Evolutive Mechanism for E-Learning Platforms

A new approach for old methods

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Abstract—**Since the beginning of men, knowledge distinguishes us as a species and has become the key to our own evolution. Humans have a complex psycho-pedagogic model, the result of millions of years of evolution. This model compromises very often the educational structures, because each of us – despite we can be inserted in specific groups, have a personal learning curve. Like nature, that develops special strategies for the evolution of the species, it is possible to find the correct individual learning path, using one of the oldest Mother Nature mechanisms – evolutive genetic. Using tools like JAVA, XML (eXtensible Markup Language), an open source LMS (Learning Management System), i.e. Moodle, a standard as SCORM (Sharable Content Reference Model), all controlled by a GA (Genetic Algorithm), it is possible to achieve a flexible platform to help all the educational process actors. The goal is to create a self universal monitoring and learning system,which follows the progression of individual learning – by using a mathematical function applied to a genetic algorithm, maximizing the results and achieve the subject "learning curve".**

Keywords: Java, XML, SCORM, Genetic Algorithm

I. Introduction

In current societies the growing need for a fast acquisition of knowledge, as well as the need to maintain the one already acquired, has led to the birth of various concepts of learning, such as the E-Learning.

However, the proliferation of various platforms and associated philosophies has not always achieved a full interaction between those who are learning and those who are transmitting the knowledge. The fast pace of modern life does not allow us the time to attend assisted classes and the aversion older people tend to feel towards new technologies are determinant factors for the global results not matching the expectations when it comes to the learning process.

In this article, the authors suggest a new transversal approach to the concept of E-Learning by using GA, Java and a LMS, SCORM compatible, thus fully innovating the applicability of the concept of E-Learning, taking it to a whole new level.

2nd Section – Presents the GA structure, and the statistic support function.

3rd Section – Presents the KB and the communication path structure between the LMS, the GA and the user.

4th Section – Presents the objectives and conclusions of the work done until now.

II. The Genetic Algorithm

The genetic algorithm 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 Knowledge Block, according to the previously achieved results.

The student results after an activities sequence build 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.

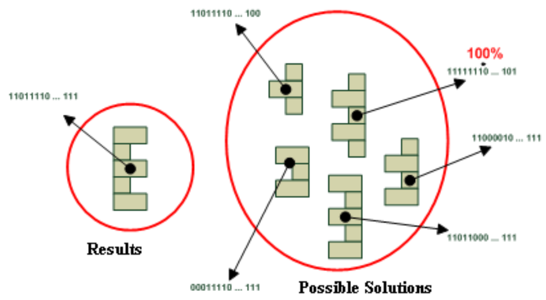

Fig. 1 – Binary correspondence of the population and possible solutions

978-1-4244-6571-2/10/$26.00 ©2010 IEEE April 14-16, 2010, Madrid, SPAIN

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.

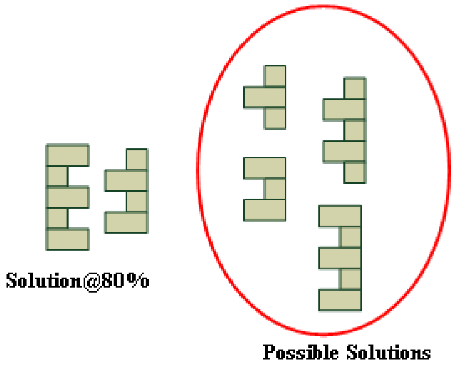

Fig. 2 - Solution @ 80%

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

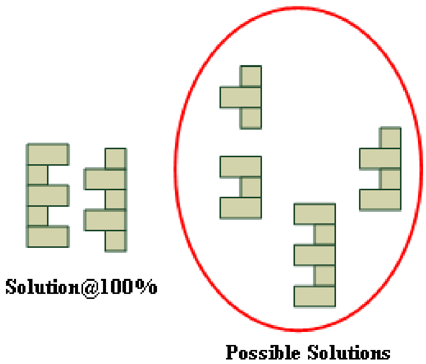

Fig. 3 – Solution @ 100%

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.

A. The Statistic Support Function

The chi-square is defined as a discrepancy measure between the observed frequencies and the expected ones (Fig. 4). [1]

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

Fig. 4 – 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.

$$x^2 = \frac{(o_1 - e_1)^2}{ej} + \frac{(o_2 - e_2)^2}{ej} + \dots + \frac{(o_k - e_k)^2}{ej} = \sum_{j=1}^{k} \frac{(o_j - e_1)^2}{ej}$$

Fig. 5 – Chi-square distribution in extended form

The two observation tables (Fig. 6), represents a possible situation of what is sought as a final value - the expected, and that in "simulated reality" is obtained - 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. 6), there are two blocks to simulate a process of classifying a given knowledge block. As it is observed in the (Fig. 6) illustration, χ^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 to approach more of 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).

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.

B. 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;

(9) Repeat (1) at least 9x (or as desired);

(10) Get Final Sum;

(11) Apply acquired weight (next module=objective to be achieved + obtained weight);

(12) Repeat (1) N times until obtain binary or objective;

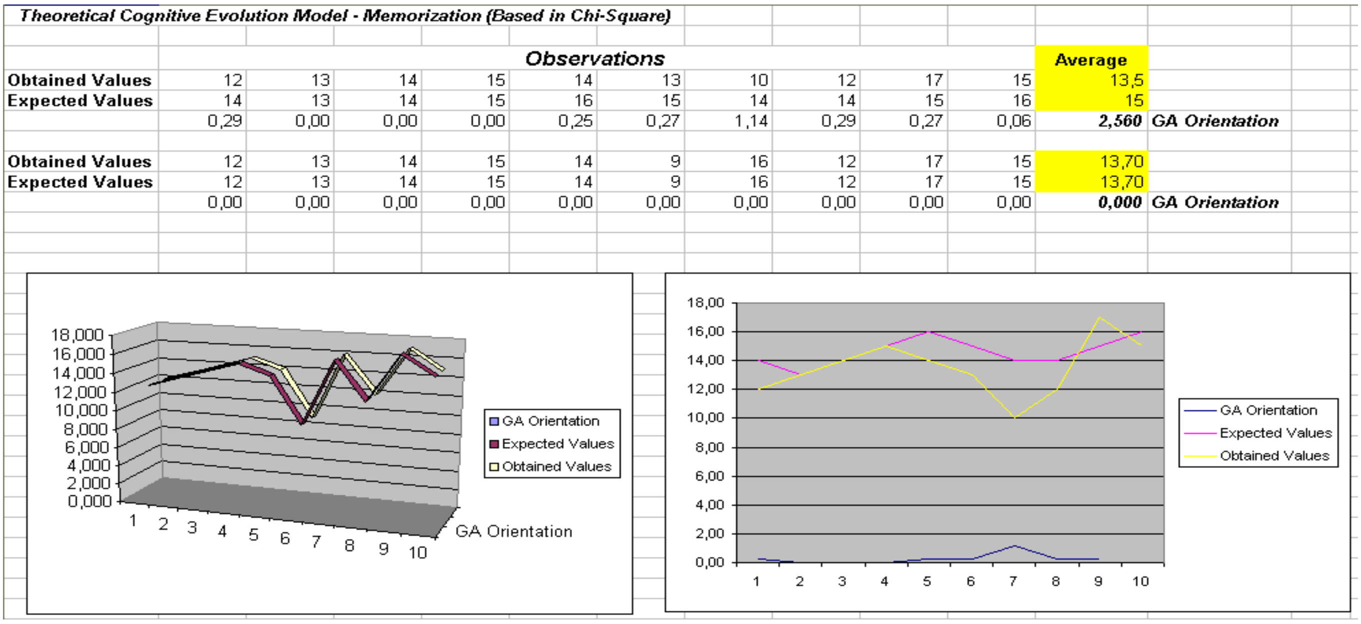

Fig. 6 – Theoretical Cognitive Evolution Model – Memorization

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.

III. The knowledge block

The Knowledge Block (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.

TABLE I. KB Coding

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

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.

TABLE II. KB Difficulty Level

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

$$20_{10} - <65535_{10}><1111111111111111_2>$$
$$9{,}20_{10} - <X_{10}><Y_2>$$

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

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.

TABLE III. KB Cognitive Profile ID

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

Considering that of the 10 (ten) cognitive profiles universally recognized [2], 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.

TABLE IV. KB EDUCATIONAL LEVEL

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

In a similar way, the remaining 5 bits will identify the educational level best befitting the KB. The choice of such a wide identifier has to do with 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 all the information between KB and GA will be made through XML files. The LMS, in turn, will provide the user with the KBs appointed by the GA, in a dynamic way, changing the links, according to the information received.

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      <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. 7 – 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. 7) [3]. The LMS, in turn, will provide the user with the KBs appointed by the GA, in a dynamic way, changing the links, according to the information received.

IV. OBJECTIVES

The authors aim at implementing a new paradigm, creating a system that, in most cases, will manage without the physical presence of a tutor. It will allow the student to 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 should it be done under the traditional methods.

V. CONCLUSION

The theoretic part of the work is ready. The authors have already designed all the interactions and mechanisms that will allow to proceed 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 GA results. In the future, it will be taken into account the possibility of this solution to include the capacity to make several choices of KBs, allowing the improvement of two or more cognitive profiles.

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