

# A Utility-based Semantic Recommender for Technology-Enhanced Learning

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**Abstract**—In this paper, we present the design of a Knowledge-based recommender system for Technology Enhanced Learning based on Semantic Web Technologies. It uses a knowledge model for representing the current state of the learner, pedagogical strategies, and learning objects. To create a learner model, the learners' activity and progress is tracked and higher-level learner features (i.e., *Didactical Factors*) are extracted. For a given learner state and set of pedagogical rules, the Recommendation Engine infers learning objects that lie on the learners personalized learning path. Furthermore, utility functions are used to compute a relevancy score for the best-fit learning objects. We describe the semantic-based recommendation approach on a conceptual level, discuss the strengths and weaknesses on the recommender framework and discuss future research.

**Keywords**—Semantic Web Technologies; Personalization; Recommender Systems; Utility-based Recommender;

## I. INTRODUCTION

We present a knowledge-based recommender system that uses Multi-Attribute Utility Theory (MAUT) to recommend learning objects as well as sequences of learning objects to individual learners. The recommender is tightly integrated into a standard Learning Management System (LMS). In particular, user-tracking information is leveraged for adaptive learning.

Our approach builds upon pedagogical knowledge that explicitly specifies the basic factors that are likely to underlie the recommendation process. The main knowledge sources from which our recommender draws are the *Learner Model*, the *Pedagogical Model*, and the *Learning Resources Model*, all formally described in a modular ontology framework. The overall approach is constraint-based, i.e. we derive a set of recommendable learning objects (LOs) that fulfill didactic requirements based on knowledge about how to relate the current state of the learner (captured by *Didactic Factors*) to suitable learning resources. In particular, ordering constraints are incorporated into our recommendation model, based on didactically meaningful sequences of learning objects (i.e., *Learning Pathways*). Providing navigational guidance to individual learners is crucial, since it can help to overcome the problem of disorientation and information overload.

Our recommender approach uses a combination of logic-based knowledge descriptions and utility-based recommendation. The main benefit of this approach lies in its support

for ranking LOs and effectively handling different types of constraints, i.e. *Hard and Soft Constraints*.

In our TEL-Recommender system, the learner is actively supported by means of a recommendation dialogue used to provide meta-cognitive feedback, explain recommendations along with a ranking factor and offer motivational messages. A dialogue is also initiated by the system to acquire missing profile information, including elicitation of learners preferences.

A basic aspect of the design was to have the recommendation process transparent for the learner. We therefore foster an open learner modelling to promote a self-awareness of the learning process. Information about the learners profile and tracking data (provided by the LMS) are made explicit.

The rest of this paper is divided into five sections. Section 2 introduces the ontology framework based on Semantic Web standards. In section 3, we describe the design of the recommender system, including its strengths and weaknesses. In section 4, we refer to related work. Section 5 concludes the paper.

## II. ONTOLOGY FRAMEWORK

### A. The Learner Model

Our system manages a learner model that captures the current state of the learner, which is characterized by a set of Didactic Factors (DFs) devised by didactical experts as a basis for the recommendation of learning objects and as a trigger for feedback messages. This model results from user tracking, i.e. *implicit* information about the individual's learning history (e.g., order of accessed LOs, completion status, learner's preferences for certain media and knowledge types, learning pace) as well as *explicit* information provided by the system (e.g., connectivity, assessment results). In order to overcome the general user-modeling problem (of having no reliable learner profile), a major design decision for the choice of DFs was that their values are either directly given by the LMS (e.g., personal data like age, gender, EQF level, spoken languages, and disabilities), or can be computed with a high degree of certainty (e.g., implicit learner observations). To this aim, firstly, only DFs have been chosen that are particularly relevant for discriminating LOs from each other. Second, missing learner information is gathered through an interactive dialogue. Furthermore,

the importance of individual DFs is defined using *Hard Constraints*, reflecting basic learner requirements, and *Soft Constraints* that express preferences regarding the way in which learners would like to be taught. This approach also provides a solution for relaxing constraints: Whenever too many constraints result in low coverage (i.e. the sparsity problem), constraints can be relaxed to derive suboptimal solutions.

### B. Learning Resources

Learning objects (LOs) are defined as small, self-contained, reusable units of learning and are described following the learning standards and specifications IEEE LOM. We define metadata vocabulary based on Dublin Core and reference to domain ontologies for semantically describing the content of LOs. In our LO repository, learning objects are annotated with values for estimated learning time, suitability for age, gender, language, EQF level, difficulty level, disabilities, and educational topic. It also provides fine-grained concepts for Knowledge Types (KTs), e.g., orientation, example, assignment, etc., and Media Types (MTs), e.g., text, video, audio, etc.

### C. The Pedagogical Model

The pedagogical background knowledge is described in the Pedagogical Ontology (PO) [1] and based on Web Didactics [2]. In the PO, learning material is organized into Knowledge Domains (KDs), Courses (CCs), and Knowledge Objects (KOs), forming a hierarchical graph structure. The learning path network that we seek to model is based on the curriculum modeling language IMS Learning Design that provides constructs allowing instructional designers to specify sequences of activities. However, it extends this conceptual metadata schema with classes and properties for the description of learning pathways specified as fully connected sequences (from the start to an end node) on two hierarchical levels (i.e., CCs/KOs), namely *Macro- and Micro Learning Pathways*, used to guide the learner towards his/her learning goal. We use property paths to link learning objects so that LOs reachable from the current learner state as well as abstract learning pathways based on knowledge types can be inferred automatically (see [3], [4] for details).

### D. The Recommendation Strategy

The most fundamental principles of our recommendation strategy are, firstly, that any recommended learning object should lie on the learners learning path and not have been completed and second, that it should match the current state of the learner, reflected by *Didactical Factors*. Due to the high expressiveness of our ontology-based framework, the recommendation strategy as well as the adaptation mechanism can be described on a high abstract level. For instance, a switch of forward/backward navigation can be triggered by the setting of DF values (e.g., repetition of certain KOs

within a CC whenever the learner's test results are low). Depending on the domain, DFs might need to be (de)activated and their weights configured on an individual basis.

## III. THE RECOMMENDATION FRAMEWORK

### A. The Reasoning Module

The Reasoning Module acts like a content-based filtering system and, together with the Ranking Module, finds best-fit learning objects for a certain learner in a specific state. We apply inference techniques to find matches between the state of the learner and LO features. In particular, we perform instance retrieval and define complex constraints such as conjunctive A-Box queries for complex data types for selecting appropriate LOs. Interoperability and sharing of learning resources is facilitated by use of Semantic Web standards, best practice vocabularies and taxonomies for LOM meta-data elements. All learning resources are labeled with a globally unique IRI, which can be used to retrieve more open educational resources on the web semantically linked to them. Scalability has been assessed in an independent quantitative evaluation study and shows that our recommendation algorithm can handle medium-sized curriculum courses in real time. In particular, reasoning requests for different users can be delegated to various external DL Reasoners (e.g. HermiT, Pellet), using the Reasoning Broker Herakles [5].

### B. The Ranking Module

Learner-specific utility functions have been incorporated into our system to better focus on the personalized gain of a recommendation, following thus a utility-based recommender approach. The multi-attribute utility theory has been chosen as the underlying mathematical model to evaluate and rank alternatives. The utility is thus related to finding good (sequences of) items in a learner adaptive way. In our utility model, different weights  $w$  are assigned to DFs, reflecting their importance with respect to the overall utility. Furthermore, a parameter  $d$  for the degree of a match is used to calculate the similarity between the state of the learner and the items. In case of a perfect match, the desired value and the actual value are the same. In case of a partial match, a distance measure is used to compare these values, where  $d$  is in the  $[0,1]$  interval and approximated with the trapezoidal, non-symmetric membership function. For any  $i \in \text{Learning Objects}$ , the Recommendation Score is computed based on the formula in (1) (i.e.,  $w(k)$  weight of the feature  $k$ ;  $n$ : number of DFs;  $d(i,k)$ ; matching degree of the feature  $k$ ):

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

The optimal learning objects  $i$  for learner  $u \in \text{Users}$  are those that maximize the score as specified in (2).

$$\forall u \in \text{Users} : i = \arg \max_{i \in \text{Items}} \text{RecommendationScore}(u, i) \quad (2)$$

Since we define DF weights in the range of 1 to 10, they have a great influence on the ranking and recommendation results. All weights have been determined based on the experience of didactical experts who reached an agreement by use of the Delphi method.

If the coverage of the data set is low, the utility function is crucial for outweighing alternatives, finding good tradeoffs that try to preserve accuracy, while relaxing some of the didactic constraints. While this problem is NP-hard in general, an implementation based on utility functions handles the computation in an efficient way (linear time).

**Recommendation Process:** For a given setting of DFs and available learning resources, the system recommends LOs based on the Reasoning and Ranking Model. To find the best-fit learning objects for a particular learner, the system calculates the utility on all LOs, providing an ordered list with top-n recommendations.

Since our declarative approach supports the definition of complex learning pathways, we incorporated ordering as a hard constraint into our model. We infer LOs that are part of the learners micro- and macro-learning pathway. The utility score is then calculated only for LOs that form part of the sequence. To avoid that longer sequences are preferred, the scores are normalized by the length of the sequence. To enhance efficiency, normalization can also be based on the sum of the estimated learning time per LO.

#### IV. RELATED WORK

Semantic recommender systems that consider didactic knowledge have been proposed by Shen et al. [6] and Yu et al. [7]. In [6], the authors propose to recommend items based on the competency gap analysis and the IMS simple sequencing specification. Learning objects are described by metadata and linked to a concept hierarchy used as background domain knowledge. It entails binary relationships between concepts such as *prerequisite* and *partOf*. The learner profile is updated dynamically (w.r.t. the learning progress) and consists of a set of concepts acquired after learning a respective LO. A similar approach is followed by [7], who propose to compute the semantic relevance of LOs by taking the conceptual proximity among concepts in the knowledge graph into account. In contrast to [6] and [7], we perform curriculum sequencing based on a predefined learning path specification corresponding to the pedagogical strategy to be implemented, following [2]. The focus of our work is thus to support a complex navigation structure similar to a guided tour, building on work in adaptive educational hypermedia systems [8] and a formal description of LPs [9]. Modelling curricula by means of didactic ontologies that inherently capture valid learning pathways paves the way in order to link to open source educational resources on the Web.

#### V. CONCLUSION

In this paper, we presented a utility-based recommender system that uses ontologies and reasoning techniques to select and rank learning objects. The recommender system allows to define expressive constraints for guiding a learner through the realm of knowledge. A major advantage of the MAUT model is that it makes the impact of attributes used for ranking explicit and, as a linear model also offers good interpretability. The feasibility of our approach has been tested on different curricula courses in a formal setting. For reliably measuring the personalization capability of the recommender we plan to harvest Open Source Educational Resources (OERs), in order to increase the coverage of items. Ideally, our knowledge base is extended by linking to resources on the web, leveraging on items semantics. In future work, we also intend to evaluate the utility of the TEL-application as a whole by considering historic data to define the expected learning gain.

#### ACKNOWLEDGMENT

The research leading to these results has received funding from the EC's 7th Framework Programme (FP7/2007-2013) under grant agreement N 318496.

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