

Competency-based Learning Object Sequencing: Comparing Two Evolutionary Approaches

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Tecnologías de la Información para la Formación y el Conocimiento (TIFyC)
Information Technology for Education and Knowledge (ITEK)

- Concepts
- Framework
- Sequencing
 - Sequencing Approaches
 - Obstacles
- Our Approach
- Results
- Conclusions
- Future work

- **Fields**
 - e-Learning
 - Adaptive Hypermedia
 - Natural Computing

- e-Learning
 - Learning Object (LO)
 - Reusable Piece of Learning Materials
 - LO = Assets & Metadata (MD)
 - Learning Management Systems (LMS)
 - Standards
 - IEEE Learning Object Metadata (LOM)
 - ADL Shareable Content Object Reference Model (SCORM)

- **Natural Computing.** Kori (2008) taxonomy:
 - Nature as inspiration
 - Classic techniques
 - Cellular automata, neural networks, ALife
 - Evolutionary computation
 - **Genetic Algorithms**, Evolution Strategies, Genetic Programming, Learning Classifier Systems, ...
 - Swarm intelligence
 - **Particle Swarm Optimization**, Ant Systems
 - Nature as implementation substrate
 - Nature as computation

- Particle Swarm Optimization (PSO)
 - Optimizer originally developed by Eberhart & Kennedy (1995) and intended to work on continuous spaces
 - A set of particles ‘flies’ through the solution space sharing the information that they gather
 - Every iteration each particle updates its position

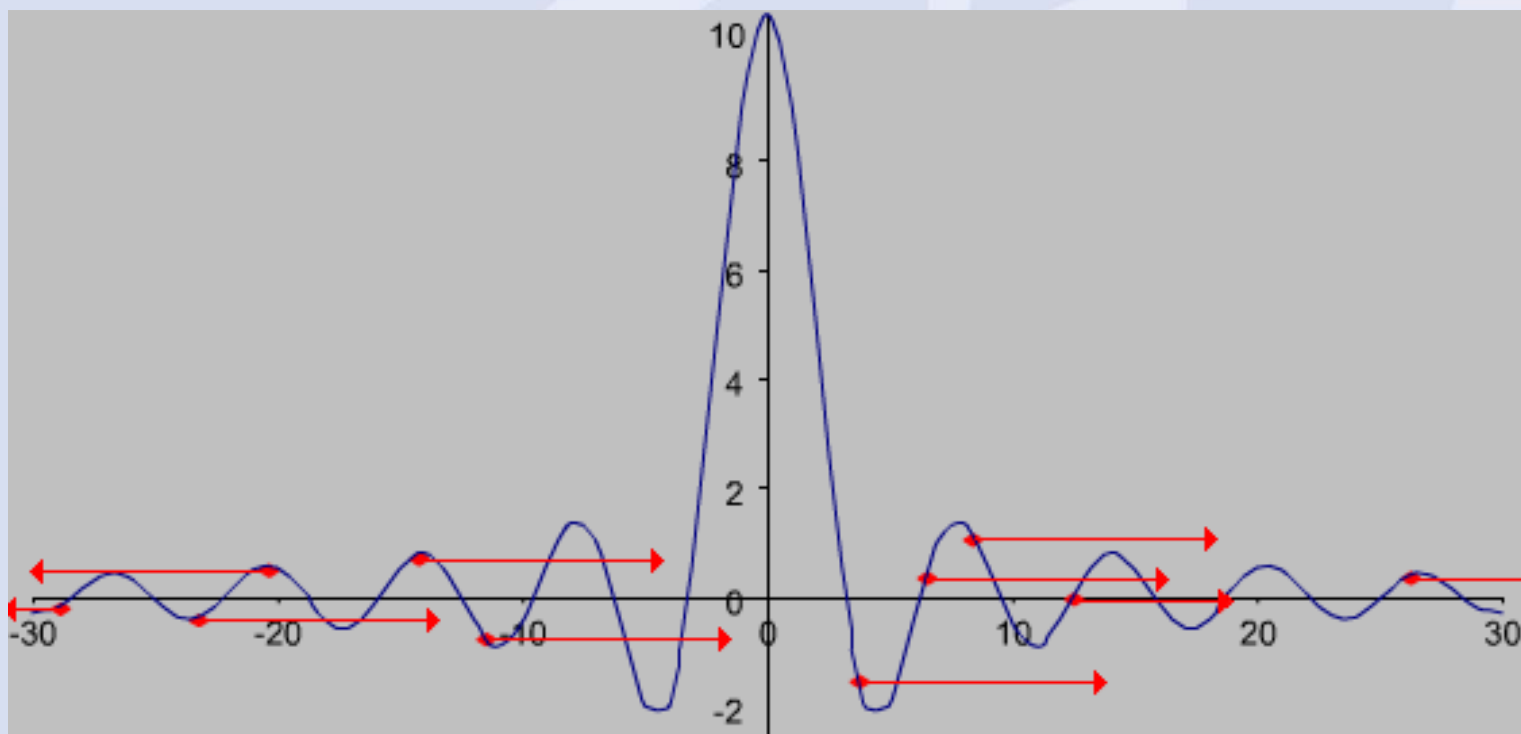
$$\vec{V}_{new} = \underbrace{w \times \vec{V}_{old}}_{\text{History}} + \underbrace{c1 \times \text{rand}(\square) \times (\vec{P}_{pbest} - \vec{X})}_{\text{Own knowledge}} + \underbrace{c2 \times \text{rand}(\square) \times (\vec{P}_{nbest} - \vec{X})}_{\text{Social knowledge}}$$

$$\vec{X}_{new} = \vec{X}_{old} + \vec{V}_{new}$$

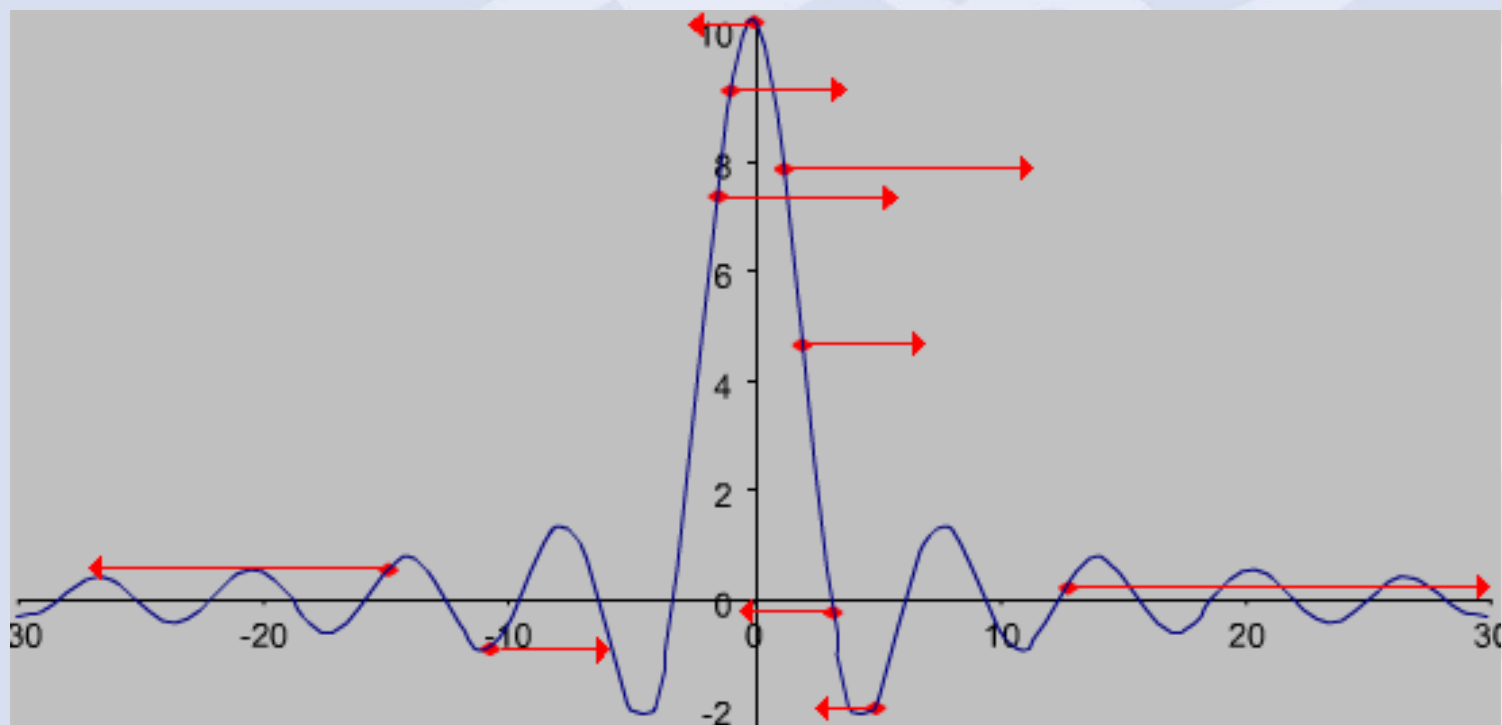
- Particle Swarm Optimization (PSO)

$$f(x) = 10 \sin(x) / x$$

- Iteration 0: Random positions and speeds. 10 particles.



- Particle Swarm Optimization (PSO)
 - After 10 iterations



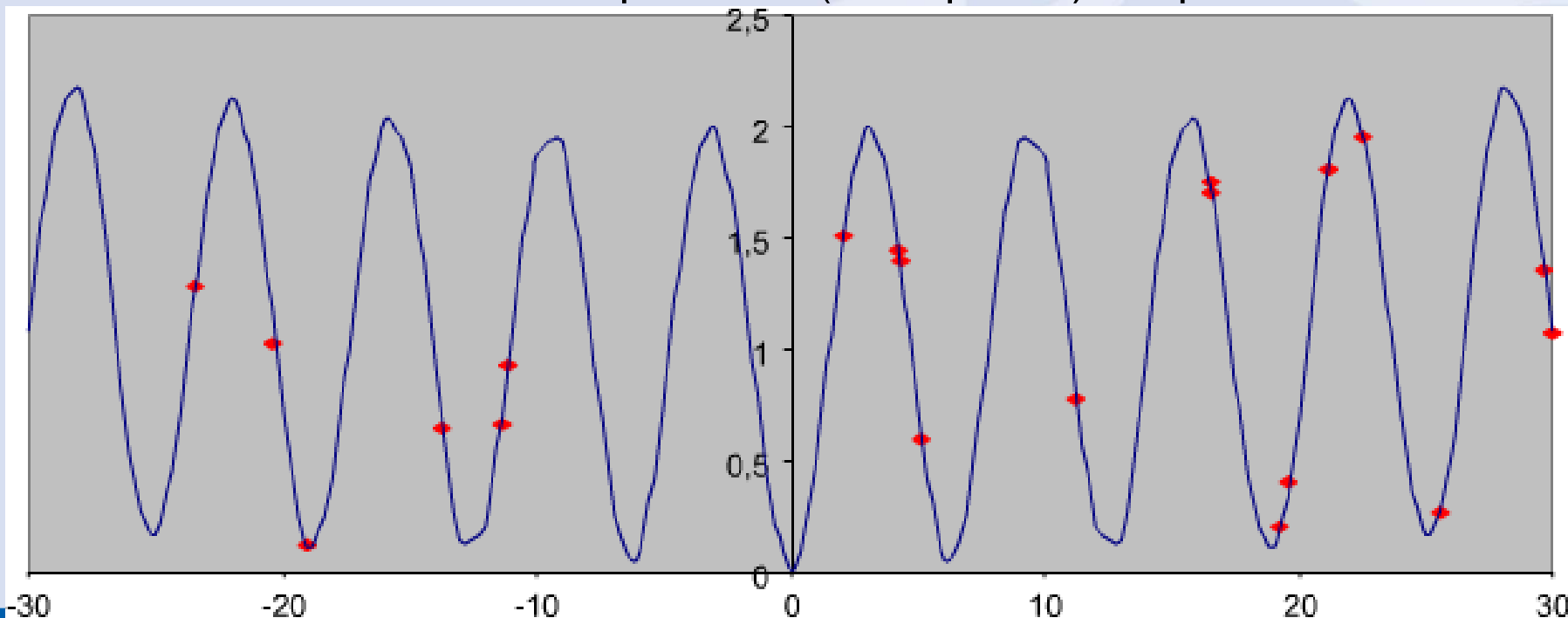
Best solution found $x=-0,066$, $f(x)=9,992$. Time 80ms.

- Particle Swarm Optimization (PSO)

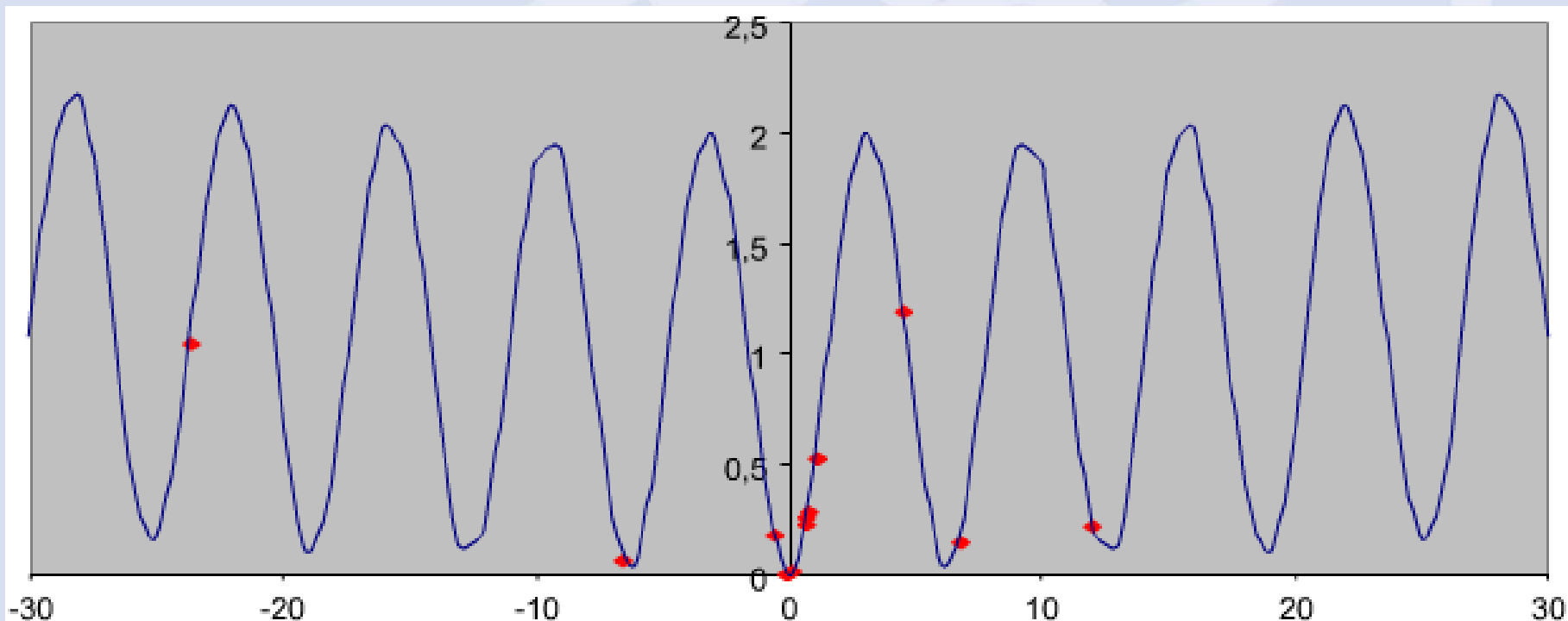
Griewank Function

$$f(x) = \frac{1}{4000} \sum_{i=1}^N x_i^2 - \prod_{i=1}^N \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$$

- Iteration 0: Random positions (and speeds). 20 particles.

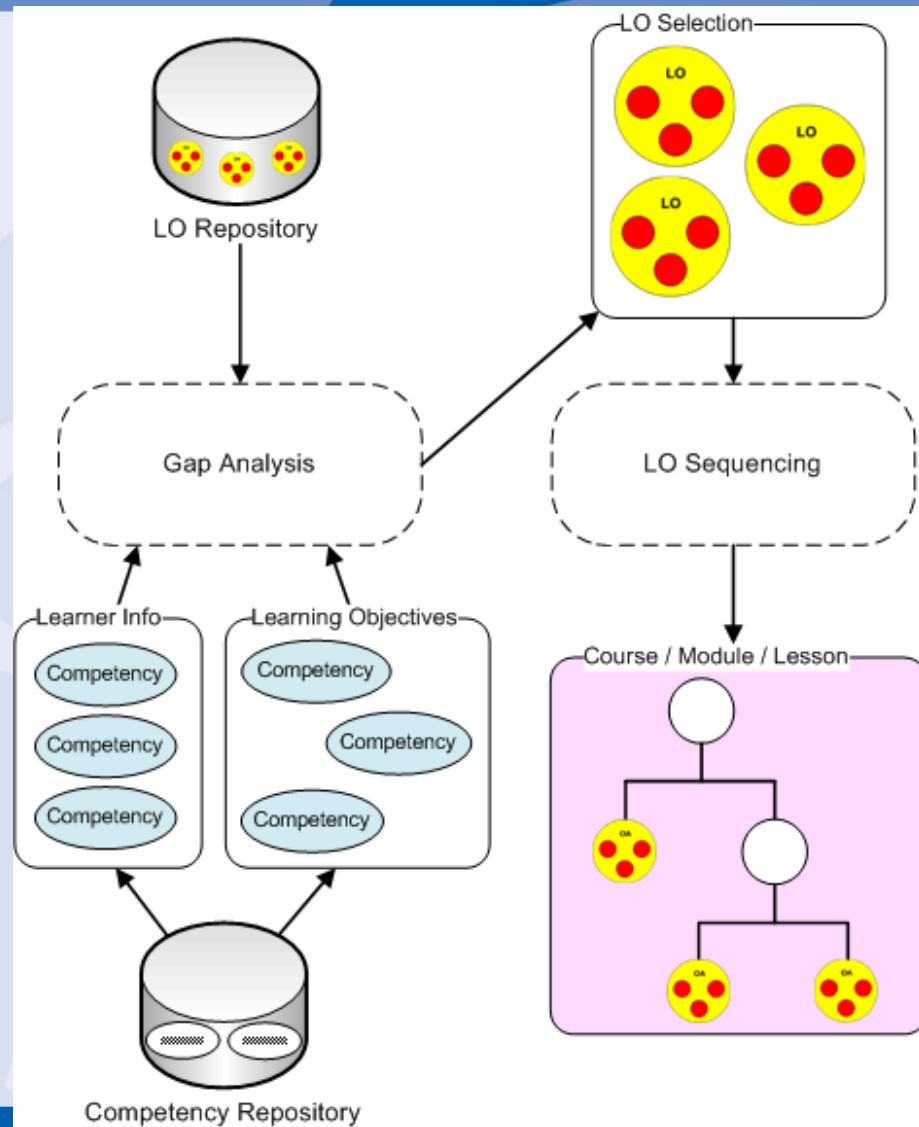


- Particle Swarm Optimization (PSO)
 - After 50 iterations



Best solution found $x=-4,475 \times 10^{-4}$ $f(x)=-1,002 \times 10^{-7}$, time 1683ms.

- **Competency-driven content generation model**
 - Current model: Instructors create courses targeting generic learner profiles.
 - Tasks: Search, sequence, package
 - Proposal: Automate these tasks to build personalized learning courses
 - Based on:
 - Learning Object (LO) Paradigm (Wiley, 2000)
 - e-Learning Standards and Specifications Conformance
 - SCORM, RDCEO, LOM



- Competencies for interoperable Learning Object Sequencing
 - Competency views
 - Pedagogic: What learners know, What learners want to know
 - LO: Prerequisites and Learning Outcomes
 - Competency Standards
 - IMS "Reusable Definition of Competency or Educational Objective" (RDCEO) specification
 - IEEE Learning Technology Standards Committee (LTSC) "Standard for Learning Technology - Standard for Reusable Competency Definitions" specification
 - HR-XML Consortium "Competencies (Measurable Characteristics) Recommendation"
 - Objective: Create Reusable Definitions of Competencies (RCDs)

- Curriculum sequencing objective:
 - “to provide the student with the most suitable individually planned sequence of knowledge units to learn and sequence of learning tasks [...] to work with” (Brusilovsky, 1999)
- Sequencing Approaches (Gutiérrez & Pardo 2007):
 - UML-based
 - UML-guide (Dolog, 2003), CADMOS-D (Papasalouros, 2004)
 - Graph-based
 - AHA! (de Bra, 2003), Sequencing Graphs and SIT (Gutiérrez, 2004)
 - Stochastic
 - Pedagogical suggestions (Semet, 2003), auxiliary material generation (Huang, 2008)

- **Obstacles**

- Standardization issues in actual e-learning systems
 - SCORM Content Aggregation Model (or IMS SS)
 - IEEE LOM

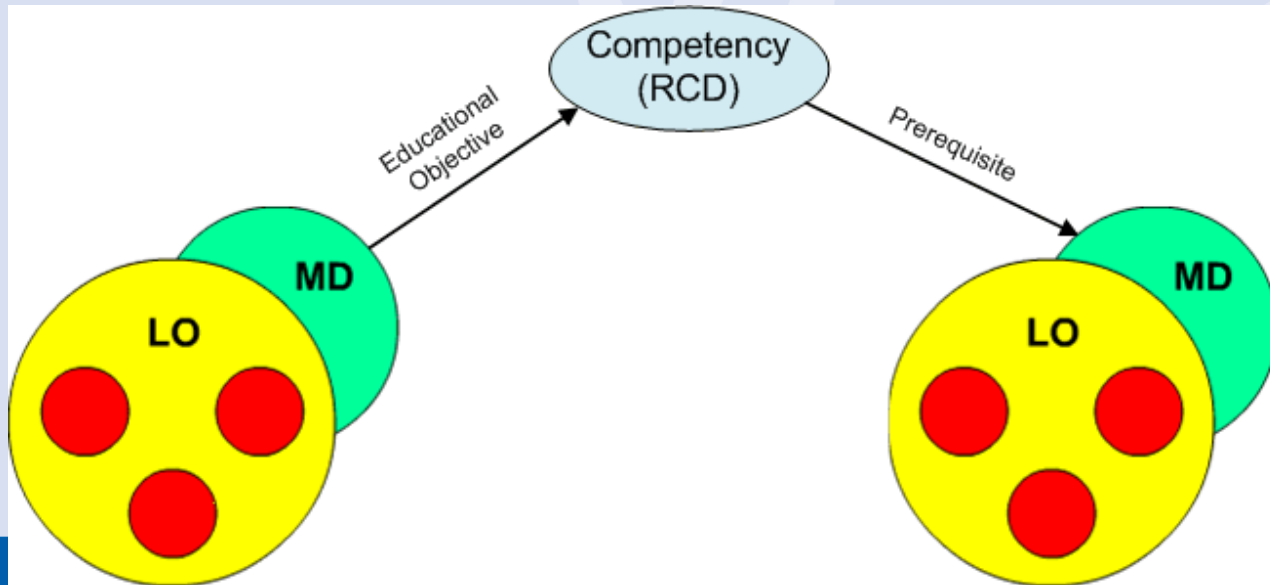
Real reusability and interoperability are really far

- Domain dependence vs domain independence
 - Difficulty to build models and they are domain dependent
- For stochastic approaches
 - Different runs = different results

- Objectives
 - Build personalized courses for today e-learning systems
 - Define sequences of learning objects in a interoperable way
 - Create a domain independent sequencing mechanism
- Mechanism
 - Graph approach: to model sequences and its restrictions
 - Stochastic approach: to find feasible sequences

- The Model

- LO sequencing through competencies
- LOM records to link learning objects with competencies:
 - LOM element 9, 'Classification'
 - element 9.1 'Purpose' set to 'prerequisite' or 'educational objective'
 - element 9.2 'Taxon Path' used to reference the competency



- The Problem

- Given a Random Sequence of Learning Objects find a correct (feasible) sequence
- Modelled as a Constraint Satisfaction Problem (CSP)
 - Variables: LOs Positions in the Sequence
 - Constraints: Competencies (LOs Relations)
 - Operations: Permutations of LOs within the sequence (PermutCSP)
 - State: Sequence
 - Objective: Find a sequence that satisfies all constraints
 - Fitness function: Standard penalty function

$$\text{fitness}(s) = \sum_{i=0}^n s[i].pr_n$$

- The agents (the stochastic part)
 - Problem modelled as a Constraint Satisfaction Problem and two intelligent agents implemented to solve it:
 - Particle Swarm Optimization (PSO): Discrete-PSO (Hu, 2003) with velocity check
 - Genetic Algorithm (Holland, 1975): Order recombination, swap mutation and generational replacement with elitism (k -size tournament selection and a duplicate elimination policy)
 - Output: a personalized SCORM package

- PSO Agent Pseudocode

```

SEQUENCING_PSO(input_sequence, w, c1, c2) {
  INITIALIZE the swarm
  DO {
    FOR EACH particle {
      CALCULATE fitness value
      IF (new fitness < gBest) SET gbest = currentValue
      IF (new fitness < pBest) SET pbest = currentValue
      CALCULATE new velocity as
         $V_{new} = w \times V_{old} + (c1 \times rnd() \times (pbest - currentValue)) + (c2 \times rnd() \times (gbest - currentValue))$ 
      NORMALIZE Velocity as
         $V_{norm} = V_{new} / \max(V_{new})$ 
      CHECK  $V_{norm}$  limit
      FOR EACH v in  $V_{norm}$  {
        IF ( $v > \text{length}(X)$ )  $v = \text{length}(X)$ 
      }
      UPDATE particle value
      FOR i = 1 to  $\text{length}(V_{norm})$  {
        IF ( $\text{rand}() < V_{norm}[i]$ ) SWAP  $\text{currentValue}[i]$  for  $\text{currentValue}[\text{indexOf}(\text{currentValue}, \text{gBest}[i])]$ 
      }
      CHECK Mutation
      IF ( $\text{currentValue} = \text{gBest}$ ) swap two random positions from currentValue
    }
  } UNTIL termination criterion is met
}

```

- GA Agent Pseudocode

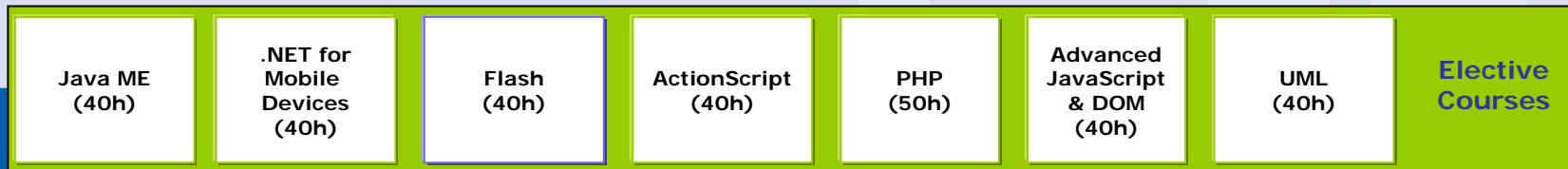
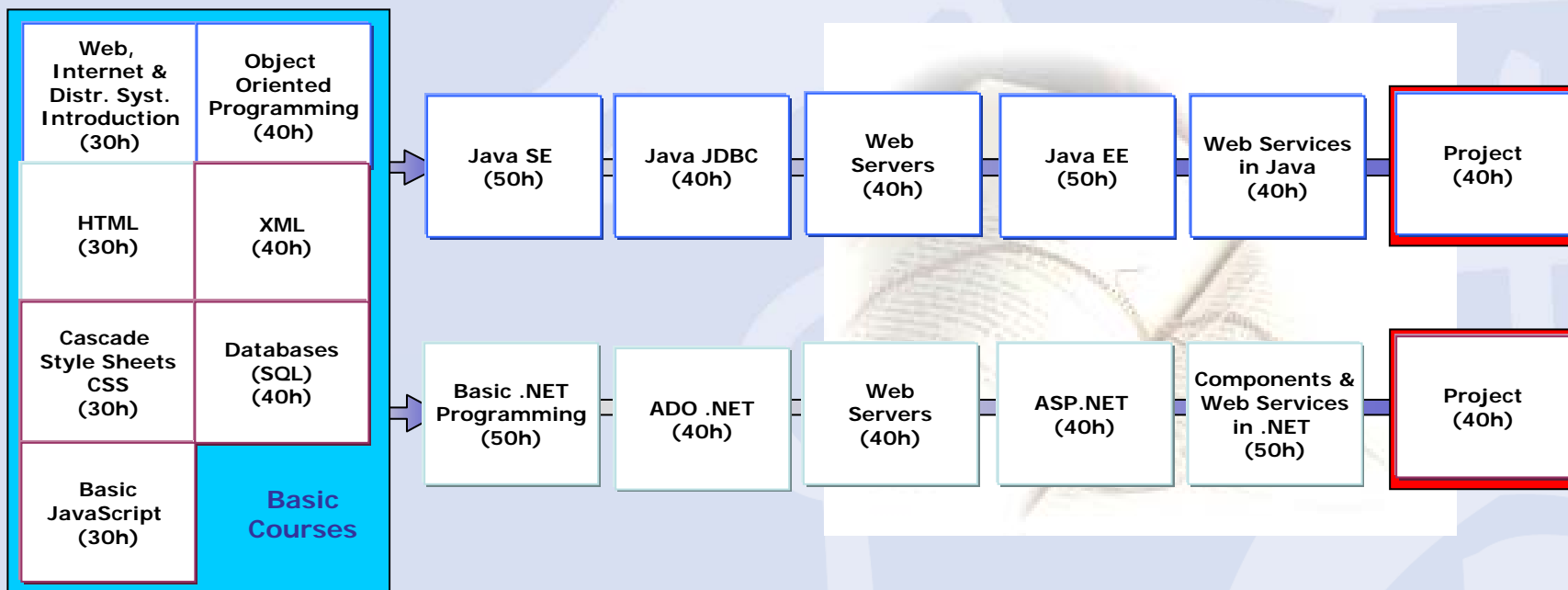
```
SEQUENCING_AG(input_sequence,  $\mu$ , k, p, n)
BEGIN
  SET population[0] = input_sequence
  Randomly INITIALIZE the rest of the population  $\mu$ 
  EVALUATE each individual
  SET bests = n individuals with best fitness
  SET n_generations = 0
  REPEAT UNTIL (termination criterion satisfied) {
    SELECT  $\mu/2$  couples using k size tournaments
    Perform an ORDERED RECOMBINATION of the  $\mu/2$  couples
    Offspring SWAP MUTATION with probability p
    ELIMINATE DUPLICATES
    survivors SELECTION for the next generation {
      PERFORM a generational replacement
      FOR-EACH i in bests
        IF fitness(i) > fitness(best offspring) REPLACE a random offspring with i
      }
    SET bests = n individuals with best fitness
  }
}
END
```

- Agents implemented and tested in real and simulated scenarios:
 - Real scenario: Sequence of LOs in a MSc Program. Web Engineering Program (23 LOs, 50 Constraints):
 - Basic courses (7) must be taken before any other (course).
 - Restrictions between two basic courses may occur.
 - ‘Itinerary’ courses (5) must be taken in a fixed ordered sequence.
 - Compulsory courses (5). There may be restrictions between two of them
 - Elective courses (6). Additional constraints regarding any other course may be set.

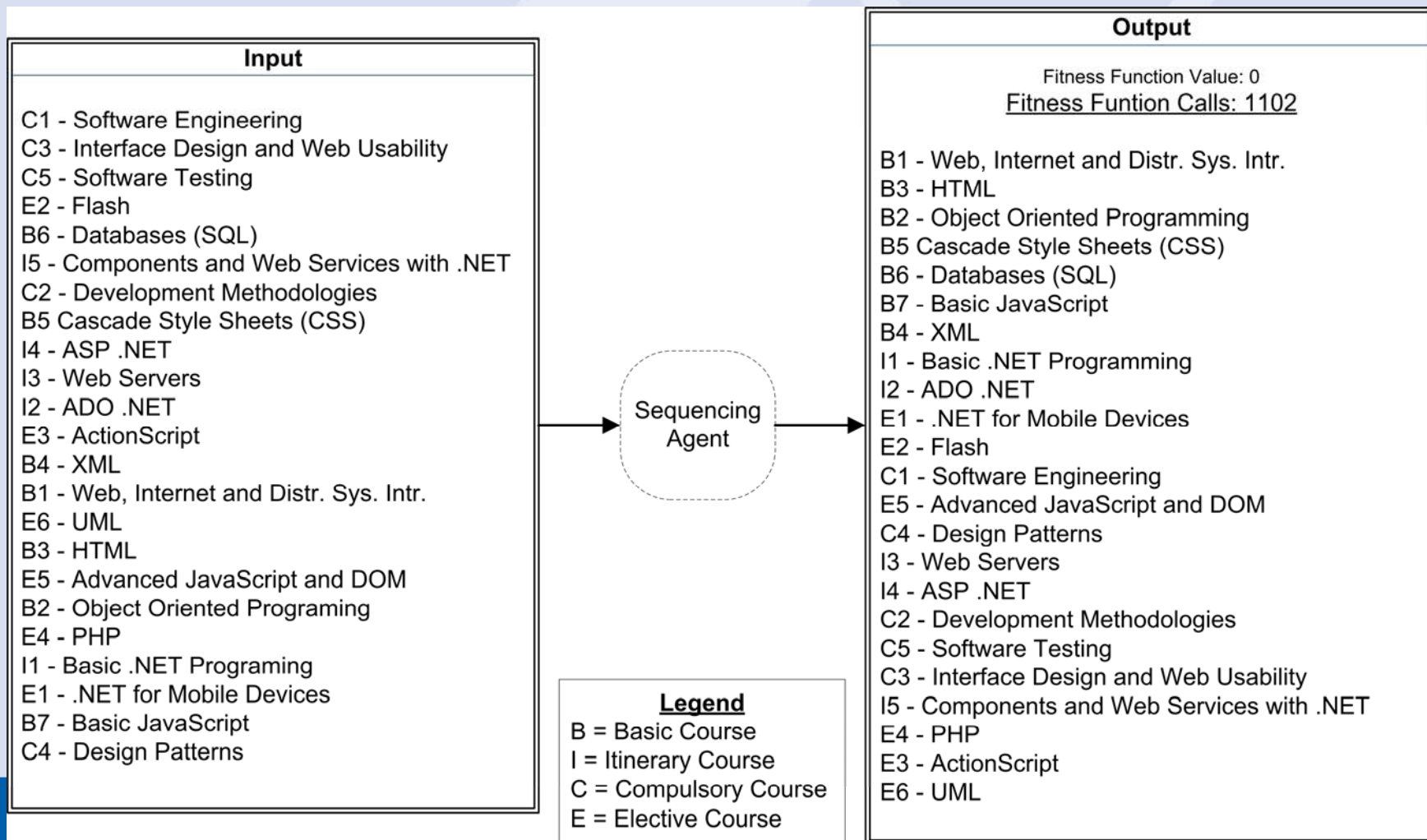
Search space size: $23!$ States ($2,5 \times 10^{22}$)

Ratio total solutions / feasible solutions is $8,9 \times 10^{12}$ (just an estimation)
 - Simulated scenarios: 5, 10, 20, 30, 40, 50, 60, 75 and 100 LOs with only 1 valid (feasible) sequence (solution)

WEB ENGINEERING MASTER PROGRAM

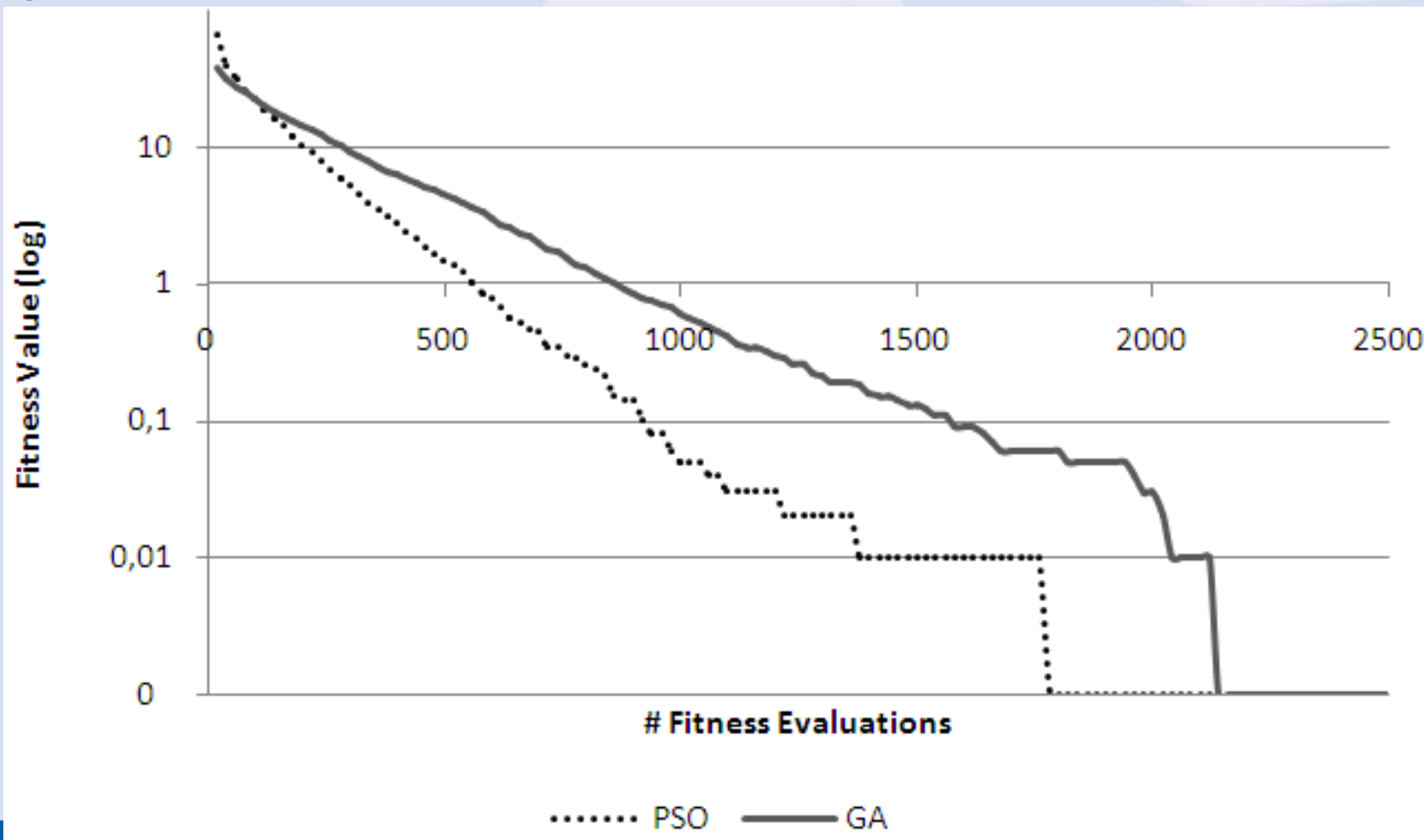


- Agent Execution Example

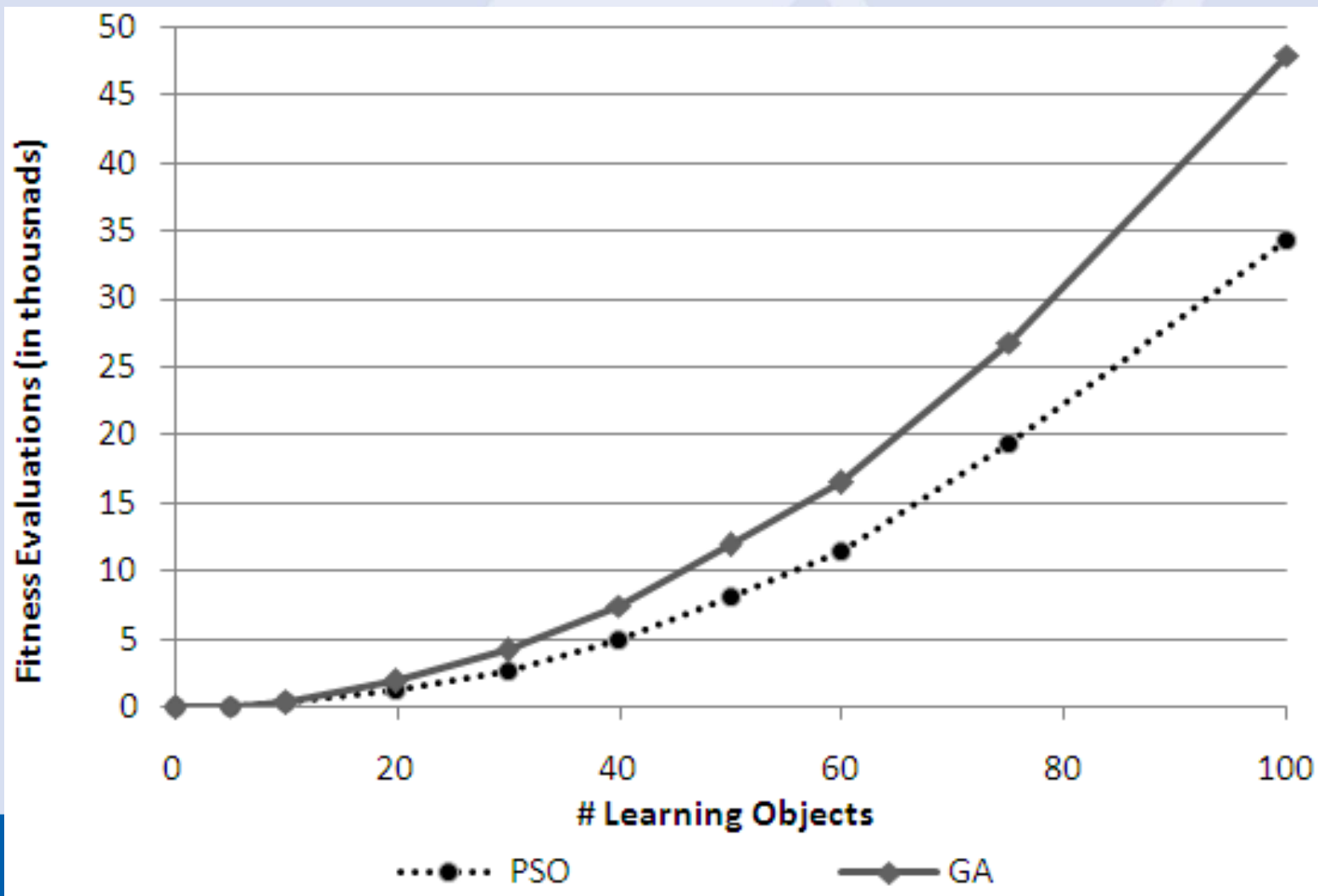




- Agents Comparison



- Scalability





- **Conclusions**

- It is possible to create personalized courses for wide-use e-Learning systems taken care of standards
- Learning objects, metadata and competencies can be used to define domain independent sequences
- An AI approach may be employed to solve the sequencing problem
- Two evolutionary agents have been designed and implemented
- Both agents succeed but PSO outperforms GA in all the scenarios

- **Future Work**
 - Scalability
 - Exact Techniques
 - Hybrid Techniques
 - Artificial Ants
 - Tree-like courses
 - Genetic Programming
 - Gap Analysis Subprocess
 - Interface
 - Curriculum recommendation to Learners

- Brusilovsky, P.: Adaptive and Intelligent Technologies for Web-based Education. *Künstliche Intelligenz, Special Issue on Intelligent Systems and Teleteaching*, 4, 19-25 (1999).
- De Bra, P., Aerts, A., Berden, B., Lange, B.d., Rousseau, B., Santic, T., Smits, D., Stash, N.: AHA! The adaptive hypermedia architecture. *Proceedings of the fourteenth ACM conference on Hypertext and hypermedia*. ACM Press, Nottingham, UK (2003)
- Dolog, P., Nejd, W.: Using UML and XML for generating adaptive navigation sequences in web-based systems. In: *Proceedings of UML 2003*. (2003)
- 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.
- Gutiérrez, S., Pardo, A., Kloos, C.D.: Beyond simple sequencing: Sequencing of learning activities using hierarchical graphs. In: *Web-Based Education 2004*. (2004)
- Gutiérrez, S. & Pardo. A.: Sequencing in Web-Based education: Approaches, Standards and Future Trends, *Studies in Computational Intelligence (SCI)* 62, 83–117 (2007)
- Holland, J., *Adaptation In Natural and Artificial Systems*, Michigan (USA): The University of Michigan Press (1975).
- Hu, X., R.C. Eberhart, and Y. Shi. *Swarm intelligence for permutation optimization: a case study of n-queens problem*. in *Proceedings of the 2003 IEEE Swarm Intelligence Symposium*. (2003)
- Huang, T.-C., Huang, Y.-M., Cheng, S.-C.: Automatic and interactive e-Learning auxiliary material generation utilizing particle swarm optimization. *Expert Systems with Applications* 35 (2008)
- L. Kari and G. Rozenberg, "The many facets of natural computing," *Communications of the ACM*, vol. 51, pp. 72-83, (2008).
- Papasalouros, A., Retalis, S., Papaspyrou, N.: Semantic description of educational adaptive hypermedia based on a conceptual model. *Educational Technology and Society* 7 (2004)
- Semet, Y., Lutton, E., Collet, P.: Ant colony optimisation for e-learning: Observing the emergence of pedagogical suggestions. In: *IEEE Swarm Intelligence Symposium*. (2003)
- D. A. Wiley, "Connecting LOs to instructional design theory: A definition, a metaphor, and a taxonomy," in *The Instructional Use of LOs*, D. A. Wiley, Ed., (2000).

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Thank you & Questions

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