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

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Abstract. We investigate a novel approach to e-Learning using Semantic Web technologies and aiming to optimise the learners' experience incorporating pedagogical strategies into the learning process. The increasing availability of Semantic Web based educational resources and the establishment of open metadata standards like IEEE LOM pave the way for enhanced e-Learning systems that support personalised learning based on a reasoning framework and formal ontologies. We use ontologies to describe learning objects and the learner state, and define pedagogical recommendation axioms that specify which learning objects are best suited for a particular learner in a specific situation. Recent pedagogical findings suggest that the individual learning can be optimised by means of guidance through learning pathways, *i. e.*, a particular order in which learning objects have to be studied. To this end, we offer an OWL model for learning pathways as structured sequences. We show the strengths and limits of OWL and propose a solution to overcome problems such as handling of soft constraints and ranking of result sets. The calculation for ranking is based on individual weights for specific contextual as well as learner profile features and considers the degree of match between learning objects and learner's needs. The validity of our approach is shown by means of real-life course material, i.e. a complete course on the Philosophy of Didactics, implemented as a prototype system and interfaced to variouss standard Learning Management Systems.

1 Introduction

Today, sharing and designing course materials is facilitated by the availability of international standards that allow the integration of freely available resources. However, to make learning more interesting for an individual student, enhanced user adaptation is required. This is a key aspect of advanced Technology Enhanced Learning (TEL) systems as they are expected to be used by several learners without assistance of a human tutor.

We propose an ontology-based approach for user adaptation based on a set of learner attributes (*e. g.*, age, gender, learning speed) and the course material being annotated with essential metadata. *Learning Objects* (*LO*s)[5] are defined as small, self-contained, reusable units of learning and generally form part of a course. More specifically, adaptation takes place according to the learners' behaviour, performance, profile, learning history, contextual situation (the so-called *Didactic Factors*), and the specified learning goal along with the learning pathway settings, resulting in a personalised recommendation. This kind of adaptation was examined before in terms of its potential to provide a personalised and improved learning pathway offered to students together with a customised guidance along the learning pathway [26].

Ontologies provide a uniform model for the different aspects of a learning process that can be conceptualised as the navigation through a network of available *LO*s, thus requiring techniques for dynamic and adaptive sequencing of *LO*s. One major contribution of this paper is an enhanced OWL model for e-Learning that is used in tandem with an OWL reasoning framework. It is also applicable for dynamic courseware generation based on more abstract concepts, *e. g.*, the type of the *Learning Object* (*i. e.*, *Knowledge Type*). This is particularly useful in web-scale e-Learning settings, where the set of *LO*s is generally very large, resulting in a high number of pathway relations between them, and thus extensive manual annotation effort.

However, two important issues that need to be addressed clearly show the limits of purely knowledge-based semantic approaches, namely ranking of result sets and handling of soft constraints. The former problem is particularly important when dealing with MOOCs (Massive Open Online Courses) that often deliver a large number of hits. In this case, a prioritisation of *LO*s w.r.t. an appropriate ranking scheme is required that reflects the relative importance of *LO*s for a particular learner. On the other hand, when dealing with closed learning environments, it can also happen that a complete satisfaction of all constraints might not be possible. Therefore, we propose an extension of the ontology-based framework which comprises the calculation for ranking *LO*s based on individual weights for specific *Didactic Factors* and considering the degree of match between *LO*s and learner's needs.

In our work, we focus on the recommendation of *LO*s considering all required features are given. In our setting, they will be provided by a standard Learning Management Systems (LMS) (*e. g.*, Moodle, Clix, ILIAS). In our application scenario, learners are offered navigational recommendations, yet, they are free to choose whether or not to follow them.

In the remainder of this paper, Sect. 2 discusses related work in the field of ontology-based frameworks for personalised e-Learning with a critical review. Section 3 describes our recommendation approach, including an extended module for integrating ranking on top of the reasoning process. Section 4 depicts implementation and validation aspects, before Sect. 5 concludes the paper.

[5] In this paper we also talk about *Knowledge Objects*.

2 State of the Art: Ontology-based Frameworks for e-Learning

Various ontological frameworks were proposed for e-Learning [15, 14, 28, 9, 24, 5, 17], focusing on incorporation of open standards and personalised recommendations [7, 23].

Knowledge integration in most cases considers the metadata of the learning resources, complemented by a domain model and a learner model [15, 14]. In our work, we explicitly refrain from integrating domain ontologies for the course content since these resources are often not readily available, and building up an ontology from scratch generally requires enormous human effort. We therefore claim that as few assumptions as necessary should be made about the e-Learning domain. On the other hand, we stress the importance of domain-agnostic pedagogical strategies set up by didactic experts. We build up a knowledge base that serves as a playground for tutors to evaluate if the didactic recommendations meet their desires and guide the learner correctly.

Different logical frameworks for ontologies have been used for e-Learning, with varying expressiveness and complexity, ranging from simple taxonomies [13], to more complex representations with axioms that constrain the interpretation of the model. The most common knowledge representation formalisms adopted for e-Learning are F-logic [15, 14, 28, 9], OWL-DL [12], the Semantic Web Rule Language (SWRL) [24], and OWL-S [5]. In our approach, we use OWL 2 DL, a W3C standard that builds on Description Logics and extends the earlier OWL standard by several language features while still preserving decidability.

A fundamental aspect of e-Learning are so-called "learning pathways" that aim to optimise the individual learning experience. The most common formal approach to learning paths is based on the IEEE SCORM and IMS simple sequencing specification[6]. However, various different implementations are used.

In ontology-based frameworks, often an additional domain ontology layer is integrated [27, 11] where a "$hasResource(C, LO)$" relation is used to link a *Learning Object* to a domain concept. In order to reach a learning goal, the order of concepts is constrained by a partial ordering relation "$isRequiredBy(C_1, C_2)$". A similar modelling approach is offered by Yu *et al.* [30] based on a binary relation "$hasPrerequisite(C_1, C_2)$", which describes content dependency information at the course level to generate a learning pathway.

We offer an extension of the ontology-based approach that takes into account the fundamental characteristics of a learning pathway, such as modular composition, nested composition, optional parts, and sequencing. Thus, our approach is more expressive, since we seek to model entire structured sequences, following the learning pathway specification as suggested by Janssen *et al.* [16]. Finite state (FS) frameworks also have been used for learning pathway modelling and almost exclusively rely on Directed Acyclic Graphs (DAGs) [2, 17]. The main focus of this work, however, has been on efficiency rather than expressiveness with the aim of shortest path analysis, using Weighted FS networks.

[6] `http://scorm.com/scorm-explained/technical-scorm/sequencing/`

The main approach to ranking considers a hybrid approach (*i. e.*, semantic and arithmetic). Shen *et al.* [27, 11] use competency gap analysis to this aim, favouring learning content that might help the user to progress towards his/her learning goal. Yu *et al.* [30] give preference to *Learning Objects* that are in a close taxonomic relationship of the respective domain to the learning goal of the user, specified as `dc:subject` metadata entry.

Both approaches thus require a separate domain model. Opposed to this, we rank the *Learning Objects* according to the degree of relevance to the learner and select the highest scoring *Learning Objects*, considering that different *Didactic Factors* have a different impact on the overall recommendation and to what degree learning objects fulfil the recommendation constraints.

2.1 Strengths of Ontology-based Frameworks

Information sharing, integration and reuse. Ontologies support the use of well-established standards for defining and sharing *Learning Objects* within different e-Learning platforms. International metadata standards exist that offer a set of metadata descriptors such as LOM (Learning Object Metadata) and SCORM (Shareable Content Object Reference Model), cf. Aroyo *et al.* [4], Dolog *et al.* [9]. Specifically, in different educational environments, this increases interoperability and enables reusability of learning material.

Semantic Search and Reasoning. Ontology-based approaches have become increasingly popular, since they offer additional reasoning capabilities and thus support semantic search of *LO*s [8]. Unlike the search paradigm on the Web, the focus is on searching for structured data, where *LO*s are semantically annotated on the metadata level. Consequently, a more precise information need can be expressed by means of a complex constraint query. Moreover, *LO*s are generally related to each other via structural relationships reflecting, *i. e.*, the learning pathways, and this semantic graph can also be exploited for search.

2.2 Weaknesses of Ontology-based Frameworks

Efficiency. Reasoning in expressive Description Logics has exponential runtime complexity in the worst case. However, implementations of state-of-the-art OWL reasoners are typically optimised to show acceptable runtime behaviour in many real-world scenarios. Modelling in the tractable OWL 2 Profiles, however, comes with considerable compromises regarding expressiveness.

Support of complex conjunctive queries. Especially in cases where no resource completely satisfies all conjuncts of a given complex conjunctive class expression, it would be of interest to determine the winner among the competing candidates, *i. e.*, the learning resources which fulfil most of the constraints. A naive approach to instance retrieval inference may often return an empty result set, since some constraints might not be satisfied. We thus need to find an optimal solution that satisfies a maximal subset of the constraints.

Sequences. In e-Learning, *Learning Objects* are organised into sequences that describe an optimal navigational path towards a learning goal. At present, there is no support for defining sequences in OWL as would be needed for reasoning over learning pathways. However, by use of Ontology Design Patterns (ODP), best practice solutions can be adopted that allow for regexp-like queries [10].

2.3 Limits of Ontology-based Frameworks

Ranked Retrieval. In order to retrieve a ranked list of suitable Learning Objects with a recommendation factor, standard Boolean Retrieval, as facilitated in OWL, is not enough, since it does not support the scoring of objects but delivers an unordered result set. Instead, the results should be ranked reflecting the degree of relevance to the learner. A semantic search algorithm that integrates ranking based on RDF graphs and similar to the PageRank scoring algorithm has been investigated by Kasneci *et al.* [18], while an account based on exploiting semantic relationships between entities has also been proposed [1, 3]. SPARQL allows to rank results by means of the "ORDER BY" predicate [22] but the data used for computing the order has to be available in the RDF graph explicitly.

Support of Soft Constraints. Preferences behave like soft selection constraints. In this sense, no exact match is required and therefore soft constraints should be satisfied if possible, but may be violated if necessary. A metric generally aims to provide an idea for how close a result is to the learners' needs, *i. e.*, to which degree a *Learning Object* is relevant. The challenge related to the ways in which such vague knowledge in terms of OWL and its reasoners should be incorporated is well recognised, and some fuzzy and rough extensions have been proposed (cf. [19, 25, 21]), however, a standard semantic web compliant solution regarding vagueness is not available yet.

3 Enhanced Framework for Personalised e-Learning

This section presents an approach for recommending learning material. It is based on a modular ontology design, and an extension for ranking the results.

3.1 Modular Ontology Design

We propose a modular ontology design in order to cover static pedagogical background knowledge as well as course and learner specific, dynamic knowledge.

In the *pedagogical ontology* [29] learning material is organized into Courses (KDs), Lessons (CCs), and Knowledge Objects (KOs)[7], forming a hierarchical graph structure. It provides concepts for *Knowledge Type* (KT), *e. g.*, orientation, example, assignment, *etc.*, and *Media Type* (MT), *e. g.*, text, video, audio, *etc.* and metadata vocabulary for describing KOs, such as, *hasDifficultyLevel*, *hasEstimatedLearningTime*, *hasLanguage*, *hasRecommendedAge*, *isSuitableForBlind*, *isSuitebleForDeaf*, or *isSuitableForMute*. Moreover, classes and properties

[7] We use the term *Knowledge Object* instead of the frequently used term *Learning Object* in order to differentiate between concrete learning material and the more abstract course topics.

for specifying learning pathways (*LP*s) are formalized, distinguishing between macro- and micro-level learning pathways on the *CC* and *KO* level, respectively. The *cognitive map* and *content map* are instantiations of the *pedagogical ontology*.

The *learner model ontology* with associated instance data, i.e. the *learner state ontology*, defines classes and properties for describing the current learner state, a snapshot characterized by *Didactic Factors (*DF*s)* that currently hold, including the completion state of *KO*s and *CC*s, and current learning pathways.

3.2 Specification of Learning Pathways

We follow a flexible approach to LP modelling that uses auxiliary individuals for connecting *KO*s (here: $CKO_{(i,j)}$).

$$\begin{aligned} \mathit{MicroLP} &\sqsubseteq \mathit{LP} && (1)\\ \mathit{MyMicroLP} &\sqsubseteq \mathit{MicroLP} && (2)\\ &\mathit{MyMicroLP}(\mathit{CKO}_{(1,2)}) && (3)\\ &\mathit{hasPredLP}(\mathit{CKO}_{(1,2)}, \mathit{KO}_1) && (4)\\ &\mathit{hasSuccLP}(\mathit{CKO}_{(1,2)}, \mathit{KO}_2) && (5) \end{aligned}$$

A learning pathway is described as a subclass of *MicroLP*, which contains only the connector individuals, in this example *MyMicroLP*. Using the same principle, it is possible to specify the currently selected learning pathway:

$$\begin{aligned} \mathit{CurrentLP} &\sqsubseteq \mathit{LP} && (6)\\ \mathit{CurrentLP} &\sqsubseteq \exists \mathit{isCurrentLP}.\mathbf{Self} && (7)\\ \mathit{MyMicroLP} &\sqsubseteq \mathit{CurrentLP} && (8) \end{aligned}$$

3.3 Hard and Soft Criteria Based on *Didactic Factors*

Hard and soft criteria are defined in the learner model ontology and describe classes of *KO*s that fulfill the respective constraints.

Hard criteria define requirements a *KO* must meet in order to be included in the recommendation. An example are the disabilities DFs.

Soft criteria define requirements a *KO* should meet in order to be included in the recommendation. For instance, the learner might prefer reading text rather than seeing a video in the user settings. In order to specify the importance of soft criteria, a weight can be assigned to each soft criterion (see Sect. 3.5).

3.4 Specification of Recommendation Axioms

***Knowledge Object* Restriction Type 1 (learning pathway successors).** This restriction type describes *KO*s that are successors of the current or previous *KO* w.r.t. the current learning pathways[8]. Only *KO*s are considered, that have

[8] Both macro- and micro-level learning pathways are considered.

not yet been completed. There are three sets of KOs determined. For all three queries, let the current macro- and micro-level learning pathways be defined as in axioms (2), (3), (4), and (5), and furthermore in axiom (8).

1. **Direct successors of the current *KO*.** A property connecting any KO with its direct successors w.r.t. the current learning pathway can be inferred via the property chain

$$hasPredLP^{-} \circ isCurrentLP \circ hasSuccLP \sqsubseteq hasDirectKOSuccessor \quad (9)$$

In case the current KO is the last KO within a CC, the current macro-level LP has to be considered. This requires two additional constructs:

(a) Marking the first and last KO w.r.t. a micro-level LP within a CC by asserting the connector individuals as described in axiom (3) to an additional class *FirstLPElement*, or *LastLPElement*, resp.:

$$FirstLPElement(CKO_{(i,j)}) \quad (10)$$
$$LastLPElement(CKO_{(k,l)}) \quad (11)$$

(b) An auxiliary property connecting all KOs of a CC with all KOs of the successor CC according to the current macro-level LP:

$$\begin{aligned} &isContainedByCC \circ hasDirectCCSuccessor \circ isContainedByCC^{-} \\ &\quad \sqsubseteq nextKOsInNextCCs \end{aligned} \quad (12)$$

.

The direct successors of the current KO can now be determined by retrieving all individuals for the following class expression:

$$\begin{aligned} &\exists hasDirectKOSuccessor^{-}.CurrentKO \\ &\sqcup (\exists nextKOsInNextCCs^{-}.(CurrentKO \sqcap \\ &\qquad \exists hasSuccLP^{-}.(CurrentLP \sqcap LastLPElement)) \\ &\quad \sqcap (\exists hasPredLP^{-}.(CurrentLP \sqcap FirstLPElement))) \end{aligned} \quad (13)$$

Micro-level learning pathways for KOs do not necessarily have to be explicitly defined, but can also be inferred based on general didactical knowledge in terms of *Knowledge Type* or *Media Type* pathways[9] represented in the pedagogical ontology [29]. KO successors based on KT pathways can be retrieved as in class expression (13), however, two additional subproperty axioms are necessary. Let KTs be put in a pathway relation using auxiliary connector individuals as in axioms (3), (4), and (5), with according connector properties *hasPredKT* and *hasSuccKT*. Property assertions for *hasPredLP* and *hasSuccLP*, *i. e.*, on the KO level, can be inferred as follows:

$$hasPredKT \circ hasKT^{-} \sqsubseteq hasPredLP \quad (14)$$
$$hasSuccKT \circ hasKT^{-} \sqsubseteq hasSuccLP \quad (15)$$

[9] We only discuss KT pathways here. MT pathways are handled analogously.

where *hasKT* is the property assigning *KT*s to *KO*s. In order to infer *KO* successors based on a *KT* pathway now simply requires an axiom making the class describing the *KT* pathway subclass of *CurrentLP*.

2. **All (direct and indirect) successors of the current *KO*.** A property connecting any *KO* with all its successors (direct and indirect) w.r.t. the current learning path can be inferred via a transitive superproperty of *hasDirectKOSuccessor*:

$$\mathit{hasDirectKOSuccessor} \sqsubseteq \mathit{hasKOSuccessor} \tag{16}$$

$$\mathbf{trans}(\mathit{hasKOSuccessor}) \tag{17}$$

3. **Direct successors of the previous *KO*.** Direct successors of the previous *KO*, *i. e.*, the *KO* visited before skipping, can be retrieved analogously, replacing *CurrentKO* with *PreviousKO* in class expression (13).

***Knowledge Object* Restriction Type 2 (unfinished predecessors).** This restriction type describes *KO*s that are predecessors of the current *KO* the learner has not yet completed. According to the completion state described by the classes *CompletedKO*, *PartiallyCompletedKO*, and *UnseenKO* (as disjoint union of the class *KO*), the unfinished predecessors can be retrieved as follows:

$$\neg \mathit{CompletedKO} \sqcap \exists \mathit{hasKOSuccessor}.\mathit{CurrentKO} \tag{18}$$

***Knowledge Object* Restriction Type 3 (soft criteria).** This type of *KO* restriction describes sets of *KO*s that fulfill soft criteria. The class expressions specified in the learner model ontology associated to these soft criteria are evaluated independently from each other and deliver different sets of candidate *KO*s that are used for the ranking algorithm in the subsequent post-processing.

3.5 Extension: Ranking

We provide an extension of the framework, integrating ranking into the learning object recommendation in a post-processing step based on the reasoning results. Our approach is most similar to Kerkiril [20] and Alian *et al.* [2] based on Simple Additive Weighting, a widely used multi-attribute decision technique.

In our work, *DF* features have a weight that indicate their relative importance. The highest scoring "most recommended" *KO* is calculated based on this model, combining all feature weights to an overall score.

We use the RecScore in (19) to calculate the suitability of a learning object for a certain learner in a certain context. Linear ranking functions define the aggregated score of ranking predicates as a weighted sum. In this case, the weightings need to be defined a-priori by the tutor. The basis for ranking is provided by

1. **Degree of Match.** Parameter d is used to define when constraints given as a key value pairs match. For instance, a Portuguese KO can be recommended to a native speaker of Spanish because it tends to be comprehensible, even though it does not match the learner profile perfectly.
2. **Weights describing the importance of a feature.** Different weights can be assigned (by the tutor) to individual features, reflecting their importance with respect to all other feature constraints. For instance, the DF "gender" in most pedagogical frameworks seems to be of minor importance for recommendations.

The recommendation score of a learning object and formula used for ranking is thus:

$$\text{RecScore}(KO_i) = \sum_{k=1}^{n} w(k)d(i,k) \tag{19}$$

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 DF features.

Accordingly, the results that best match the axiom (figuring the learners' needs) are ranked higher in the list. The ranking algorithm takes into account the weight values for each feature and looks for the highest overall score, so that the number of features that are satisfied can still be low, if they are assigned a high overall weight. Since the weight values are subjective, we allow to manually edit them. In our framework, all DF features are independent of each other.

4 Implementation and Validation

In this section, we present implementation details of our hybrid recommendation framework. A message-oriented architecture, illustrated in Fig. 1. is used to implement an asynchronous publication process over a set of loosely coupled software components which get active in reaction to user actions. The different ontology modules make up a central part of the application logic.

At first, the learner status is analyzed and the learner state ontology is instantiated accordingly. Information about the course becomes available via the Cognitive Map and the Content Map[10]

Then, the reasoning module is invoked to offer enhanced learner adaptation based on the "recommendation axioms ontology" which comprises all class expressions and axioms from Sect. 3.4. Since this can partially be done in parallel, *e. g.*, when evaluating soft criteria, we utilise a reasoning broker framework [6]

[10] For the design of the curricula a specific authoring tool has been developed. Thus, course annotation is supported by a user-friendly visual editor, that strictly adheres to our OWL modelling approach, used as an intermediate exchange format.

which comprises several standard OWL reasoners (FaCT++, Pellet or HermiT), and using the latest standards for OWL access protocols (OWLAPI, OWLLink).

Finally, in the *ranking* stage, the various result sets from the reasoning stage are taken to compute a recommendation score as presented in Sect. 3.5.

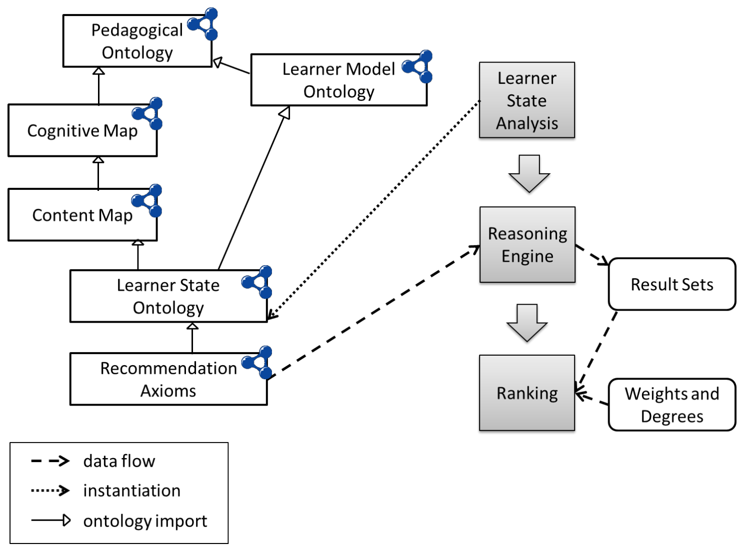

Fig. 1. Implementation architecture of ontologies and software components.

A curriculum of 125 hours from the domain of Philosophy of Didactics, comprising 103 CCs, 1133 KOs, and 4 macro- and 2 micro LPs, has been modelled in adherence to our semantic model to test the functionality of our approach. It can be adopted to different pedagogical strategies and is highly adjustable, e.g. allowing to configure individual DF weights and recommendation axioms. This is important because a didactical theory seeks to investigate how learning works, and is never fixed from the start.

In the near future we plan to conduct an integrative testing in real settings to assess a) the contribution to the learning experience, b) the learner's satisfaction levels with the system, and c) the usefulness from the learner point of view.

5 Conclusion

We have presented a novel approach to personalized learning based on Semantic Web technologies, aiming to optimise the individual learning experience.

We show how OWL can be extended to cope with some inherent limits. In particular, we offer a formalization of a learning pathway as a structured sequence which can be used for dynamic couseware generation based on more abstract classes, *e. g.*, KTs and MTs. Moreover, we present a solution to deal with complex conjunctive queries and show how to incorporate soft constraints: Different result sets delivered by the OWL reasoner are combined and ranked according to a specific weighting scheme in a post-processing step.

We plan to extend our framework by a dialogue module that provides meta-cognitive feedback in terms of motivational messages and explanations why a specific recommendation was given. Since the feedback messages are generated together with the reasoning/inferencing, the same justifications for the conclusions can be drawn.

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