Competency-based Intelligent Curriculum Sequencing: Comparing Two Evolutionary Approaches

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Abstract

The process of creating e-learning contents using reusable learning objects (LOs) can be broken down in two sub-processes: LOs finding and LO sequencing. Although semiautomatic tools that aid in the finding process exits, sequencing is usually performed by instructors, who create courses targeting generic profiles rather than personalized materials. This paper proposes an evolutionary approach to automate this latter problem while, simultaneously, encourages reusability and interoperability by promoting standards employment. A model that enables automated curriculum sequencing is proposed. By means of interoperable competency records and LO metadata, the sequencing problem is turn into a constraint satisfaction problem. Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) agents are designed, built and tested in real and simulated scenarios. Results show both approaches succeed in all test cases, and that they handle reasonably computational complexity inherent to this problem, but PSO approach outperforms GA.

1. Introduction

Web-based adaptive courses and systems are supposed to be able to achieve some important features including the ability to substitute teachers and other students support, and the ability to adapt to (and so be used in) different environments by different users (learners) [1]. These systems may use a wide variety of techniques and methods. Among them, curriculum sequencing technology is "to provide the student with the most suitable individually planned sequence of knowledge units to learn and sequence of learning tasks […] to work with". These methods are derived from adaptive hypermedia field and rely on complex conceptual models, usually driven by sequencing rules [2]. E-learning traditional approaches and paradigms, that promote reusability and interoperability, are generally ignored, thus resulting in (adaptive) proprietary systems (such as AHA! [3]) and non-portable courseware. But e-learning approaches also expose their own problems. They lack flexibility, which is in increasing demand. "In offering flexible [e-learning] programmes, providers essentially rule out the possibility of having instructional designers set fixed paths through the curriculum" [4]. But offering personalized paths to each learner will impose prohibitive costs to these providers, because the sequencing process is usually performed by instructors. So, "it is critical to automate the instructor's role in online training, in order to reduce the cost of high quality learning" [5] and, among these roles, sequencing seems to be a priority.

In this paper, an innovative sequencing technique that automates teacher´s role is proposed. E-Learning standards and the learning object paradigm are used in order to promote and ensure interoperability. Learning units' sequences are defined in terms of competencies in such a way that sequencing problem can be modeled like a classical Constraint Satisfaction Problem (CSP) and artificial intelligence approaches could be used to solve it. Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) are AI techniques that have proven a good performance for solving a wide variety of problems. So, GAs and PSO are used to find a suitable sequence within the solution space respecting the constraints. In section 2, the conceptual model for competency-based learning object sequencing is presented. Section 3 describes both evolutionary approaches (PSO and GA) for solving the problem. Section 4 presents the results obtained when agents are tested in simulated scenarios as well as in a real world situation (course sequencing in an online Master in

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Engineering program). And finally, in Section 5 conclusions are summarized and future research lines are presented.

2. Competency-based Sequencing

Competencies can be formally described as "multidimensional, comprised of knowledge, skills and psychological factors that are brought together in complex behavioral responses to environmental cues" [6]. Some e-learning trends are trying to standardize competency definitions so that they could be interchanged and processed by machines. According to RDCEO [7] and IEEE [8] nomenclature, a competency record is called 'Reusable Competency Definition' (or RCD). RCDs can be attached to LOs in order to define its prerequisites and its learning outcomes. We have used this approach to model LO sequences. By defining a competency (or a set of competencies) as a LO outcome, and by identifying the same competency as the prerequisite for another LO (figure 1), a constraint between the two LOs is established so that the first LO must precede the second one in a valid sequence.

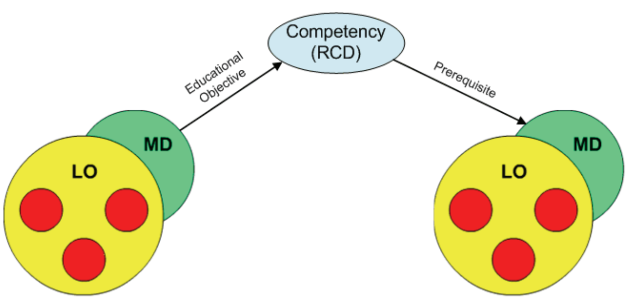

Fig 1. LO sequencing through competencies

Meta-Data (MD) definitions are attached to LOs, and within those definitions references to competencies (prerequisites and learning outcomes) are included. LOM [9] records have been used for specifying LO Meta-Data. LOM element 9, 'Classification', is used to include competency references.

3. Competency-based Intelligent Sequencing

Given a random LOs' sequence modeled as described above (with competencies representing LOs prerequisites and learning outcomes), the question of finding a correct sequence can be envisaged as a classical Constraint Satisfaction Problem (CSP). In this way, the solution space comprises all possible sequences (n! will be its size, total number of states, for n LOs), and a (feasible) solution is a sequence that satisfies all established constraints. LO permutations inside the sequence are the operations that define transitions among states.

Genetic algorithms are an evolutionary computation technique that mimics gene's evolution to solve problems. A random initialized population of individuals is created. Each individual contains a coded state or solution (gene) to the problem; and an iterative process of recombination, mutation and selection is used to evolve population and, simultaneously, the solution. GAs that use specific representation and operators for handling permutations are called permutation GAs or permut-GAs and can be employed to solve constraint satisfaction problems [10]. Permut GA with order recombination, swap mutation and generational replacement with elitism was implemented in order to test its performance for solving the LO sequencing problem.

On the other hand, particle swarm optimization is an evolutionary computing optimization algorithm that mimics the behaviour of social insects like bees. A random initialized particles population (states) flies through the solution space sharing the information they gather. Particles use this information to adjust dynamically their velocity and cooperate towards finding a solution. Goodness of each solution is calculated using a function called fitness function. Original PSO [11, 12] is intended to work on continuous spaces. A version that deals with permutation problems was introduced in [13]. This discrete approach was employed and a full-informed version of the PSO was implemented in order to test its performance for solving the LO sequencing problem. Several ways to tune the PSO agent were tested [14], but only a velocity check policy improved performance. Finally, the fitness function for both agents was a standard penalty function.

4. Experimental Results

Both algorithms for LOs sequencing described above were designed and implemented using the object oriented paradigm. We wanted to test their performance in real and simulated scenarios. As a real-world problem, we chose a problem concerning course sequencing for a Master in Engineering (M.Eng.) program in our institution. The (web engineering) M.Eng, program comprises 23 courses (subjects) grouped in:

- Basic courses (7) that must be taken before any other (kind of course). There may be restrictions between two basic courses, for example the 'HTML' course must precede the Javascript course,

- Itinerary' courses (5) that must be taken in a fixed ordered sequence.
- Compulsory courses (5). There may be restrictions between two compulsory courses.
- Elective courses (6). Additional constraints with respect to any other course may be set.

All courses have an expected learning time that ranges from 30 to 50 hours. They are delivered online using a LMS, namely EDVI LMS [15], and every course has its metadata record. Competency records were created to specify LOs' restrictions, and LOM metadata records were updated to reflect prerequisite and learning outcome competencies as detailed in section 2. A feasible sequence must have 23 LOs satisfying all constraints. The graph showing all LOs and constraints is too large to be shown in this paper, and so it is also difficult to calculate the exact number of feasible solutions. Some estimation have been used, we have estimated that the relation among feasible solutions and total solutions order is $8{,}9 \times 10^{12}$. This number reflects the number of states (non-feasible solutions) for each feasible solution.

One hundred tests were run computing mean fitness values evolution using the best configuration found for each agent (figure 2). Both agents converge, but PSO approach outperforms GA.

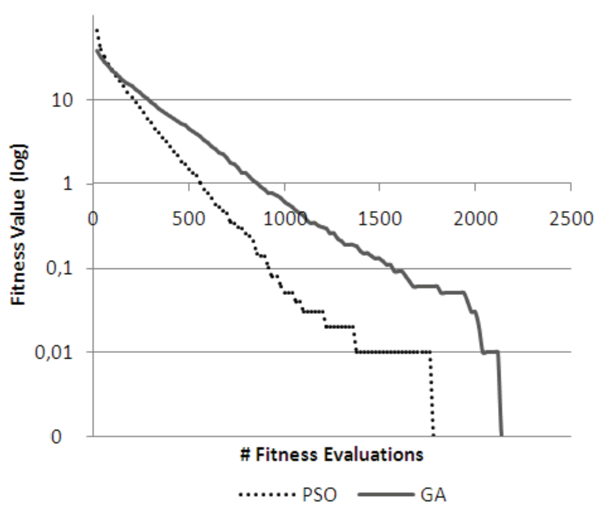

Figure 2. Agents' performance in a real world problem.

The tested scenario may seem to have many feasible solutions so that it is questionable whether PSO would still achieve a good performance in 'challenging' scenarios. So, additional test sequences of 5, 10, 20, 30, 40, 50, 60, 75 and 100 LOs with only one feasible solution were designed. Each test suite was run 100 times for each agent and mean values were computed. Figure 3 shows the results and it also supports the argument that PSO outperforms GA. It could also be inferred that both agents handle reasonably combinatorial explosion for this particular problem. It should be noted that while the number of learning objects grows linearly the size of the solution space grows exponentially.

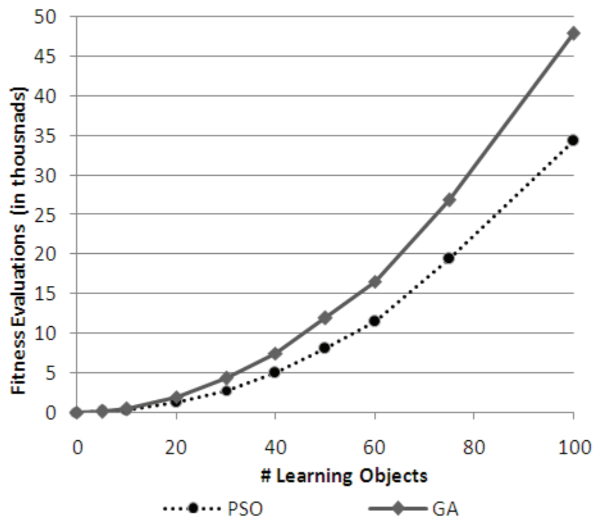

Figure 3. Agents' scalability in simulated scenarios

5. Conclusions and Future Work

Automated LO sequencing is a recurring problem in the e-learning field that could be approached employing models that ensure interoperability along with artificial intelligence techniques. The purpose of the study was to design, develop and test two agents that perform automatic LO sequencing through competencies in order to study the completeness and performance of both approaches. A model that employs competencies as a mean for defining constraints between learning object has been presented, so that a sequence of LOs is represented by relations among LOs and competencies. New sequences can be derived if permutation operations are allowed between LOs in the sequence. Hence the sequencing problem is turn into a permutation problem, and the aim is to find a sequence that satisfies all restrictions expressed in the original model. A GA that handles permutation problems has been developed and the PSO for permutation problems has been adapted to the LO sequencing problem. Results show that both agents succeed in solving the problem and that PSO implementation outperforms GA agent.

Further implications arise from the model proposal (section 2): (1) E-learning standards are promoted. XML records and bindings are used, so elements will be easily interchanged and processed by compliant systems. (2) Instructor's role is automated reducing costs. Sequencing process works even in complex scenarios were humans face difficulties. Instructors could spend saved time performing other activities within the learning action. And (3), the model can be extended to an automated intelligent system for building personalized e-learning experiences. But this third implication is linked to future work. Sequencing process can be complemented with gap analysis process and competency learner modeling techniques to build personalized courses.

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6. References

[1] P. Brusilovsky, "Adaptive and Intelligent Technologies for Web-based Education," Künstliche Intelligenz, Special Issue on Intelligent Systems and Teleteaching, vol. 4, pp. 19-25, 1999.

[2] P. Karampiperis, "Automatic Learning Object Selection and Sequencing in Web-Based Intelligent Learning Systems," in Web-Based Intelligent E-Learning Systems: Technologies and Applications, M. Zongmin, Ed. London. UK.: Idea Group, 2006.

[3] P. De Bra, A. Aerts, B. Berden, B. d. Lange, B. Rousseau, T. Santic, D. Smits, and N. Stash, "AHA! The adaptive hypermedia architecture," in Proceedings of the fourteenth ACM conference on Hypertext and hypermedia Nottingham, UK: ACM Press, 2003.

[4] B. van den Berg, R. van Es, C. Tattersall, J. Janssen, J. Manderveld, F. Brouns, H. Kurvers, and R. Koper, "Swarm-based sequencing recommendations in e-learning," in Proceedings 5th International Conference on Intelligent Systems Design and Applications, 2005. ISDA '05., Wroclaw, Poland, 2005, pp. 488-493.

[5] A. Barr, "Revisiting the -ilities: Adjusting the Distributed Learning Marketplace, Again ?," Learning Technology Newsletter, vol. 8, pp. 3-4, January/Aprl 2006.

[6] J. Wilkinson, "A matter of life or death: re-engineering competency-based education through the use of a multimedia CD-ROM," in IEEE International Conference on Advanced Learning Technologies, 2001. Proceedings, 2001, pp. 205-208.

[7] IMS, "Reusable Definition of Competency or Educational Objective - Information Model," IMS Global Learning Consortium, 2002.

[8] IEEE, "Learning Technology Standards Committee (LTSC). Standard for LearningTechnology - Data Model for Reusable Competency Definitions," IEEE, 2008.

[9] IEEE, "Learning Technology Standards Committee (LTSC). Learning Object Metadata (LOM). 1484.12.1," IEEE, 2002.

[10] A. E. Eiben and J. E. Smith, Introduction to Evolutionary Computing. Berlin (Germany): Springer-Verlag, 2003.

[11] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in Proceedings of the Sixth International Symposium on Micro Machine and Human Science. MHS '95., Nagoya, Japan, 1995, pp. 39-43.

[12] J. Kennedy and R. Eberhart, "Particle swarm optimization," in Proceedings., IEEE International Conference on Neural Networks., Perth, WA, Australia, 1995, pp. 1942-1948 vol.4.

[13] X. H. Shi, Y. Zhou, L. M. Wang, Q. X. Wang, and Y. C. Liang, "A Discrete Particle Swarm Optimization Algorithm for Travelling Salesman Problem," in Computational Methods, 2006, pp. 1063-1068.

[14] L. de-Marcos, C. Pages, J. J. Martinez, and J. A. Gutierrez, "Competency-Based Learning Object Sequencing Using Particle Swarms," in 19th IEEE International Conference on Tools with Artificial Intelligence. ICTAI, Patras, Greece, 2007, pp. 111-116.

[15] R. Barchino, J. M. Gutiérrez, and S. Otón, "An Example of Learning Management System," in IADIS Virtual Multi Conference on Computer Science and Information Systems (MCCSIS 2005), Virtual, 2005, pp. 140-141.