Tracking the Adaptive Learning Process with Topics Ontology

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Abstract. We focus on an ontological model of the learner's context in the organized education process at a university level. Extending an existing temporal context model to cover topics of study, their mutual hierarchy, and their relations with other entities in the course we yield a complex model of the learner's context. Such a model enables tracking of the student's learning goals within a course and providing personalized recommendations w.r.t. the current level of students' topic understanding as well w.r.t. the current point in time within the course. We also outline how the unified knowledge-graph representation allows for a more flexible design of visualizations and user interfaces.

Keywords: Ontology · Personalization · Learner's context.

1 Introduction

One of the widely acknowledged [9] desired features of virtual learning environments (VLE) is their *adaptability*, or personalization, towards individual users' needs. The traditional view is often rooted in intelligent tutoring systems as described by Wollf et al. [16], building on three models: the *expert model* – or the learning domain model; the *student model* – capturing the learner's understanding of the learning domain and individual learning needs, and the *instructional model* – covering the organization and execution of the learning activity. These models are sometimes extended with other layers and components [4], but mostly the key functions are based on modelling of the user's state of understanding of the expert model [5], and possibly some individual user's needs (e.g. learning styles), and deriving recommendations to engage with selected learning materials or other learning objects [2]. This paradigm is thus predominantly user-centred and its key component is often referred to as user modelling [5].

While user modelling already paves ways for useful personalization features, as pointed out by Brusilovsky and Milán and by Aroyo et al., it is essential to position the learning process with respect to the "context of user's work" [5] or the "circumstances in which it occurs" [4]. As we prefer to say, the state of the user model needs to be framed within a broader *learner's context* consisting of different relevant aspects, including: user's understanding of the expert model; the logical organization of the content in the expert model (e.g. preceding and consecutive topics); user's preferred learning styles; usage platform and paradigm (e.g. desktop vs. mobile); physical location; personal and social context; and, within organized higher education, also the progress of a course and a study program.

In our university setting, we support in-person courses with a VLE, where students find learning materials and information, they can submit assignments, and track their results. The system enables: course and user management, management of learning materials, assignments specification and submission, peer review, code review, and teamwork peer feedback, development and crowdsourcing of online quizzes including their administration, evaluation of students' work and tracking of their progress.

Previously [7] we have enriched this VLE by an ontological model explicitly representing the temporal aspects of the learner's context, capturing events framing a university course with the aim to tailor the user experience for the students. The system organizes the learning path of a student on the timeline of the course and it is able, e.g., to recommend useful study materials relevant to an upcoming test. It features a fully semantic data representation and the ontological model was published and it can be reused by other systems to support analogous features. On the other hand, our system, so far, did not feature the expert model and was not able to provide more fine-grained personalized recommendations akin to more traditional adaptive e-learning systems.

In this report, we describe how the ontological model is extended to cover the course topics space and the student's understanding of these topics. This allows us to: visualize the topics space of a course and indicate an individual student's coverage of the learning content; but also to visualize a course's topical coverage of a wider topics space in the study program. The topics space is integrated with other entities in the ontology such as assignments, quizzes and learning materials, which allows to generate more fine-grained recommendations for the students that are respective to the current context of the course and of their learning progress as well. The ontological representation captures contextual properties such as the subtopic–supertopic relation and the topic prerequisite relation which allows to further improve the orientation in the topics space but also the quality of the resulting recommendations. The fully semantic representation based on knowledge graphs has further benefits for e-learning system design – it allows us to design visualizations and user interfaces in a flexible and unified way.

2 Related Works

A number of recent studies have focused on ontology-based recommendations in educational environments [9,11,15]. While conventional recommenders are usually based on ratings, ontology-based recommender systems enhance the recommendation process with ontological domain knowledge about the learner and learning materials [13]. They are becoming popular in the field of education specifically due to their ability to personalize learner profiles based on characteristics such as their background, learning style, preferences, etc. [15].

According to Roussey et al. [12] ontologies can be categorized based on their scope into the following categories: domain ontology, application ontology, reference ontology, general ontology, and top-level ontology. Several surveys of ontology recommender systems in educational settings show that the huge majority of such systems make use of domain ontology and only a few use other ontologies, e.g. a reference ontology, a generic ontology, or a task ontology, also mostly in combination with a domain ontology [11,15].

Another view of ontology classification [3] is based on how ontologies are used in e-learning: curriculum modeling and management, describing learning domains (subject domain ontology and learning task ontology), describing learner data, and describing e-learning services. In most knowledge-based recommender systems in education, ontology is used to represent knowledge about the learner, learning objects as well as domain knowledge [13,8] in order to establish a relationship between learners and their preferences about learning resources.

Ontological educational recommender systems usually generate recommendations for learners, most commonly learning objects [11] or learning objectives [6], but also learning paths, feedback, or learning devices. However, there are also recommender systems that provide recommendations for teachers, e.g. the best teaching strategies or pedagogical scenarios to use in the context of a particular class, new resources to augment the course curriculum, etc. [6].

Several authors report the use of multiple ontologies in their systems for e-learning, most often maintained separately. Huang et al. [8] use three independent ontologies (course ontology, learner ontology, and learning object ontology) in their personalized system for recommending learning paths, learning contents, and learning experiences. The recommendations are generated using the similarity matching between the respective ontologies.

Zhuhadar and Nasraoui [17] proposed a hybrid recommender system using two domain ontologies – one for representing learning materials and the other for representing learners. They combine the content-based and the rule-based models to provide the learner with recommendations for learning concepts.

A framework for a smart e-learning ecosystem designed by Ouf et al. [10] employs four separate ontologies and a semantic reasoner to provide the learner with a personalized learning package consisting of a learner model and all components of the learning process: suitable learning objects, favorite learning activities, and the right teaching methods based on their individual preferences and needs.

Personalization is proving to be an important component in learning environments for MOOCs as well. For example, Agarval et al. [1] propose a hybrid recommender system for MOOCs with two domain ontologies that exploits clusters-based collaborative filtering and rule-based recommendation using SWRL. The two ontologies used (learner ontology and course ontology) are designed individually, but the course ontology has been modeled with respect to the structure of the learner ontology. The system recommends individual course elements, learning paths, and general tips and suggestions about learning.

In contrast to the previously mentioned systems, Shishehchi et al. [13] propose a personalized knowledge-based e-learning recommendation system using

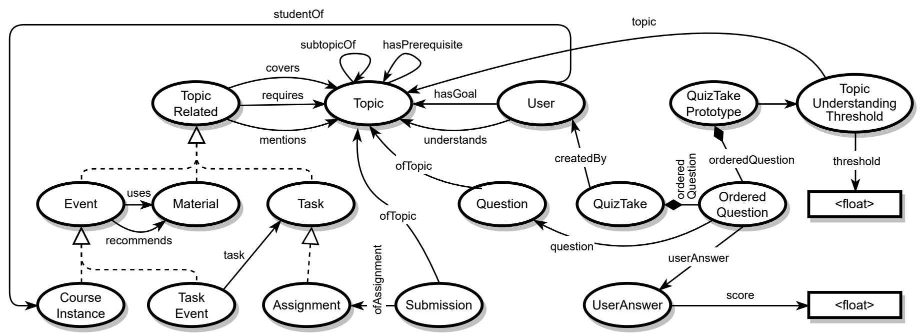

Fig. 1. Overview of the ontological model.

a common ontology for learners and learning materials. The ontology class representing the learning material consists of two subclasses: learning topic and learning activities (exercises and quizzes). The learner class has subclasses representing the learner's learning style, profile, history, and background knowledge. Learners are recommended learning materials, activities, examples, etc., based on the learner's request and their previous knowledge.

The PLSP recommender system also proposed by Shishehchi et al. [14] provides the learner with a personalized learning sequence in the area of programming, depending on the learner's level of proficiency. The knowledge module of the system is based on a single domain ontology representing learners, learning activities, and learning materials. The recommender module built on semantic rules and ontology representation presents the learner with recommendations for learning material and learning material sequences based on the learner's request.

3 Ontological Model

Recently we have enriched our system with a semantic contextual layer that enables to organize and track the educational process within courses w.r.t. to the passing time of the course run [7]. This brings in a certain level of contextual adaptivity, e.g. recommending learning materials that are relevant at the given point in time. To further improve the adaptive capabilities we have now enriched the learner's context by integrating the representation of the topics space.

Our VLE builds purely on an integrated, fully semantic data representation, captured by a knowledge graph in the RDF format, and stored in the Virtuoso triple store. This model covers all functions and all data managed by the system. The model is rather complex; a simplified representation of the relevant part is depicted in Fig. 1. We now briefly describe the most relevant parts or the model.

Courses and events. The model stores information about courses, comprising multiple course-related events (lectures, lab sessions, tests, homework assignments, etc.). From the events within one course, the system generates a timeline which aids students' orientation in tracking the course. This part of the model and the system was covered in detail in our previous work [7].

Topics space. The core class of the current work is the Topic class. Its instances form a hierarchical topical space which stands for the *expert model*. Each topic represents a certain part of the knowledge the students may learn in one of the courses. The topics may be inter-related by two properties: subtopicOf enables to divide a topic into multiple subtopics, when it is reasonable to assume that the parent topic is completely covered by its subtopics, i.e. that mastering all subtopics implies mastering the parent topic; requires enables to indicate that this property's target topic is a prerequisite for the source topic, i.e. mastering the former is recommended before attempting the latter.

User's knowledge. The User class encapsulates all user data, most of which is not of our interest here. What is relevant is that it also enables tracking the topics which are the user's learning goals via the hasGoal property, and those which the user has achieved via the understands property.

Evaluation outputs. There are different possible ways how to actually track the user's progress towards their learning goals. The model features data about user actions from which this can be partly deduced. Once the instructors grade the user's submission to an assignment, the achievement of the goal may be deduced if the assignment covers the given topic (Assignment, Submission together with the ofTopic property). Similarly, when the user takes a quiz in the system, achievement of the goal may be deduced if the automatic evaluation of the questions on the goal's topic passes a threshold set by the instructors (QuizTake, related classes, the threshold data property).

Study materials. The Material class represents different internal or even external documents serving as learning materials. The model allows to express that a material (and also selected other entities) exhaustively covers a certain topic, non-exhaustively mentions one, or requires one (mastering it is necessary before studying the material). This enables producing recommendations for the users to study certain learning materials to achieve the learning goals.

Reflecting to the aforementioned traditional model of adaptive learning systems, the study materials and the topics would fall under the expert model, the user's data including the topic understanding would fall under the user model, and the course and its partition into the events, including assignments and quizzes would fall under the instructional model. However, we prefer to view the timeline of events and the topical annotations as a representation of the learner's context respective to a given point in the course run together with the individual point on the learner's path.

4 Model Population and System Functions

In order to make use of all the rich semantic information specified in the model the key questions concern (a) how to populate the model with actual data, and (b) how to make use of the data in the system to the benefit of the users.

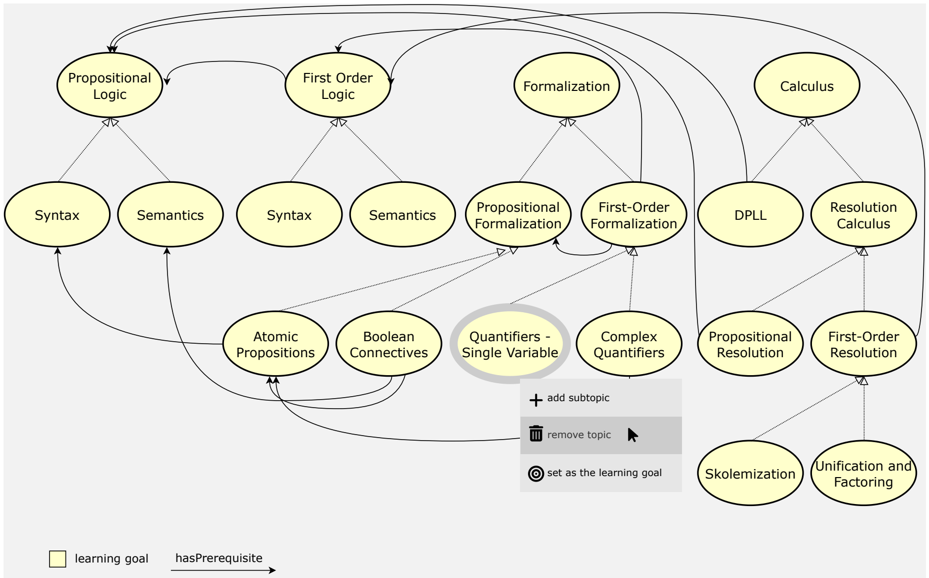

Fig. 2. Instructor's view of the topics user interface.

4.1 The Topics Space

Creating a meaningful and sufficiently granular hierarchy of topics is critical to the overall success of the system. For the purpose of the deployment of the system within a single university or a study program, we assume:

- The hierarchy of topics will be global and shared by all courses. This will enable to visualize how a certain course fits within a global hierarchy, which courses cover the required topics a student should master before enrolling in another course, etc.
- Topics will be created and updated collaboratively by a group of instructors. We assume manual editing (but we do not rule out automatic import from existing ontologies in the future).
- An instructor will be able to set learning goals for each individual course by marking certain topics in the global hierarchy as goal topics of that course. As we assumed that a supertopic is completely covered by its subtopics, the goal topic's subtopics automatically become goal topics of the course.

The two latter function will be enabled by a unified instructor's interface sketched in Fig. 2.

4.2 User Model

For the model of student knowledge, there are potentially three ways of building and updating the data:

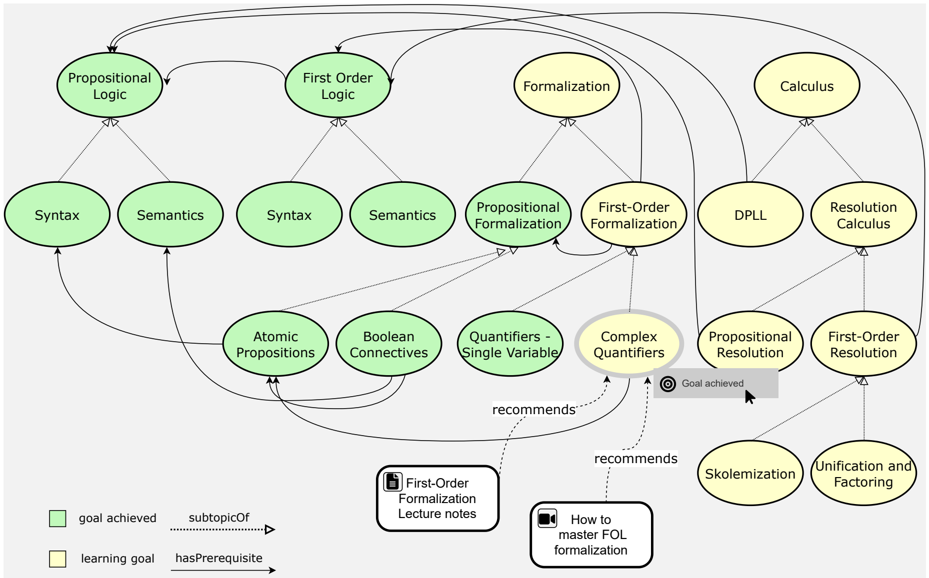

Fig. 3. Student's view of of the course topics space.

1. *Self-directed:* The students manually mark the mastery of a given topic in the course's topic hierarchy view. This option is visible in the student's overview of the course topics in Fig. 3.
2. *Informal:* Topic mastery is updated automatically based on informal formative tasks (exemplified in our model by quizzes) prepared by the instructors. Each quiz may cover one or multiple topics and for each of them it may specify a *topic understanding threshold*. If a student's overall score from the questions on a given topic surpasses the threshold, the topic is marked as understood by the student.
3. *Formal:* The topic mastery is updated automatically, in a similar fashion as in the informal mode, however, the thresholds are defined over formal evaluation points awarded to the students by instructors for the submitted formal assignments.

The three modes of building the student's knowledge model will be configurable by the instructors depending on which one they want to use in their course. We assume that modes can also be combined. Creating such a model will enable the system to offer the following functions:

– Tracking the student's progress (for both the students and the instructors) by viewing the topics marked as understood by the given student in the course topic hierarchy view. The student's version of the interface is depicted in Fig. 3. Thanks to the assumption that a supertopic is completely covered by its subtopics, the goal of the supertopic is automatically achieved once the student understand all of its subtopics. This assumption is useful to avoid

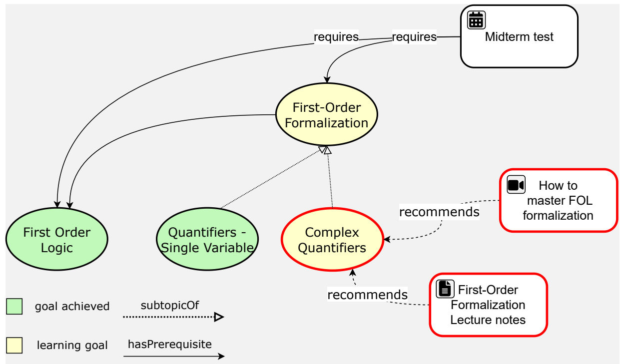

Fig. 4. Recommendation view.

confusing situations. Students can also activate any topic, see its related study materials, and mark it as understood (in the self-directed mode).

– The state of the student's topic mastery within the course, together with the overall context of the course may be used for adaptive purposes such as to produce individualized recommendations of study materials to follow at a given moment. An example is shown in Fig. 4 where shortly before the midterm test the student is given an overview of the topics required by the test with a recommendation of study materials covering the topics the student has not mastered yet.
– The student's individual knowledge model may also be visualized w.r.t. the global topics hierarchy. This would also enable to produce recommendations at the level of courses, such as which course to take next to fill in a student's gap in a certain area of the topics.

We have discussed how the proposed ontological model needs to be maintained, but more importantly, how it allows to provide new useful functions to the benefit of the users (both students and instructors).

5 Universal User Interface

Representing the data in a knowledge graph based on a well-defined ontological model also enables to define more flexible and more universal user interfaces, as explained in this section.

The interfaces in Figs. 2–4 all visualize individual entities that exist as objects in our knowledge graph. Therefore for building each view in the user interface, it is essentially required:

1. to obtain the entities of interest together with the links that we want to include from the knowledge graph;
2. to define an appropriate visualization style (shape, colour, etc.) for each entity based on its type;

3. to define possible actions for each entity based on the view, entity type, and user level; and finally
4. to visualize them using a suitable graph visualization tool.

For example, the topics related to a given course, together with their interlinks respective to the subtopicOf and hasPrerequisite relations may be obtained using the following query:[1]

```
CONSTRUCT {
  :t1 a :Topic. :t2 a :Topic. :t3 a :Topic. :t4 a :Topic.
  ?t1 :subtopicOf ?t2.
  ?t3 :hasPrerequisite ?t4
} WHERE {
  ?t1 :subtopicOf ?t2.
  ?t3 :hasPrerequisite ?t4.
  :t1 a :Topic. :courseXY :covers ?t1.
  :t2 a :Topic. :courseXY :covers ?t2.
  :t3 a :Topic. :courseXY :covers ?t3.
  :t4 a :Topic. :courseXY :covers ?t4
}
```

In order to generate the student's view in which topics that the student already achieved as their learning goal are distinguished (i.e. marked in green in Fig. 3), it suffices to obtain these topics and mark them by a distinctive class. To this effect, the following query is run and the resulting graph is merged with the one obtained by the previous query by the `UNION` operation:

```
CONSTRUCT {
  :t a :CoveredTopic
} WHERE {
  :t a :Topic.
  :courseXY :covers :t.
  :studentYZ :understands :t
}
```

Here the class :CoveredTopic is not part of our underlying model but is merely used for visualization purposes.

6 Conclusions

We have described an ontological model that we adopted in our VLE in the scope of organized education at our university. Specifically, we have focused on extending the model to cover the course topics space, its hierarchical organization, and its integration with other relevant entities of the model. This extension allows

[1] For simplicity of presentation we assume all entities to pertain to the default namespace ":" and that :courseXY is the individual respective to the current course instance of interest in this view. In the following query, :studentYZ is the individual respective to the user (or the student whose progress the teacher wishes to visualize).

us to greatly improve the representation of the learner's context respective to the point of time within a course run but jointly also to the student's level of understanding of the covered matter.

We have consecutively presented novel features enabled by this extension. This includes the organization of the topics hierarchy and using it to track the learning goals of a course and the progress of an individual student. But thanks to the tight semantic integration with other stored data in a unified contextual layer, it now especially allows us to provide much more sophisticated personalized recommendations for individual students. Finally, we have discussed how the unified knowledge-graph representation allows for a more effective and flexible design of user interfaces.

Our approach differs from what has been reported in the literature in several respects:

- We build one comprehensive ontology that covers all data stored and manipulated by the system (thus a complex application ontology rather than just isolated domain ontologies used for recommendations).
- We focus on organized courses of formal education, in contrast to many studies which focus on self-directed e-learning scenarios. Therefore we need to account for courses, learning sessions, evaluation activities, grading, and their organization in time.
- To achieve the above, our ontology provides a model of an integrated learner's contextual space connecting the topical and the temporal aspects.
- Tracking of the student's position in this contextual space allows us to proactively recommend relevant learning activities and materials at any given time without the learner needing to request them from the system.
- Our unified knowledge-graph representation offers other benefits, such as flexible visualization and user interface generation.

In the future, we would like to further extend the richness of the model of the learner's contextual space, e.g. by accounting for students' individual needs, such as learning styles, access modality (desktop or mobile), but also a richer notion of access circumstances (during individual study time, during the lecture or lab session, on the go, etc.), and possibly others.

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