Enhanced e-Learning Experience by Pushing the Limits of Semantic Web Technologies

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An Intelligent Tutoring System should be

- user-adaptive: The system configures itself to the learner. Thus, individual aspects of the learner are considered.
The e-Learning Experience

An Intelligent Tutoring System should be

- user-adaptive: The system configures itself to the learner. Thus, individual aspects of the learner are considered.
- didactically-enhanced, i.e. incorporates pedagogical and methodological knowledge into the learning process.
Need to find best fit Learning Objects for a particular Learner

I am a scholar of Astronomy, age 20, male, and like to find old books, original work by old masters, preferably with hand-drawn sketches.

Please have a look at Copernicus’ works 1543, available as digitalized images.
..respective a didactic Learning Strategy

Your learning pace is good. Please skip the next exercise and continue with the work of Galilei.
Need for a Knowledge-based Approach

- **Information sharing, integration and reuse**
  - Well-established metadata standards for defining and sharing Learning Objects, e.g. LOM (Learning Object Metadata), SCORM (Shareable Content Object Reference Model) exist

- **Semantic Search and Reasoning:**
  - Support of semantic search of structured data
    - precise information need can be expressed
  - Semantic graph including structural relationships can be exploited for search
Challenges

• **Relaxing complex conjunctive queries.** It is not always possible to fulfill all feature constraints. We need to find an optimal solution that satisfies a maximal subset of the constraints.
  ➔ Basic Approach: Query Rewriting, i.e. successively relax the constraints imposed in the extended query

• **Soft Constraints and Preferences** No exact match is required: soft constraints should be satisfied if possible, but may be violated if necessary.
  ➔ Basic Approach: Extension of DL with Fuzzy Logic [Straccia 2011], Probability Theory [Giugno & Lukasiewicz], etc.
Challenges

- **Ranked Retrieval** Standard OWL DL only yields an unordered result set without ranking. In situations where more than one item is part of a recommendation result, a ranking is required.

  ➔ Basic Approach: SPARQL ORDER BY, Fuzzy Set Theory, IR Measures based on Vector Similarity, etc.
Challenges

- **Sequences**: (Structured) linear sequences are not supported in OWL DL
- Need to support Left-Right Parsing/Generation to predict the next state, e.g., prediction of successors, predecessors
- Can we parse such structures in OWL DL directly?
  - Basic Approach: Rewriting [Hirsh and Kudenko, 1997], General list patterns [Drummond et al., 2006]; N-ary relations [Hayes, 2007]
Basic Approach

Combination of a

- **Logic-based approach** based on an OWL reasoning framework to describe learner, learning material and pedagogical model
  - Choice of OWL 2 DL as recommended W3C Standard
  - Main tasks: Instance retrieval based on Recommendation Conditions
  - Advantage: Decidable, but N2ExpTime Complexity

- **Non logic-based approach** to give a relevancy score for the best-fit Learning Object
  - Choice of Utility functions
  - Multi-attribute Utility Theory (MAUT) frequently adopted decision making technique with complete theoretical foundation
  - Focus on modelling aspect such as coherence and preference
  - Advantage: intuitive to decision makers (i.e. tutors)
Overall Architectural Design: Hybrid Recommender Framework

Figure: Hybrid Recommender Framework
Modular Ontology Framework

- **Pedagogical Ontology**
  - Learning material organized into Courses (\(KD\)s), Concept Containers (\(CC\)s), and Knowledge Objects (\(KO\)s), all disjoint.
  - ObjectProperties connect \(KO\)s to \(CC\)s, and \(CC\)s to \(KD\)s, respectively.
  - Knowledge Types of \(KO\) are, e.g., *orientation*, *example*, *assignment*, etc., and Media Types, e.g., *text*, *video*, *audio*, etc.
  - Metadata for \(KO\)s, such as, *hasDifficultyLevel*, *hasEqftLevel*, *hasLanguage*, *hasEstimatedLearningTime*, *isSuitableForMute*

- **Learner Model Ontology**
  - Classes and properties for describing the current learner state characterized by *Didactic Factors*, e.g., *interaction willingness*, *session length*, *internet connectivity*, *motivation level*, etc.
Modular Ontology Framework

- **Extension: Learning Pathway Modelling in OWL 2 DL**

  Structured sequences can be formally described by a regular grammar.

  Our OWL modelling supports

  - retrieving direct successors and predecessors w.r.t. to a certain state
  - inferring transitive closure, i.e. all indirect successors and predecessors within a Concept Container
  - switching to the next level at the end or beginning of a Concept Container
  - inferring pathways based on semantic attributes, so called *Knowledge Type* or *Media Type Pathways*, for automatic courseware generation
Modular Ontology Framework

• **Extension: Learning Pathway Modelling in OWL 2 DL**
  
  • Auxiliary Individuals
    
    \[
    \text{MyMicroLP} \sqsubseteq \text{MicroLP} \\
    \text{MyMicroLP}(CKO_{(1,2)}) \\
    \text{hasPredLP}(CKO_{(1,2)}, KO_1) \\
    \text{hasSuccLP}(CKO_{(1,2)}, KO_2)
    \]

  • Self Restrictions
    
    \[
    \text{CurrentLP} \sqsubseteq \exists \text{isCurrentLP}.\text{Self} \\
    \text{MyMicroLP} \sqsubseteq \text{CurrentLP}
    \]

  • Property Chains
    
    \[
    \text{hasPredLP} \circ \text{isCurrentLP} \circ \text{hasSuccLP} \sqsubseteq \text{hasDirectKOSuccessor}
    \]

  • Transitive superproperty
    
    \[
    \text{hasDirectKOSuccessor} \sqsubseteq \text{hasKOSuccessor} \\
    \text{trans}(\text{hasKOSuccessor})
    \]
Modular Ontology Framework

- Extension: Knowledge Type Learning Pathways in OWL 2 DL
  - Subproperty Axioms
    
    \[
    \text{hasPredKT} \circ \text{hasKT} \sqsubseteq \text{hasPredLP} \\
    \text{hasSuccKT} \circ \text{hasKT} \sqsubseteq \text{hasSuccLP}
    \]

- Example:
  "SimulatedMultiStage" is a Knowledge Type Pathways defined as the following sequence: Orientation - Explanation - Simulation - Assignment

Figure: Knowledge Type Pathway
Recommendation Axioms

Informal description:

1. **Recommendation Axiom 1.1** Proceed to the next Learning Object that is either partially complete or unseen.

2. **Recommendation Axiom 1.2** Proceed to one of the following Learning Objects on the learning path that form part of the lesson, either partially complete or unseen.

3. **Recommendation Axiom 1.3** Proceed to the previous Learning Object that is either partially complete or unseen.

4. **Recommendation Axiom 1.4** Proceed to one of the preceding Learning Objects on the learning path that form part of the lesson, either partially complete or unseen.

5. **Recommendation Axiom 2** Proceed to a perfect matching Learning Object w.r.t. the setting of Didactical Factors reflecting the current learner state.
Ranking Strategies

All results sets specified by the Recommendation Axioms are computed by the reasoner. For any Learning Object that fulfills Recommendation Axiom 1, i.e. is on the learning path, a recommendation score is computed based on the results for Recommendation Axiom 2.

- **Hard Ranking**: Didactical Factors of current learner state need to match with Learning Object features.
- **Soft Ranking**: Didactical Factors of current learner state need not perfectly match with Learning Object features.
- **Mixed Ranking**: Combination of Hard and Soft Ranking. User specifies in advance which Didactical Factors need to be fully satisfied.
Recommendation Score

1. **Degree of Match.** Parameter $d$ is used to define when constraints given as a key value pairs match.

2. **Weights** Different weights can be assigned (by the tutor) to individual features, reflecting their importance with respect to all other feature constraints.

Recommendation score:

$$\text{RecScore}(LO_i) = \sum_{k=1}^{n} w(k)d(i, k)$$

where

- $w(k)$ is the weight of feature $k$, and thus its contribution to the final result.
- $d(i, k)$ is the matching degree of the feature $k$, represented by a floating-point value ranging from 0 to 1.
- $n$ is the number of Didactic Factors.
Degree of Match

**Degree of Match** varies according to the user profile

- Learning Object best-suited to a learner gets highest score, lower scores (closer to 0) otherwise.
- Suitability of a Learning Object depends on User Profile
  
  **Scores for different Age Groups:**

- Scores can be approximated, e.g. with a Gaussian distribution
Weights

- Weights reflect the importance of each attribute to the overall utility. Their values are specified by didactic experts.

Example: Suitability of a Learning Object depends on specified age

<table>
<thead>
<tr>
<th>Kids</th>
<th>Children</th>
<th>Adolescents</th>
<th>Adults</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>6</td>
<td>4</td>
<td>2</td>
</tr>
</tbody>
</table>

Table: Weights for different Age Groups

- Utility defined as additive sum over multiple attributes
Validation - Reasoning

- Functionality successfully tested
- Work in progress: Optimization
  Efficient runtime complexity needed.
  Main focus is on
  - Question Answering: conjunctive queries over a huge A-Box
  - Support of inferencing (e.g., datatype reasoning, property inclusion)
  → Find best trade-off between scalability and expressivity.
Validation - Ranking

- Functionality successfully tested
- Work in progress: Fine tuning of DF weights
  No Benchmarking Data available
  Main focus is on
  - Generation of artificial data for testing
  - Definition of Ground Truth Data ranked by human experts

→ Final Evaluation to test goodness-of-fit planned on
  - Blind test data
  - Evaluation measures: Precision@K (K=3), Normalized Discounted Cumulative Gain (NDCG).
Concluding remarks

- Novel approach to personalized e-Learning that can be adopted to different pedagogical strategies.
- Novel representation of learning pathways in OWL 2 DL.
- Ranking solves a number of issues, e.g. including handling of soft constraints.
- If ranking is carried out in a post-processing step, reasoning results can be more easily reused.
- Recommendation approach successfully implemented and interfaced to the Learning Management System Moodle.
- Tests were performed on an authentic course with real learning material.
- Evaluation with real learners to test the overall approach is running.