments adaptable to the needs of each student (Alves, 2010).

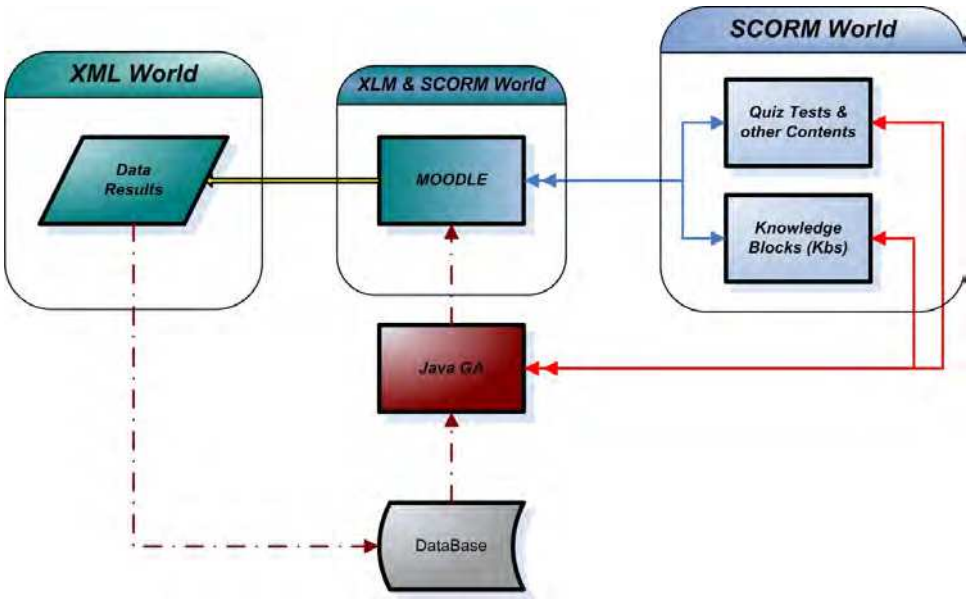


Fig. 6. Evolutive Platform Structure

1. Quiz Test & other Contents are created with SCORM compliant software[1] and imported to the (LMS), after be chosen by the Java GA, consulted the database that contains the student statistics data;
2. KB are created with SCORM compliant software[2] and imported to the (LMS) after be chosen by the Java Genetic Algorithm (JGA), consulted the database that contains the student statistic data;

[1] e.g. Hot Potatoes, Reload Editor or others;

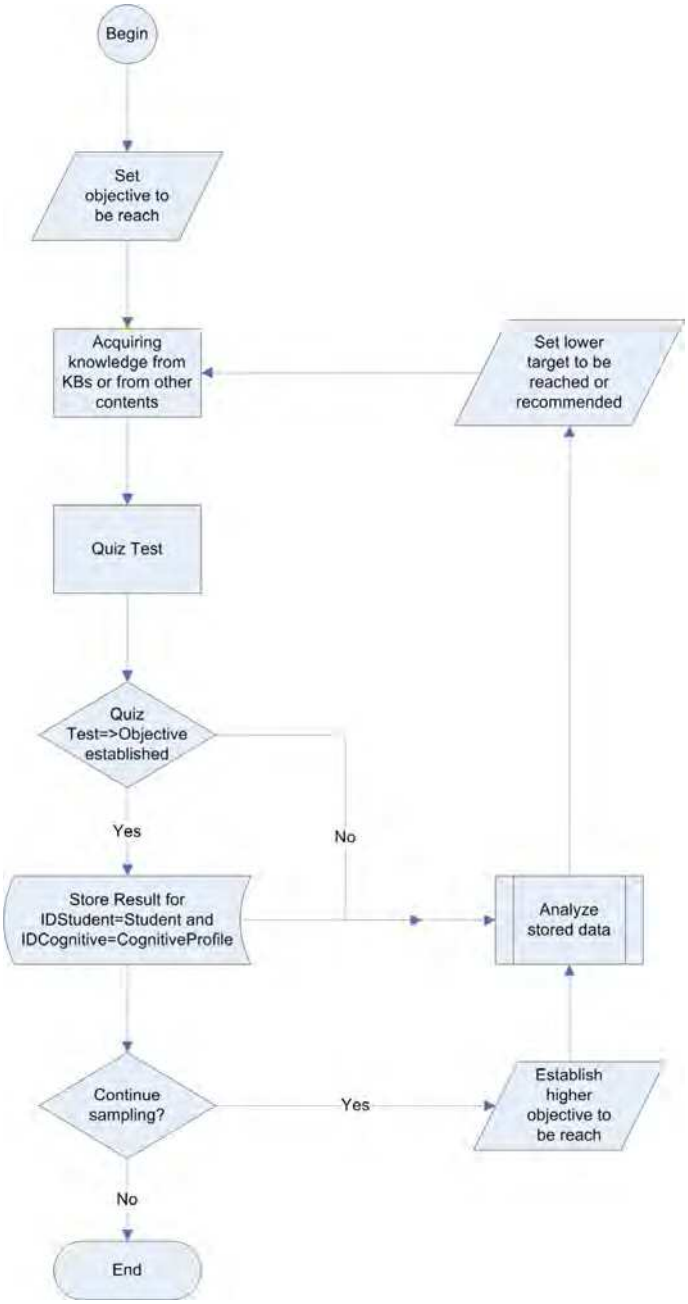


Fig. 7. Algorithm Structure - first samples – training phase

[2] e.g. Hot Potatoes, Reload Editor or others;

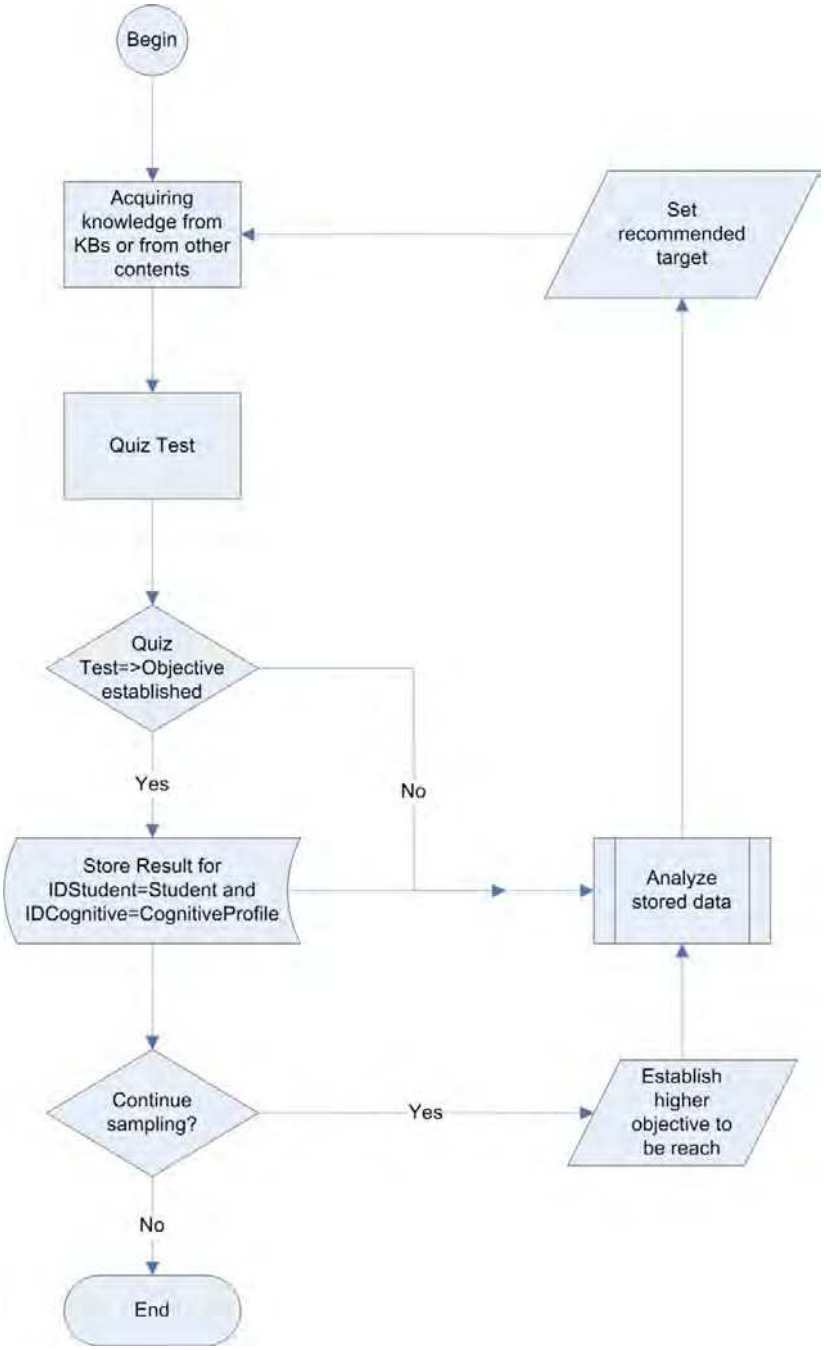


Fig. 8. Algorithm Structure - cruising speed

3. The Moodle (LMS) produces results in XML format, which are stored in a database system for subsequent consultation by the JGA;

The flowcharts from (Fig. 7 and 8), represent the sequence of actions to meet to get the best KB. They differ only in one point. From the moment the algorithm has sufficient sampling, no longer need an intervention, passing to auto regulatory mode, using the information contained in databases on a particular student and their profile.

4.1 The genetic algorithm

The GA has an important role in implementing this solution, since its performance will greatly affect the final results. It should be as dynamic as possible in order to achieve various goals, according to the predetermined guidelines. This should be achieved by giving weights to the cognitive profile or profiles, which are meant to be improved. The basic idea is to get the "fitness function" to be improved as much as possible in order to get a better approach to the most correct KB, according to the previously achieved results.

The student results after activity sequence builds a set of binary values. The idea is to maximize the minimum obtained by the individual, i.e., find what difficulties are visible and redirect all the intellectual effort to overcome the problems, never forgetting the positive objectives already achieved.

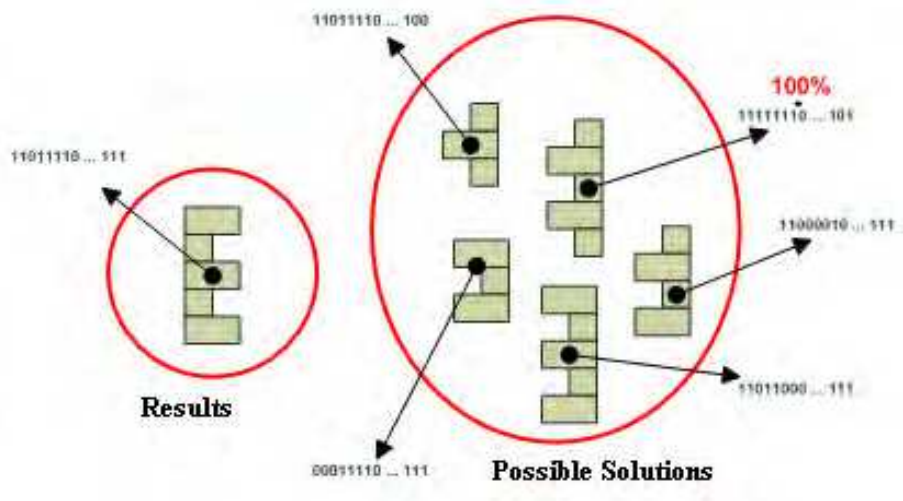


Fig. 9. Binary correspondence of the population and possible solutions

The GA will select the KB that matches the student's difficulties. If the match is not 100% exact, 80% will be considered a fair value in the acquisition of the new block.

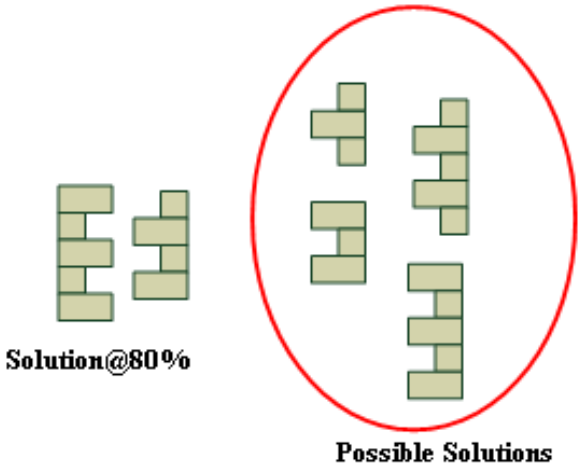


Fig. 10. Solution @ 80%

The 100% match will be an ideal situation that the GA mechanisms will try to achieve.

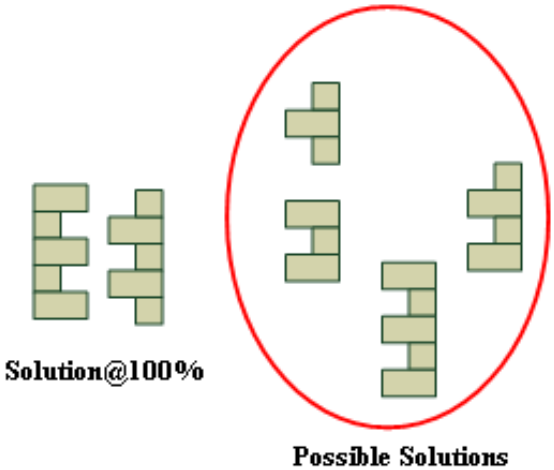


Fig. 11. Solution @ 100%

This ideal situation will be only achieved after several cycles of study of the behavior of the individual. This ideal situation is also dependent on the availability of the block that has the desired binary value.

4.2 The fitness function

The fitness function allows assigning probabilities to the units likely to be visited by the learner. The highest probability is that relating to the most suitable unit. In this case we use two statistical functions to get the necessary values to choose the most appropriate KB.

4.2.1 Chi-square

The chi-square is defined as a discrepancy measure between the observed frequencies and the expected ones (Spiegel, 1994).

$$Q = \sum_{i=1}^{k} X_i^2$$

Equation. 1. Chi-Square distribution

The GA uses this discrepancy measure, as its evaluation function. The obtained value will be used as a weight, to select the best candidate block.

$$x^2 = \frac{(o_1 - e_1)^2}{ej} + \frac{(o_2 - e_2)^2}{ej} + \cdots + \frac{(o_k - e_k)^2}{ej} = \sum_{j=2}^{k} \frac{(o_j - e_1)^2}{ej}$$

Equation. 2. Chi-Square distribution in extended form

The two observation tables (Fig. 12), represent a possible situation of what is sought as a final value - the expected, and obtained through "simulated reality" - obtained. The difference between what is expected and what we get is the deviation that must be compensated to achieve the objective - the expected value. In the simulation (Fig. 12), there are two blocks to simulate a process of classifying a given KB. As it is observed in the (Fig. 12) illustration, $\chi 2$ suffered a decrease from the 1st to 2nd KB, which can be understood as an improvement in the GA orientation, as the 2nd block better approach the individual's cognitive reality. It is still observed - and in spite of the illustration represents a random simulation of what is desired that the orientation of GA is forced immediately when the discrepancies between expected values and obtained values are significant (between points 5 and 7 in the χ axis in the graph to the right, and between 5 and 8 in the graph to the left).

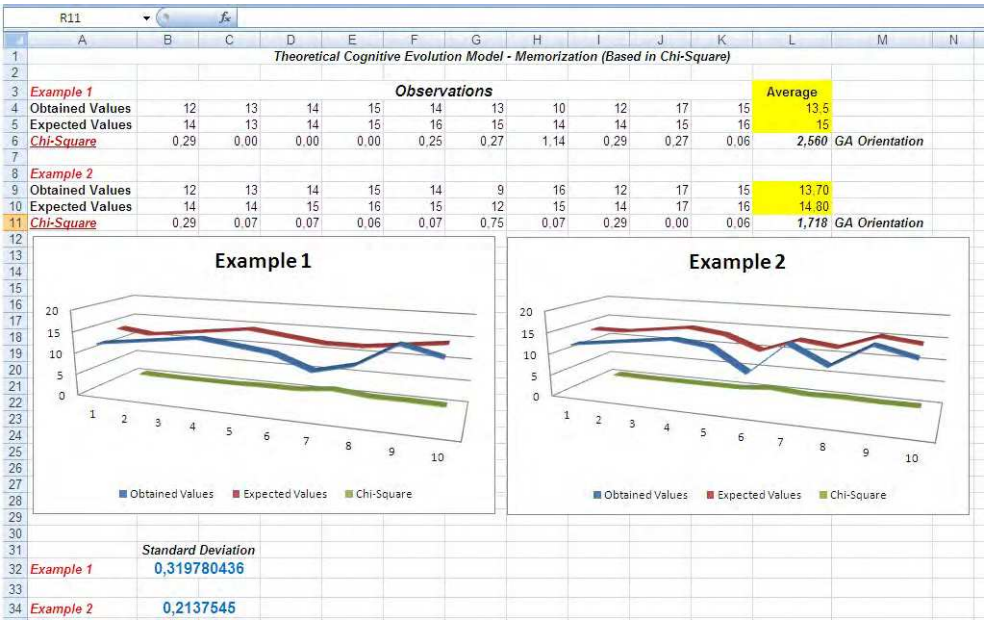
4.2.2 Standard deviation population

When all available values are used, it is called a population; when only a subset of available values is used, it is called a sample.

$$s = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \overline{x})^2},$$

Equation. 3. Standard Deviation Population

Where $\{x_1, x_2, \ldots x_N\}$ are the observed values of the sample items and $\bar{x}$ is the mean value of these observations. This correction (the use of $N - 1$ instead of N) is known as Bessel's correction. The reason for this correction is that s^2 is an unbiased estimator for the variance σ^2 of the underlying population, if that variance exists and the sample values are drawn independently with replacement. However, s is *not* an unbiased estimator for the standard deviation σ; it tends to overestimate the population standard deviation. The term *standard deviation of the sample* is used for the uncorrected estimator (using N) while the term *sample standard deviation* is used for the corrected estimator (using $N - 1$). The denominator $N - 1$ is the number of degrees of freedom in the vector of residuals, $(x_1 - \bar{x}, \ldots, x_n - \bar{x})$ (Wikipedia - Standard Deviation, 2011). In order to get the increase by which the GA will guide the choice of the degree to be achieved, we turn to the second statistical function - Standard Deviation Population, which collects the values of the individual result from several samples from the calculation of Chi-square. This value will allow us to pick a particular KB, guiding the student in obtaining their optimum value.



	Theoretical Cognitive Evolution Model - Memorization (Based in Chi-Square)											
Example 1					Observations						Average	
Obtained Values	12	13	14	15	14	13	10	12	17	15	13.5	
Expected Values	14	13	14	15	16	15	14	14	15	16	15	
Chi-Square	0.29	0.00	0.00	0.00	0.25	0.27	1.14	0.29	0.27	0.06	2,560	GA Orientation
Example 2												
Obtained Values	12	13	14	15	14	9	16	12	17	15	13.70	
Expected Values	14	14	15	16	15	12	15	14	17	16	14.80	
Chi-Square	0.29	0.07	0.07	0.06	0.07	0.75	0.07	0.29	0.00	0.06	1,718	GA Orientation

	Standard Deviation
Example 1	0,319780436
Example 2	0,2137545

Fig. 12. Theoretical Cognitive Evolution Model – Memorization

4.2.3 Genetic algorithm pseudo-code

The theory is based mainly on the following two assumptions:

- H_0 is ignored until the learning curve of the individual is understood;
- H_0 is considered for future evolutionary terms after 1st premise has been achieved;

The use of the two hypotheses is due to the fact that the 1st objective is to understand the cognitive reality of the individual, and then improve it.

Algorithm for Individual Cognitive Sequence (10 samples example):

1. Establish objective to be reached (0-100% or 0-20);
2. Start ranking process (w/ sample = target);
3. Get cognitive binary of the individual;
4. Perform statistical operation on results;
5. Repeat (1) at least 9x (or as desired);
6. Get Final Sum;
7. Apply acquired weight (next module=objective to be achieved + obtained weight);
8. Repeat (1) N times until obtain binary or objective;

The algorithm begins by setting up a target, regardless of prior knowledge of the cognitive profile of the individual. The sequence (1 to 4) will be repeated at least 10 times and the value statistically treated to obtain a weight. The result will be used in obtaining the next module by the GA, with the aim to get closer to the maximum desired.

4.3 Knowledge blocks

Notwithstanding their indisputable assets, the reusability and inoperability of learning objects has been presented as a major problem in adaptive learning, inasmuch solutions of their technical linking are not directly presupposed. Standards have been thus adopted by the e-learning community to facilitate and foster interoperability and reuse of learning artifacts among different e-learning platforms. The pertinent use of predefined sets of metadata promotes the exchange of Learning Resources (LR) among different e-learning systems and content providers, while offering higher potentials for finding existing learning content as well. Such standards for the learning resources are Learning Object Metadata (LOM) and Sharable Content Reference Model SCORM[3] (Kerkiri et al., 2010).

Adopting educational standards, like SCORM, comes as a solution to the above problems for content reusability, accessibility interoperability and durability. It's expected that the adoption of such standard will help authors to construct more effective courses faster with less effort and at a lower cost (Kazanidis & Stratzemi, 2009).

Authors would save much time and effort if they could easily find and reuse qualitative educational content from other courses and or platforms. Moreover, they would save time if there where no need to update their courses when the host platform was updated to a new version. Thus, the need to have reusable, accessible, interoperable and durable (RAID) content has led to the creation of learning technology specifications. For the time

[3] specifications of SCORM can be found in Advanced Distributed Learning (ADL, 2004)

being the most popular educational standard is SCORM (ADL, 2009) which was implemented by the ADL (Advanced Distributed Learning) Initiative (Kazanidis & Stratzemi, 2009).

SCORM is a collection of specifications and standards for the development, packaging and delivery of educational content. More specifically, it describes the components used in learning and how to package them for exchange between compliant systems; how they should be described using metadata in order to enable search and discovery; and how to define sequencing rules for the content objects (ADL, 2009). SCORM consolidates the work of other standards and organizations, such as ARIADNE, AICC, IMS, and IEEE's LTSC into one unified reference model. The application of SCORM ensures the reusability, accessibility and durability of the educational material, as well as interoperability between (LMS) (Kazanidis & Stratzemi, 2009).

4.3.1 The knowledge block structure

The KB is a simple structure that has SCORM compatibility and a binary codification, allowing the GA to be the most suitable choice to which specific case.

Reserved for Future Use	Educational Level	Cognitive Profile ID	KB difficulty level
00000000	00000	000	0000000000000000

Table 1. Knowledge Block Coding

Regardless of the used operator – crossover, mutation or both, 16 bits are up front considered enough for a KB selection to be uploaded in the (LMS), without the risk of a premature convergence into a specific solution by the GA.

Binary Value	Decimal Value
0000000000000000	0
…	…
111010111000110	9,20 ≈
…	…
1100110000000110	15,94 ≈
…	…
1111111111111111	20

Table 2. Knowledge Block Difficulty Level

$$20_{10} – <65535_{10}><1111111111111111_2>$$

$$9,20_{10} - <X_{10}><Y_2>$$

$$X = <30150_{10}><111010111000110_2>$$

After being provided the results in decimal base, by the GA, those will be converted by an internal mechanism - a 3 simple rule in order to achieve the corresponding binary value of KB closer to the desired.

Cognitive Profile	Binary Representation
Logical-Mathematical	000
Linguistic	001
Musical	010
Spatial	011
Naturalist	100

Table 3. Knowledge Block Cognitive Profile ID

Considering that of the 10 (ten) cognitive profiles universally recognized (Gardner, 1993), only 5 (five) will be subject to analysis, since the remaining four – Corporal, Intrapersonal, Interpersonal and Existential can not be considered in the context of this work, because they are virtually impossible to quantify due to their strong abstract nature, we therefore will need only a 3 bit code to represent them.

Educational Level	Binary Representation
1st Grade	00000
…	…
Bachelor's	01000
…	…

Table 4. Knowledge Block Educational Level

In a similar way, the remaining 5 bits will identify the educational level best befitting the KB. The choice of such a wide identifier is related to the possibility of reaching 32 possible levels of identification, in a specific educational system. In Portugal, these values can easily go up to 23 levels. The exchange of the information between KB and the GA will be made through XML files. The (LMS), in turn, will provide the user with the KB appointed by the GA, in a dynamic way, changing the links according to the information received.

4.4 XML

XML and Java technology are recognized as ideal building blocks for developing services and applications that access services. Java Architecture for XML Binding (JAXB) is an XML binding model that defines the way of automatic mapping XML documents into objects in a programming language.

Two major processes, marshalling and unmarshalling, take care of the mapping between Java objects and XML documents, which makes JAXB surpass traditional Simple API for XML (SAX) and Document Object Model (DOM) approaches. Its advantages are (Liu & Shih, 2010):

- Simplicity: It is Java procedure to derive the classification (Schema-Derived Classes & Interfaces) through the outline that Binding Compiler compiles out, so does not need to deal with XML file by oneself, and does not deposit and withdraw the content tree without according to the order;
- Extensibility: The programmer can revise the schemas and derive the classification independently, and let the procedure accord with systematic requirements even more. Additionally, when XML Schema is changed to some extents, it just needs to recompile

Schema, and increase some more procedures newly, instead of needing to revise the original procedures.

- Efficiency: Because all content tree data is produced by JAXB according with the definition of XML Schema, no invalid methods on objects exist. Even it could use the Unmarshaller class to verify whether XML file is effective.

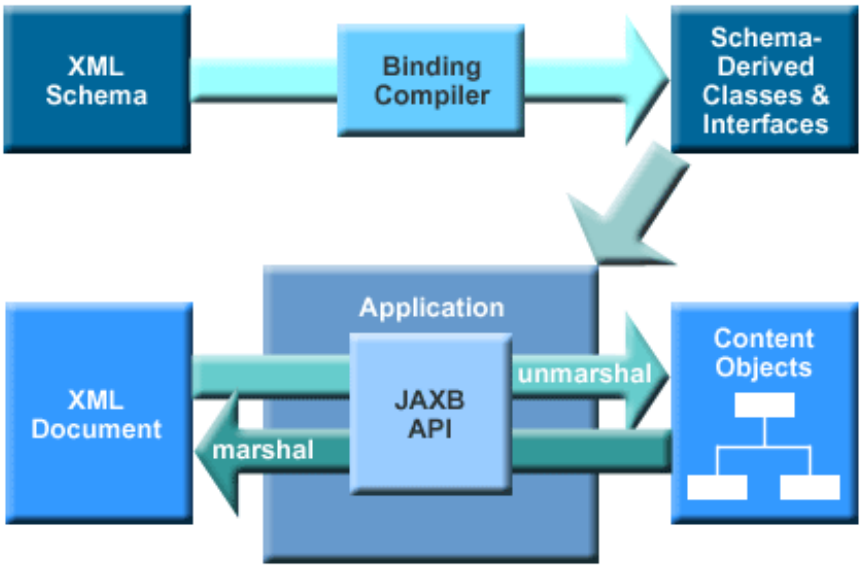


Fig. 13. Java Architecture for XML Binding (JAXB)

```
<language>
      <typename>
            <tysource sourcetype="imsdefault"/>
      <tyvalue>German</tyvalue>
      </typename>
      <contentype>
            <referential>

                  <indexid>language_01</indexid>
            </referential>
      </contentype>
      <proficiency profmode="OralSpeak">Excellent</proficiency>
      <proficiency profmode="OralComp">Excellent</proficiency>
      <proficiency profmode="Read">Good</proficiency>
      <proficiency profmode="Write">Poor</proficiency>
</language>
```

Fig. 14. XML example of a record containing information of classifications

The exchange of all the information between KB and GA will be made through XML files (Fig.14). The (LMS), in turn, will provide the user with the KB appointed by the GA, in a dynamic way, changing the links, according to the information received.

5. Conclusions and future work

The theoretic part of the work is ready. The authors have already designed all the interactions and mechanisms that will allow proceeding to the development phase. Field-testing will occur during this development. There is already a partner – a local kindergarten which has volunteered to test the results.

In order to evaluate the proposed system, a class of students (21 children involved) has been divided randomly into two groups. One group uses the described system, while the other follows the normal route. The tests will be performed during the current school year, after which we will get the results. During this period, the algorithm will be modified simultaneously in order to improve performance.

In the future, it will be taken into account the possibility of this solution to include the capacity to make several choices regarding the KB to be selected, allowing the improvement of two or more cognitive profiles. We intend to use evaluation methods by computer through the algorithm Cota-Groppo (Groppo, 2010), using a new interface to communicate with the GA, in order to introduce a better accuracy in the results. The introduction of psychological states, such as emotional and affective responses should also be considered in future work (Lin and et. al., 2010).

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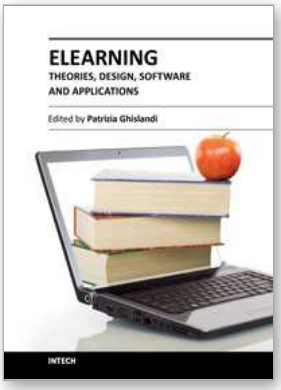

eLearning - Theories, Design, Software and Applications

Edited by Dr. Patrizia Ghislandi

ISBN 978-953-51-0475-9
Hard cover, 248 pages
Publisher InTech
Published online 11, April, 2012
Published in print edition April, 2012

The term was coined when electronics, with the personal computer, was very popular and internet was still at its dawn. It is a very successful term, by now firmly in schools, universities, and SMEs education and training. Just to give an example 3.5 millions of students were engaged in some online courses in higher education institutions in 2006 in the USA1.eLearning today refers to the use of the network technologies to design, deliver, select, manage and broaden learning and the possibilities made available by internet to offer to the users synchronous and asynchronous learning, so that they can access the courses content anytime and wherever there is an internet connection.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Jorge Manuel Pires and Manuel Pérez Cota (2012). Evolutive Platform - A Genetic E-Learning Environment, eLearning - Theories, Design, Software and Applications, Dr. Patrizia Ghislandi (Ed.), ISBN: 978-953-51-0475-9, InTech, Available from: http://www.intechopen.com/books/elearning-theories-design-software-and-applications/evolutive-platform-a-genetic-elearning-environment

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