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Modeling of e-learning based on Ant Colony algorithm

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ABSTRACT

This paper describes an approach of modeling and adaptation of the e-learning. This modeling is based of the Ant Colony Optimization (ACO). In our modeling, e-learning is schematized by a graph where nodes represent the educational elements (lessons or exercises), and arcs link navigation between them. Each of the arcs is also a value that describes its importance in relation to teaching neighboring arcs. Students are represented by virtual agents (ants) who use these links.

Keywords : Modeling E-learning, Algorithm, ACO

1.INTRODUCTION

E-learning and distance education via the Internet is a means of current and promising teaching. However, it suffers from defects mainly related to the relative absence of the teacher and, therefore, the difficulty of adapting teaching to the level and behavior of the learner.

The platforms of distance education can be seen as learning systems which are used by three types of stakeholders (or actors): Teacher, learner and administrator. The teacher can put his courses online, add multimedia educational resources and supervise the activities of learners. The learner consults or downloads online courses, has a view of the evolution of his work and conducts exercises. Sometimes, he can contact a teacher or other learners via a forum. Concerning the administrator, he installs and maintains the system. Depending on the platforms, the administrator may have a more or less important role.

One of the major challenges of e-learning is learner autonomy. Adaptive e-learning will improve the use of platforms by offering courses tailored to the results, behaviors, tastes ...of learners, unconsciously.

This paper is divided into three parts. The first part is about the state of the art of e-learning. In second part, we propose a UML modeling of adaptive e-learning using use-case diagrams and class. In the final part, we will see the technical adaptations of the path.

2.STATE OF THE ART

E-learning has been growing inexorably, in recent years, on the topic, research on the Internet shows that there are many sites talking about the e-learning.

In this section we will see how computer tools for e-learning and the existing norms and standards and works on adaptive e-learning.

2.1 Norms and standards of e-learning

The value of e-learning is to propose a set of courses to learners and to facilitate the development courses for teachers. If a teacher wishes to offer courses for several platforms, the use of a standard allows the teacher to write only once. This is another e-learning issue and only a few organizations, such as the IEEE (Institute of Electrical and Electronics Engineers), ISO (International Standard Organization) or CEN (European Committee standards), are accredited to develop standards.

Before discussing the major standards and norms, let's give two definitions to distinguish them:

- A standard is a set of compliance rules, enacted by a standards body at the national or international level.
- A standard is a set of recommendations emanating from a representative group of users gathered in a forum, such as the IETF (Internet ENGINEERING Task Force), W3C (World Wide Web Consortium), the LTSC (Learning Technology Standards Committee) and the IEEE.

a) AICC (Aviation Industry Computer Based Training Committee)

In 1988, airlines, aircraft manufacturers, producers of computer-based lessons Aviation Industry CBT Committee (AICC), meet to define common technical specifications for products of computer-assisted instruction they use.

AICC has gradually been extended to all issues related to electronic training. Compatibility with this standard provides such interoperability between platforms and heterogeneous content providing opportunities for growth and increased enrichment. As for e-learning, the AICC defines the structure of content and methods of communication between the platform and the training course content.

b) SCORM (Sharable Content Object Reference Model) SCORM is a standard that is based on AICC[1]

SCORM establishes the rules of a business model of learning through the use of the Web. This initiative should enable teachers to integrate the courses they create in other applications under different platforms. The content must be independent from the constraints of formatting to allow its integration into various applications. The content will also use interfaces and standardized data. The SCORM includes a Course Structure Format based on XML, and allows easy transfer of content by defining the elements, structure and external references. These specifications include those of IMS and ARIADNE.

c) IMS (Instructional Management Systems)

The Instructional Management Systems (IMS) Global Learning Consortium is one of the most active groups [3]. Its role is essential to coordinate the works as those mentioned above. The IMS working group created in 1997, is composed of members from education, business and government organizations. The IMS's main objectives are to define technical specifications for interoperability of applications and services of Education and distributed to support the incorporation of the specifications in Web technologies. These specifications must comply with basic principles: interoperability, accessibility, reuse, sustainability, independence and portability.

3. UML MODELING OF ADAPTIVE E-LEARNING

As we have seen in the state of the art, the autonomy of the learner [4] is one of the objectives of e-learning. We wanted, to model our system of adaptive e-learning before considering the technique used to manage the adaptation of course [5].

This model includes two types of UML diagrams: **use-case diagram** that shows the different actors of the system and the roles they can take, and class diagrams that show the relationships between different classes.

3.1 The use case diagram

In Figure 1, our model consists of six key players: the administrator, students, teachers, author, teachers-manager and tutors (this is how we call the computer players who make the necessary adjustments):

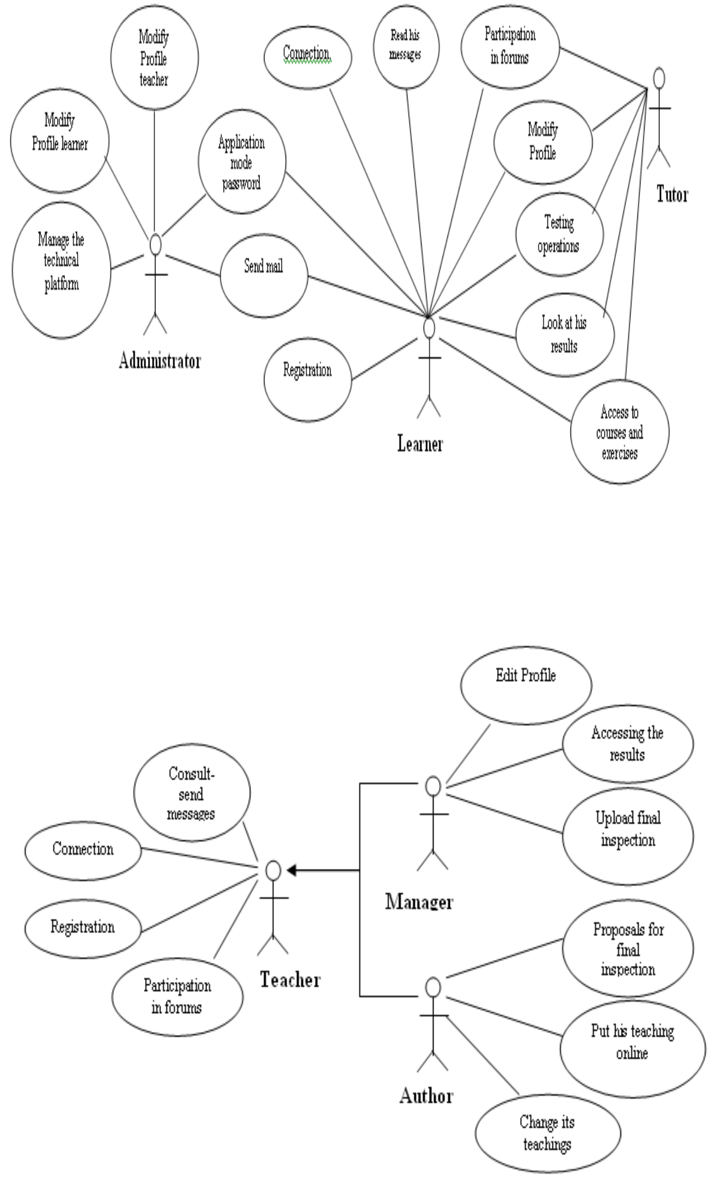

Figure 1: Use- case diagram

3.2 Actors

a) The administrator

The actor who differs very little from current e-learning systems [6] is the administrator. He deals mainly with the technical part of the platform. In our case, we have added to him the possibility to change the profile of a learner or information about a teacher.

The administrator is also there to answer questions that may arise from the different users of the platform and give them their password if it is forgotten.

b) The learner

The student who wishes to attend classes will register on the platform. Once he is registered, much information will be requested from him in order to manage his profile and to adapt the course. This information differs depending on the platform the student registers on: job training or educational training.

Once the student registered, he will be able to view the courses that are offered to him depending on his level.

*c) **Teachers***

Teachers can have multiple roles. These roles are not exclusive; it means that a teacher-author is also teacher-manager. Teachers, whatever their roles, must initially register on the platform and choose the status they want. They can also participate in forums, send emails and read their messages.

We have chosen to have several categories of teachers in order to have better organization and thus to better manage data access in the system.

The author is responsible for his lectures, exercises and continuous assessment online. He can also make changes he thinks necessary for some of his teachings.

The interest of our modeling is that for the same area, several authors will be able to offer their courses [7].

*d) **The tutor***

The tutor will adapt the course according to the learner profile. He will also review the results and the profiles of other students in order to offer all new students the best configuration.

The tutor may request advice from the head of a field when a learner hesitates. This will often be the case at the beginning of the implementation of the platform because few students have already gone through the course and then choosing the ideal course would be more difficult. We envision the use of virtual learners for system initialization.

4. ADAPTATION OF COURSES

We have defined the UML part of our system. Now we must consider how to adapt courses and settings that will go in. The AI responds to this kind of problem. We need to know to choose the algorithm that best fits our needs and study the genetic algorithms that exist to find the best one for the adjustment a platform of e-learning.

4.1ACO (Ant Colony Optimization or ant algorithm)

This method was invented in 1996 by Marco Dorigo of the Free University of Brussels [8, 9]. The original idea was inspired by a work of biologist (Deuneubourg et al 1983) on the observation of ants. These have the ability to find the shortest path between their nest and a food source by bypassing the obstacles in their path. For this, the ants work together and combine the behavior of random exploration and monitoring of chemical traces left by their sisters. These traces of chemicals, "pheromones" are used by ants to communicate [10].

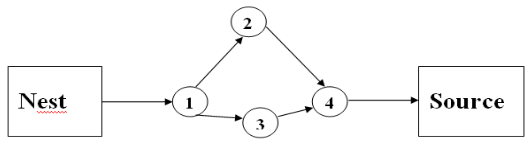

Figure 2: Illustration of ACO

For example, as shown in Figure 2, there are two possible paths to reach the source: one long and one short. Ants randomly explore both. When they find the source, they take the food, and return to the nest by releasing pheromones throughout their journey. The shortest path is also the fastest, the concentration of pheromones will grow faster, and ants which follow the chemical traces will be very quick, encouraged to follow the shortest path [11].

4.2 Application

*a) **The educational structure***

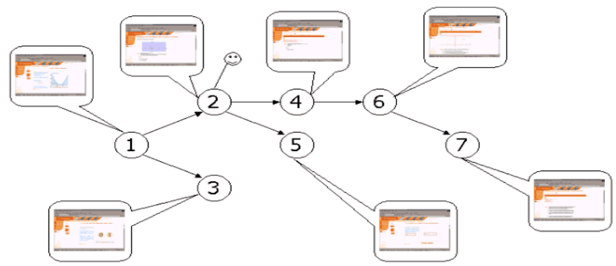

Figure 3: The platform seen as a graph, each node is a lesson, each arc an HTML link

The platform presented in figure 3 is modeled by a graph where each node represents an element of teaching (exercise, lesson... see Figure 3) and each arc is a possible navigation between two elements (hyperlink). Each of these arcs is called a real value W representing its teaching "relevance". This value is relative and places the arc in comparison with its neighbors that is to say with respect to the arcs coming out of the same node. As Figure 4 illustrates, according to the teaching team, after seeing "Tables in C language," it is four times more appropriate to see "pointers" than "the strings". The student is not obliged to follow the suggestion made by the ants: if he wishes, he can move to a node not suggested. If the arc taken doesn't exist, it is created with the value W 1 by default. When used in the calculation of fitness (see below), this value W is reduced compared to its neighbors; ie, the arc which carries the teaching weight leaving the node is considered as normalized [10].

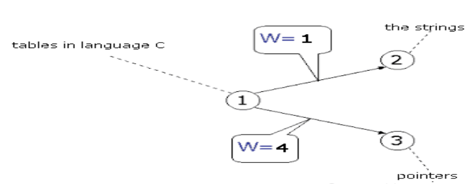

Figure 4: Close view of a node. What to do after seeing lesson1? Teachers suggest the lesson3 by assigning a weight 4 times larger in the corresponding arc.

b) Ants and pheromones: S & F

Each student who travels through the graph is represented by an "ant", a micro-agent, which sails on the underlying graph. At the end of each exercise, or each lesson followed by a questionnaire, the ant releases pheromones. If the exercise is successfully validated, the pheromones will be those of success (S); otherwise, they will be pheromones of Failure (F). Therefore each arc will carry, in addition to W, the two values S and F [12].

i) Back-propagation learning space and Scope

Pheromones, either S or F, are not just released on the arc leading the ant to node / exercise at hand, but on the last n arcs that the ant followed. This is done to reflect the fact that educational success (or failure) at a given location is determined by what has been seen before by the student. Of course, this influence decreases with time and space: the higher the node is removed in the history of the ant, the lesser significance it has. For this to be taken into account, the amount of pheromone decreases as the back-propagation advances. Numerically, n is 4 and the amplitude decreases into 1 / k "α" value departing from a predefined system parameter. Figures 5 and 6 illustrate the back-propagation: after success (or failed) at node 7, a quantity "α" of pheromone is deposited on the arc 6 -> 7, an amount "α/2" on the arc 4 -> 6, "α/3" to 2 -> 4 and "α/4" to 1 -> 2.

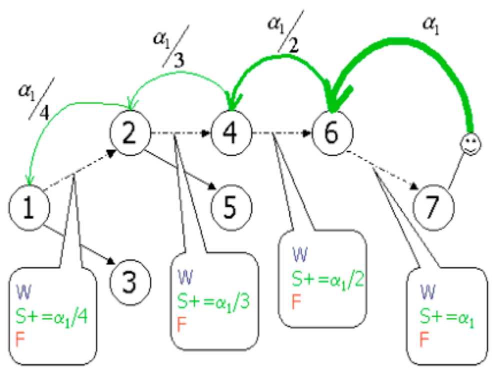

Figure 5: Back-propagation of pheromones of success.

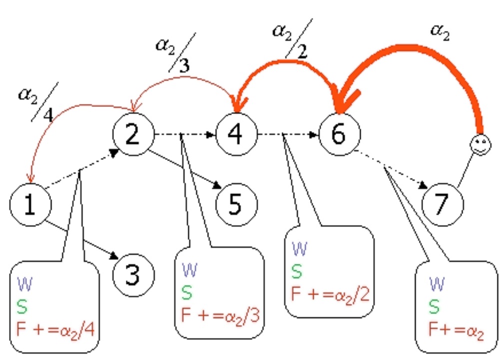

Figure 6: Back-propagation of pheromones failure.

ii) Evaporation

The fact that the natural pheromones evaporate over time is extremely important because it allows the ant colony to rely on the constantly updated information. In our artificial system, it is important to implement a form of evaporation to prevent the system from being "stuck" in a local optimum, and to open the door to the expected characteristics of dynamic adaptability.

$$S_t = \tau^x S_{t-1} \qquad (1)$$

"Equation (1)" gives the form of evaporation for the pheromones of success S (the equation is the same for F): t, the rate of evaporation, is a key parameter of the system in which we will see one of the consequences of the simulation tests described below. The period of evaporation x that says how often the evaporation is calculated is a constant learning. Typically, t = 0999 and x = 1 day.

4.3 Personal History: H

This variable belongs to each ant, and bears information onvisited nodes. Each time a node is validated, a history variable H, specific to each ant, is created, stored in database and set to h1 = 0.5 if it is a success, to h2 = 0.75 if it is a failure. This value will be later used as multiplicative factor to reduce the probability to visit that node again. When it eventually happens, H is again multiplied by h1 or h2. Just like S and F, H evaporates and tend to go back to 1 with time, following:

$$H_t = H_{t-1}\left(1+\frac{1-H_{t-1}}{H_{t-1}}\,\frac{1-e^{-\tau x}}{1+e^{-\tau x}}\right) \qquad (2)$$

where τ is a constant used to tune the evaporation speed and x is the amount of time elapsed since the last visit to that node. τ should be calibrated to correspond to the volatility of the students' memory:

$$\tau = \frac{1}{x}\ln\left(\frac{1+\alpha}{1-\alpha}\right) \qquad (3)$$

With $$\alpha = \frac{H_t - H_{t-1}}{1 - H_{t-1}} \qquad (4)$$

Provided one defines what " forgetting an exercise" means, for instance if its H value, from H_{t-1} =0.5 (one visit with success), grows back to H_t=0.9, this gives $\alpha \approx 0.8$ and the pedagogic team then only has to estimate the time it takes to " forget an exercise": one week for example (x =604800sec.) gives $\tau \approx 3.6\text{E}-6$

4.4 Fitness calculation

Using all the information described above, each arc a is given a fitness value:

$$f(\alpha) = H.(\omega_1 W + \omega_2 S - \omega_3 F) \qquad (5)$$

This value unifies in a weighted average all the factors that make an arc "desirable" or not: f is high when:

- The arc's ending node was last visited a long time ago (*H* is close to 1)
- The arc is encouraged by professors (high *W*)

- People have succeeded a lot around that node (high *S*)
- People have failed a little around that node (low *F*)

5. TESTS AND EXPERIMENT

Beyond the tests, simulations are made to obtain a comprehensive calibration of numerical parameters and to verify the system behavior in some particular cases.

The simulation experiments are conducted on a graph (Figure 7) designed randomly by hand with reasonable connectivity and a desired speed, typically set up to verify the general behavior of the system.

One of the characteristics expected from the chosen heuristic, those of social insect colonies, is the ability to automatically detect inconsistencies and to eliminate them gradually. This has to do with autonomy and intelligence vis-à-vis a trapped environment and past choices made obsolete. Starting from exercise 1, to go to Exercise 4, ants / students have two options: go through the exercise 2 or 3. The teaching staff has seen fit to encourage the passage through the exercise 3 by assigning a weight well above W (4 against 1). Students, therefore, have a probability four times higher to be offered an arc 1 --> 3 in stead of the arc 1--> 2. However, we find that the failure rate in exercise 4 is much higher (80%) when the students come from exercise 3 until they are in exercise 2 (20%). It is up to the colony to "notice" this anomaly and to overcome it gradually by the combined action of the release and evaporation of pheromones of failure and success. Thus the probabilities of edges are properly reversed to maximize the expected future success.

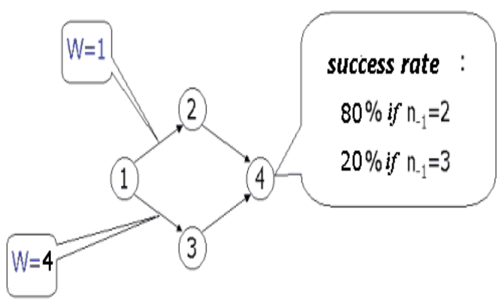

Figure 7: The natural problem described in the introduction (nests, food, long and short paths) described in educational terms.

The experiment shows that the desired behavior (a stable inversion over time of fitness measures of the two arcs) is not systematic, and it is important to be in the proper zone setting. Figures 8 and 9 illustrate the system behavior based on a key parameter: the rate of evaporation. If it is too high, the deposition of pheromones has no time to have effect, and measures of fitness continue to oscillate without either being reversed or stabilized. When t is reduced from 0.99 in 0999, or a slower evaporation, there is, as shown in Figure 9, the expected behavior: measures of the two arcs are reversed and this reversal continues. Students are encouraged to exercise the path that prepares the best result. This first experiment has two advantages: it demonstrates empirically that there is an expected feature of the algorithm implemented and can give an idea of the position of parts of parameter space that allow the existence of this characteristic.

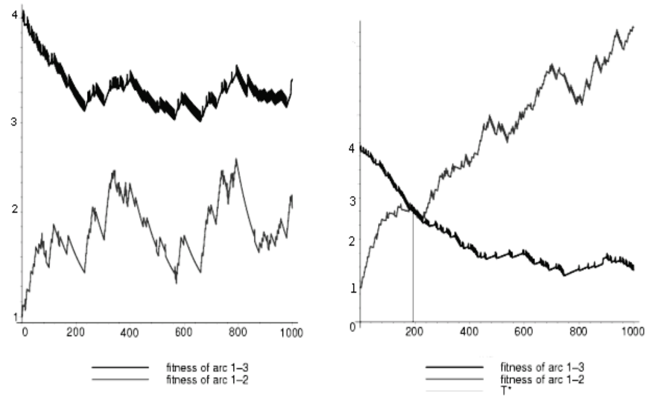

Figure 8 and **Figure 9:** and 9: behavior of the system based on the rate of evaporation.

- The left figure shows inadequate behavior where the values of fitness are not reversed but oscillate, which is due to excessive evaporation (τ = 0.99).
- The right figure shows the expected behavior, enabled by lighter evaporation (τ = 0999).

It is important to note that this example is emblematic of how we can illustrate the power of the system and calibrate it digitally to control its behavior. We should therefore focus more on the spirit of these results than on their letter. This is for two reasons: First, the numerical values are not to be taken as such because the experiments are conducted on a reduced graph and taken out of its real context and teaching. Then it is just an example since it is not necessarily desirable for teaching structure to seek systematically to circumvent the difficulties. Pedagogy is a subtle art that can also mean a form of coercion that the student may feel as meaningless, but he will reap the fruits later. Teachers can consciously make the choice of reversed pedagogy by forcing students to follow a difficult path and full of failures. It is therefore crucial that the dialogue with the educational team is placed in the foreground and the effects of self-adaptation are controlled (eg by setting numerical limits on the values of pheromones) that they do not interfere with strategy teaching faculty. The objective of the system is not a party to take over the other (students or teachers) but to find a natural compromise: nonsense to remove, to detect individual or group differences, but to keep to the fixed teaching course.

6. CONCLUSION

This paper presents the application of advanced techniques of artificial intelligence, namely optimization by ant colonies. the problem of structuring a learning system makes automatic adaptation of hypertext between chapters. In the future, we will compare the effectiveness of this method with another method based on Markov chains.

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