Creating adaptive learning paths using Ant Colony Optimization and Bayesian Networks

José Manuel Márquez, Juan Antonio Ortega, Luis González-Abril, Francisco Velasco

Abstract

This paper presents a new way to combine two different approaches of artificial intelligence looking for the best path in a graph, Ant Colony Optimization and Bayesian Networks. The main objective is to develop a learning management system which will have the capability of adapting the learning path to the learner's needs in execution time, taking into account the pedagogical weight of each learning unit and the system's social behavior.

1. Introduction

Nowadays the adaptation in learning systems is an open problem, in particular, how to dynamically adapt the learning itinerary to the learner's needs. In competences-based learning, the student has to successfully pass a set of courses to achieve one or more competences. We think that this set of courses, which is called the learning itinerary, can be personalized based on the student's learning capacities. For this act, several learning speeds (associated to a qualification in a concrete course) and learning paths are considered which are optimized depending on the student's capacities. This learning system will allow a better attendance to the student's diversity.

These courses in the learning system have to be played in a fixed order when, just before starting one course, it is necessary to have achieved all the knowledge offered by a previous one. However, looking for a stronger learning personalization, the pedagogical team can design different courses to ensure the right knowledge acquisition by the student, in his own way, taking into account his/her personal needs: language, capacity, complexity, comprehension level, etc. In this way, the pedagogical team will be able to define several personalized paths to the same competence or goal.

José Manuel Márquez Vázquez is with the Research and Development Department of Telvent. Ronda del Tamarguillo, 29. Sevilla 41006 Spain. E-mail: jose.marquez@telvent.abengoa.com..

Dr. Juan Antonio Ortega Ramírez is with the Department of Computer Systems and Languages of the University of Sevilla. Avda de la Reina Mercedes. Sevilla. 41013 Spain. . He is also director of the Centre for Scientist Research of Andalucia (www.cica.es). E-mail: ortega@lsi.us.es.

Dr. Luis González Abril and Dr. Francisco Velasco Morente are with the Department of Applied Economy of the University of Sevilla. Avda de Ramón y Cajal 1. Sevilla, 41018 Spain. E-mail: {luisgon,velasco}@us.es.

One major improvement in the competence oriented e-learning system is that it allows different learning paths adapted to the student's profile. Thus, this can evolve to re-adapt to the new needs, just like it happens in the real world, where students and their requirements and needs are constantly changing. Due to this fact, a system which is running nowadays could be not running in a future, so it is necessary to provide this skill to react against the changes. *Educational social software*, defined in [19] within a context of distance education as "networked tools that support and encourage individuals to learn together while retaining individual control over their time, space, presence, activity, identity and relationship", try to solve these problems using techniques like *collaborative filtering*.

Collaborative filtering is based on the premise that people can use the information that other people have found which benefits the whole community. Traditional collaborative filtering systems store preferences and user's evaluations on several elements, allowing any other user to utilize this information as a guide. These techniques have held the development of system for suggesting contents, which have had a major success in e-commerce[1] and are recently being applied to e-learning systems [1].

2. Background

Nowadays there are two specifications related with learning units sequencing: IMS-SS [2] and IMS-LD [3].

2.1. IMS Simple Sequencing (IMS-SS)

The main goals of IMS-SS are: i) to define the order in which learning objects are shown, and ii) to define the set of rules for selecting an item depending on the learner's behavior and answers. For this, a simple model of conditioned navigation is defined which addresses both the content structure and user actions.

Actually, the most used content packaging specifications have been designed to be compliant with the IMS' Content Packaging specification [8], adding all the sequencing information within the Manifest file or outside in a separate file.

Learning activities are hierarchically organized by using a tree structure where each node represents an activity. IM-SS forces cross the tree in pre-order: from the root to the

[1] E.g.: www.amazon.com

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leaves and from left to right within the same level, processing all the nodes in the same branch before changing to the next branch.

The designer can decide if a set of activities have to be sequenced in a strict order or they may be selected by the student. To allow this, each node has two properties: *Sequencing Control Flow* and *Sequencing Control Choice* whose state affects all the children nodes' sequencing. Each node having children nodes, has to define its own sequencing strategy, deciding between Control Flow or Control Choice.

The designer may modify the sequence of activities using rules which may be related with constraints for accessing to concrete activity (limit rules), rules involved in the success or failure of an activity (roll-up rules) or rules that directly manage the sequence of activities to be done.

However, IM-SS has several drawbacks:

–The personalization of itineraries is very difficult due to sequencing rules based on pre-conditions and post-conditions, especially those itineraries that need to define jumps, cycles, and other non-linear paths.

–It is learner-oriented and it is not possible to use with thematic adaptations nor to make suggestions automatically to the docent based on statistic measures of the students' learning process.

–A user model does not exist, so it is not possible to match sequencing actions with users' preferences.

2.2. IMS Learning Design (IMS-LD)

IMS-LD defines how to describe and code learning methodologies, and to embed them in an e-learning solution. The teacher's role is recognized. Also it permits to combine educational resources with pedagogical activities and interactions among people with different roles, adjusting itself to pre-fixed procedures and strategies [4] to ensure the consistency of the specification. IMS-LD understands the learning process independently from the contents, allowing to define different learning methodologies and strategies, keeping in mind the fulfillment of certain features such as completeness, pedagogical flexibility, personalization, portability, components usability and interoperability [5]. Meta-data are needed to create a meta-language which is used in the description of the pedagogical methodology as same as the movie screenplay [6]. It is assumed that this screenplay may explain whatever pedagogical strategy using the cinema's language: plays, acts, roles, activities and conditions. Plays are composed of acts, and these are used to synchronize different activities that may occur simultaneously. Actors who have been assigned a role, which may be of two types, student or professor role, accomplish activities. Finally, conditions allow for managing of some grade of variability in the course of the play depending on the actor's behavior.

The whole package including the pedagogical strategy's definition and all the resources for its development, is called Unit of Learning (UoL).

The main advantage of IMS-LD over IMS-SS, is the use of properties, defined by name-value pairs, which are used to evaluate conditions. These properties may be local (they only apply to the local execution thread) or global (they involve whatever execution of the UoL), and by using them it is possible to define a complex sequencing graph. However, the modification of these properties is highly limited being included in the UoL's manifest [7].

2.3. Packaging and deployment

IMS Content Packaging (IMS-CP) [8] offers a mechanism of packaging educational content like courses or whatever kind of resource needed for the educational process in a .zip compressed file. An xml-file named as imsmanifest.xml is included in the root of the .zip file to describe the whole package and how its contents and resources are organized, easing the processing of the zip file by an LMS[2]. IMS-CP is the corner stone of the content packages interchange and it has been adopted as *de-facto* standard for packaging and sharing educational content by most of the existing e-learning systems, becoming the base of the most widely accepted specifications in the e-learning world like SCORM[3] [9] or IMS-LD.

Furthermore, IMS-CP does not harm the process of deployment of components in services-oriented platforms like OSGi[4] [10]. An OSGi framework could be used to manage IMS-CP packages as OSGi bundles[5], easing the scalable services-oriented e-learning systems development, using OSGi platforms development environments[6] to create course players, and the integration with other recent emerging technologies like interactive digital TV [11].

Having in mind the results of the Passepartout[7] Project, it is feasible to distribute IMS-CP packages as OSGi bundles, making easier to control their versions and to deploy them, as it is explained in [10]. OSMOSE[8], another European R&D project, addressed the problems related to the definition of dependencies among packages, in order to automatically deploy the bundle and those other bundles on which the first one depends, like Debian's apt-get does. This situation caused the development of J-Bones[9], a dependencies solver with an integrated deployment

[2] Learning Management System

[3] Shareable Content Object Reference Model, www.adlnet.gov

[4] Open Services Gateway Initiative, www.osgi.org

[5] A bundle is a .zip or .jar archive with a file named manifest.mf that describe the bundle following the rules of the OSGi specification.

[6] E.g.: Eclipse Platform Development Environment.

[7] Project of the Eureka-ITEA program supported by the Spanish Ministry of Industry, Commerce and Tourism through the PROFIT program. www.passepartout-project.org/

[8] Project of the Eureka-ITEA program supported by the Spanish Ministry of Science and Technology through the PROFIT program. www.itea-osmose.org/

[9] J-Bones, http://jbones.forge.os4os.org/

mechanism based in the resolution process [12]. Dependencies at deployment time are solved in an atomic step, and it installs all the components (bundles) needed by the selected bundle which have not already been installed in the OSGi platform. In this case, dependencies are defined in development time or when the bundle is registered in the bundles repository, according to an invariable criterion in the time such as descriptors reciprocally associated with a bundle that allows building catalogs in the client side as shown in [13]. Nevertheless, if these dependencies are not fixed and they depend on the user's preferences, it would be possible to have a smart system in charge of setting the best dependencies for the user based on the user's profile.

3. Scenario

The proposed scenario is given by an e-learning system built on top of an OSGi framework. In this scenario, educational contents, packaged as the IMS-CP specification defines, are delivered as OSGi bundles. Both specifications are 100% compatible [10] and a graph describing the learning itinerary needed to achieve one concrete competence is possible to build. The achievement of this competence implies to have successfully passed a package of courses, each one delivered as one atomic bundle. But this package is not unique: courses and the pedagogical complexity of each one may vary from one user to another, depending on the user's learning profile. This package of courses may vary dynamically reacting to the learning process, making the total length of the learning itinerary as long as needed by the user helping him to achieve its knowledge at his own capacity, defining special paths for students of various learning methods and styles.

A smart LMS could recommend or impose the next course, taking into account the most recent results of the user in his/her passed courses and the most successful path taken by most of the users. This artificial intelligence based on the collective behavior of decentralized, self-organized systems has been named as swarm intelligence, an expression introduced in the context of cellular robotic systems [20] by Gerardo Beni and Jing Wang, inspired in the social behavior of animals [14].

Let us suppose that an enterprise wants to prepare a worker to employ him in a vacancy of higher responsibility. This vacancy requires a set of competences being owned by the applicant, and the way to achieve these competences is to pass some specific courses. With this goal, the company's pedagogical team has designed the following graph with several alternative learning paths (Figure 1) in which all the available learning paths a learner may follow is given. So, nodes represent courses and arcs are transitions between courses. Arcs rounded with a curved arrow labeled with an asterisk (*)indicate that the order in which their children are crossed are not of concern, arcs rounded with a curved arrow labeled with an ampersand (&) indicate that their children have to be crossed in the order expressed by the arrow (e.g. deep-first and from left to right) and finally, arcs rounded with a curved arrow labeled with a plus sign means that one of the children paths has to be chosen. Each node contains educational contents and exercises, usually embedded in web pages, and an evaluation test, which will send the final qualification of the student to the LMS.

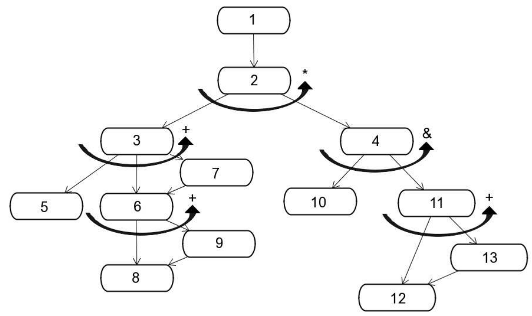

Figure 1: Sequencing graph with alternatives learning paths

The objective is to predict the best learning for the student taking into account the user's profile and the paths followed by the rest of the students.

4. Collaborative sequencing based on Ant Colony Optimization

The French company Paraschool has developed a system to solve the problem of calculating the best path which uses Ant Colony Optimization techniques to detect bad pedagogical schedules and correct them immediately [15]. The same as in Paraschool's system, in our system, a student represents an ant, moving freely in the graph (Figure 1), dropping pheromones everywhere it goes. Besides, the amount of dropped pheromones is modified as a function of the achieved success, instead of differentiating between positive pheromones and negative pheromones as made in Paraschool's system.

Let us consider as acceptable a qualification higher than 6 over 10 and to define the amount of pheromone to be dropped in the path of the late evaluated node as:

$$\phi = \begin{cases} -(1-\varepsilon).\varphi & if\ \varepsilon < \dfrac{6}{10} \\ \varepsilon.\varphi & if\ \varepsilon \geq \dfrac{6}{10} \end{cases} \qquad (1)$$

where φ represents a constant of the pheromone value and $0 \leq \varepsilon \leq 1$. In order to empower the effect of the recently dropped pheromones, the last three arcs taken by the student are reinforced as well with φ/2, φ/3 y φ/4 as it is done in [15].

Previously, the graph has been weighed by the pedagogical team, giving a weight for each node (Figure 2). This weight represents the pedagogical load of each node compared with the total load of the whole path. These weights are expressed as percentages of the total load, normalized to the range [0,1]. The weight of the common path (predicted by the pedagogical team) will be 1, and alternatives paths will have a higher weight due to being considered review courses.

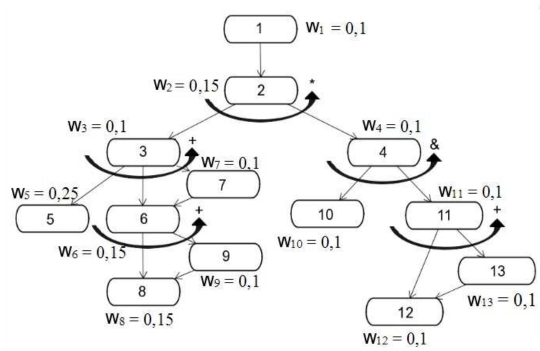

Figure 2: Sequencing graph with weighed nodes and alternative paths

The first two nodes in the graph are mandatory and common for the audience. The rest of the graph is composed by two branches: 3's an 4's. Both branches include alternatives paths. Each node i representing a course, has an associated weight, W_i, given by the pedagogical team. Examples of possible paths are: 1-2-3-5-4-10-11-12 with total weight 1 (100% of hours anticipated by the pedagogical team) or 1-2-4-10-11-13-12-3-7-6-9-8 (35% more than the 'normal' path).

A fitness function which gives us the value of how well the arc *ij* fits to the user needs is given as:

$$f_{ij} = \omega_1 \cdot W_1 \cdot P_{ij} + \omega_2 \cdot \Phi_{ij} \qquad (2)$$

and the main objective is to avoid that the system is blocked in a local minimum caused by the effect of the pheromones (which would always lead the students by the same way, optimized as the way required by the minimum effort). This function will help to decide the next node and will help to build the learning path of each student. Therefore, it must involve both the pedagogical weight and pheromones.

In (2), W_j denoted the pedagogical weight of the node j, Φ_{ij} is the amount of pheromones dropped in the arc ij, and ω_1 and ω_2 are constants to calibrate the system. P_{ij} suitability factor of the arc ij, calculated a priori based on the previous results, influencing the impact of the pedagogical weight.

5. Calculating the suitable path

To calculate the suitability factor of an arc a Bayesian network will be used. This will determine the probability a priori of having success if the arc is taken. It can be used to diagnose the causes of the scholastic failures [16] and also to choose an arc to reinforce the weak knowledge achieved by the student until then.

In a predictive reasoning Bayesian network, knowledge is propagated from the causes (evidences) to the effects. Causes are defined by the pedagogical team in order to affect in run-time to the pedagogical weight depending on the qualifications obtained by the user in previous courses. Student's qualifications in finished courses and, in our case, just those courses may be the only possible causes. In this paper, for the sake of simplicity, we will consider the knowledge achieved in a package of courses as the only cause of the yield or failure for the next course, although other causes such as collaboration, family's socioeconomic factors, etc can be taken into account as possible causes

A Bayesian network will be used, whose qualitative representation is a directed acyclic graph which shows the cognitive dependencies of each course. Each node represents a discrete variable with a finite number of states and the edges represent the causal dependency between variables. Each node will be associated to a table of conditional probability distribution over the states of a variable, so this graph does not have to be the same as the first one given by the pedagogical team. Two consecutive courses (nodes) may not have any pedagogical dependency, and in the same line, one course may depend on one or more courses not necessarily consecutive to the first one. It is even possible to have courses not depending on any other, case in which the probabilities of getting a high, medium or low qualification are not conditioned but absolute.

We are guessing that the academic performance of each learner in a course only depends on those other courses which are supporting the current course, a premise that is not absolutely true [17] because it depends on may other issues. Briefly, if the concepts of a course C depend of the concepts explained in two other courses, A and B (we will say that C pedagogically depends on A and B), the expected qualification of C depends, a priori, of qualifications the user has had in A and B.

Statistics of previous courses will help to build the initial probabilities in the Bayesian network. The probability of getting each qualification will be categorized using three levels: LOW, MEDIUM and HIGH, so if the qualification range goes from 0 to 10, LOW takes from zero to five, MEDIUM from five to seven and HIGH from seven to ten. An example of these probabilities is given in Table 1. In it the conditioned probability of the node C, which depends of nodes A and B, is shown. Note that the sum of probabilities for a specific state is always 1 (100%).

A

High	10,0%
Medium	60,0%
Low	30,0%

B

High	15,0%
Medium	57,0%
Low	28,0%

C

A	High			Medium			Low		
B	High	Medium	Low	High	Medium	Low	High	Medium	Low
High	65,0%	55,0%	25,0%	67,0%	26,0%	17,0%	28,0%	18,0%	11,0%
Medium	28,0%	35,0%	53,0%	23,0%	55,0%	45,0%	55,0%	43,0%	39,0%
Low	7,0%	10,0%	22,0%	10,0%	19,0%	38,0%	17,0%	39,0%	50,0%

Table 1: Probabilities tables for nodes A, B and C

The key of this development is the Bayes' theorem which relates the conditional and marginal probabilities of two stochastic events. Thus, the probability of hypothesis h knowing the evidence e is equal to the probability of the evidence known the hypothesis by the probability of that hypothesis and divided by the probability of the evidence:

$$P(h/e) = \frac{P(e/h) \cdot P(h)}{P(e)} \qquad (3)$$

In this network, qualifications of supporting courses are the evidences. In those nodes where it is possible to choose among several alternative paths, it is especially important to calculate the suitability factor in order to calculate which of those candidate nodes is the most recommendable to be used (3). This may be determined choosing the candidate that best adjusts to the restriction looked for. Example of these restrictions could be: sum of probabilities of having a qualification HIGH or MEDIUM is higher than 70%, the higher probability granted a MEDIUM qualification of more than 50%, etc.

This task consists on calculating the π-values [15] that informs of which values of the node X are more probable, based on the related evidence with the X's causes (according to the evidence above X). These equations are calculated directly when the network is very simple, but in a complex network, it is better if an algorithm of probability propagation and approximation methods are used (Pearl, Joint Computation, stochastic simulation, Simple Bayes, K2, Clustering, etc) [18]

An example of suitability function for the edge ij, is:

$$P_{ij} = \left\{ \begin{array}{c} P(J_{High}/I) \cup P(J_{Medium}/I) \in [0.7,1] \\ 0.33 \end{array} \right\} \qquad (4)$$

This function calculates the suitability factor for the edge ij as the sum of probabilities of getting a qualification greater than 5 (in a scale of 0 to 10) in the course of the node j (knowing the probability in the origin node i) if this sum is greater than 0.7 (more than 70%) or 0.33 (33% as default value) in other case.

6. Evaporation of the pheromones

In order to avoid a great impact in the fitness function, pheromones, like in real life, will partially evaporate with the passing of time. Because e-learning systems' users may interrupt their sessions whenever they want and they are able of continuing the course from the same point they left it, the time has to be understood in the same way. So, the evaporation rate will be simply a constant less than 1 that the LMS will multiply by the current amount of pheromones existing in the edge each time a user chooses an edge (independently of the edge chosen). Initially no edge has pheromones. The value of the total amount of pheromones dropped in an edge is calculated once the student has finished the course and needs to choose the next course. A value of ρ = 0.9 is a typical evaporation rate [15], but in the calibration process of the system any positive value less than 1 could be selected. A lower value will make pheromones evaporate faster. If we include this condition in (1), then the amount of pheromones for each edge at any given time is:

$$\phi_t = \left\{ \begin{array}{c} \rho \cdot \phi_{t-1} - (1-\varepsilon) \cdot \varphi , if \varepsilon < \frac{6}{10} \\ \rho \cdot \phi_{t-1} + \varepsilon \cdot \varphi , if \varepsilon \geq \frac{6}{10} \end{array} \right\} = \qquad (5)$$

$$\left\{ \begin{array}{c} \phi_1^* + \rho^t(\phi_0 - \phi_1^*), if \varepsilon < \frac{6}{10} \\ \phi_2^* + \rho^t(\phi_0 - \phi_2^*), if \varepsilon \geq \frac{6}{10} \end{array} \right\},$$

where $\phi_1^* = \frac{-(1-\epsilon)\varphi}{1-\rho}$, $\phi_2^* = \frac{\epsilon\varphi}{1-\rho}$ and ϕ_0 is the initial condition.

Note that if $|\rho| < 1$ then $\lim_{t\to\infty}\phi_t = \left\{ \begin{array}{c} \phi_1^*, if \varepsilon < \frac{6}{10} \\ \phi_2^*, if \varepsilon \geq \frac{6}{10} \end{array} \right\}$,that is,

ϕ_i^* is stable.

7. Conclusions and further work

In this paper it has been shown how to create adaptive educational itineraries using swarm intelligence (the ACO algorithm) but without losing the benefit of having the guide which is the design done by a pedagogical team (the Bayesian Network).

This project was initially born to solve the problem of adapting OSGi bundles to user's profiles in digital TV residential gateways, and has evolved to become a complex e-learning project that is currently in development.

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