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A personalized adaptive e-learning approach based on semantic web technology

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Abstract

Recent developments in semantic web technologies heightened the need for online adaptive learning environment. Adaptive learning is an important research topic in the field of web-based systems as there are no fixed learning paths which are appropriate for all learners. However, most studies in this field have only focused on learning styles and habits of learners. Far too little attention has been paid on understanding the ability of learners. Therefore, it is becoming increasingly difficult to ignore adaptation in the field of e-learning systems. Many researchers are adopting semantic web technologies to find new ways for designing adaptive learning systems based on describing knowledge using ontological models. Ontologies have the potential to design content and learner models required to create adaptive e-learning systems based on various characteristics of learners. The aim of this paper is to present an ontology-based approach to develop adaptive e-learning system based on the design of semantic content, learner and domain models to tailor the teaching process for individual learner's needs. The proposed new adaptive e-learning has the ability to support personalization based on learner's ability, learning style, preferences and levels of knowledge. In our approach the ontological user profile is updated based on achieved learner's abilities.

Keywords

Personalized learning; E-learning; Ontology; Adaptive learning; Semantic web

Introduction

Nowadays, personalized learning services are a key point in the field of online learning as there is no fixed learning path which is appropriate for all learners (Chen, 2008). However, traditional learning systems ignore these services requirements and deliver the same learning content to all learners. This approach may not be effective for learners with different backgrounds and abilities. In order to design an adaptive learning content, we need to enable the delivery of learning content according to particular learner's needs.

Moreover, recent developments of semantic web technologies have shown a trend of using ontologies to promote adaptive learning which allows us to create specific user profiles and content models. Ontology is a formal, explicit specification of a conceptualization (Gruber, 1993). This description has led to the emphasis that ontologies represent conceptual explanation of the specific content. They support instructors on content creation or learners on accessing content in a knowledge-guided manner.

Accordingly, in this paper we propose an ontology-based knowledge modeling technique to designing an adaptive e-learning system in which learner's knowledge, abilities, learning styles and preferences are considered in the learning process. In this system, the ontological user profile is updated based on the abilities that learner's achieve. This approach also classifies the learning contents into fine levels of categories which are explicitly annotated using descriptions from domain and content ontology.

Related Work

Nowadays, the popularity of the World Wide Web encourages the development of personalized educational Systems to support and facilitate the delivery of teaching and learning content based on the learners' needs. Personalized e-Learning systems are developed within the fields of intelligent tutoring and Adaptive Hypermedia (AH) systems. These two fields are different in the way they offer their personalized contents tailored to various learning preferences and the characteristics of the learners. The aim of the Intelligent Tutoring Systems (ITS) is to adaptively deliver content to learners. However these systems set boundaries for learners and restrict the opportunities to support free exploration. AH systems supply the most relevant content and navigation paths by adapting the content to the user's learning needs. Adaptive Intelligent Web-based Educational approach is a hybrid approach merging ITS and AH approaches. It consists of adaptive techniques which can be personalized according to the student's needs.

ELM-ART (Brusilovsky, Schwarz, & Weber, 1996) and InterBook (Brusilovsky, Eklund, & Schwarz, 1998) are examples of tutoring systems which take an integrated approach to adaptivity. ELM-ART is an intelligent interactive educational system that offers learning the programming language LISP. It provides adaptive navigational support, course sequencing, individualized diagnosis of student solutions, and example-based problem-solving support. Interbook aims to facilitate the process of creating adaptive electronic textbooks on the web based on the ELM-ART system approach. InterBook uses concept-based domain and user models to provide adaptive materials. The domain model is just a set of domain concepts for a given domain. Both of these systems are not flexible enough as they adapt the content only for the particular domain in which they are being applied (Conlan, 2006). AHA the "Adaptive Hypermedia Architecture" (De-Bra & Calvi, 1998) is developed to support an online course with adaptive navigation and adaptive presentation. In AHA the user model is constructed based on concepts in a given domain. In this system, adaptive Navigation is implemented through link hiding or link annotation and adaptive presentation is implemented through

Conditional inclusion of fragments added to content. This is a restriction of the system where the adaptive logic is distributed among the content and is not easily updated or changed. Thus, the reusability and flexibility of such system are considerably reduced.

APeLS (Conlan, Wade, Bruen, & Gargan, 2002) is developed as a service to deliver personalized educational courses based on a multi-model, metadata driven approach. It is an adaptive hypermedia system which makes use of some e-learning standards as well as some of the Semantic Web technologies. It provides a generic and extensible adaptive metadata driven engine that composes, at runtime, tailored educational experiences across a single educational content base. However, in this system users have to identify domain specific terms in a unique and machine-recognizable way. This issue can be addressed by defining a multi-model ontology to generate personalized courses. Moreover, metadata only provides the syntax of the elements in describing the adaptive use of learning objects, but ontologies can supply syntactic and semantic information that helps in the adaptation process.

Additionally, many researchers are adopting semantic web technologies to find new ways to design adaptive learning systems based on describing knowledge using ontologies. DIOGENE (Sangineto, 2008) is an adaptive e-learning platform which generate personalized courses by assembling learning material using static statistical knowledge. Statistical knowledge includes didactic information about specific domain, which is explicitly represented using ontologies. Static information represents both learners' knowledge and learner's preferred learning. A learner is monitored during the interactive test activities to collect his knowledge about specific domains. Accordingly, the system provides adaptation based on the learner's learning styles according to Felder-Solomon approach.

Henze et al. (Henze, Dolog, & Nejdl, 2004) proposed a framework for personalized e-learning based on a semantic web approach. They define ontologies for three types of resources namely domain, users and observations. In this system, rules are employed to reason over distributed information resources in order to dynamically derive hypertext relations.

Some researchers emphasize that considering the learners' levels of knowledge can promote personalized learning performance (Chen & Duh, 2008; Henze et al., 2004; Jovanović, Gašević, & Devedžić, 2009). Therefore, the ability of learner has a significant impact on personalization. Chen et al. (Chen, Lee, & Chen, 2005) presents their personalized e-learning systems using item response theory which provides personalized learning according to difficulty parameters of course materials and learners' responses. Chen et al. (Chen & Chung, 2008) also proposed a personalized mobile English vocabulary learning system based on Item Response Theory and learning memory cycles, which recommends appropriate English vocabulary for learning according to individual learner's vocabulary abilities and memory cycles. Baylari and Montazer (2009) also developed a personalized multi agent e-learning system based on item response theory (IRT) and artificial neural network (ANN) which presents adaptive tests (based on IRT) and personalized recommendations (based on ANN).

Against this background, the focus of our work is in proposing an ontology-based approach for developing personalized e-learning where personalization and adaptation are achieved by designing the domain model, user model and content model separately to increase flexibility and reusability of the system. Learners' models describe learner's characteristics like learning styles, preferences, performance and abilities. In our approach learners' abilities are also estimated based on the Item Response Theory.

Learner Ability

According to the Item Response Theory, learner's ability is used to personalize the learning content. Chen et al. (Chen & Duh, 2008) states that the difficulty level of the recommended content is highly relevant to learners' abilities. Furthermore, an inappropriate content can result in learner's cognitive overhead and disorientation during a learning process. Therefore, we propose a personalized e-learning system which delivers appropriate and specific learning content for individual learners. In the first step, learner's ability initiates at a moderate level. In different stages of learning, tests are taken from individual learners regularly and their response is analyzed according to the Item Response Theory(Baker, 2001) to dynamically estimate and update learners' abilities. In the next stage, appropriate content will be recommended based on the updated abilities.

Item response theory is a model-based approach to select the most appropriate items for examinees based on mathematical relationships between abilities and item responses. The idea of item response theory is based on the assumption that the probability of a correct answer to an item is a mathematical function of personalized and itemized variables. The item variable is referred to as the item difficulty, item discrimination, and the effect of random guessing.

There are three common mathematical models for calculating the probability of a correct answer to an item according to the number of parameters in logistic function namely one Parameter Logistic function (1PL), Two Parameter Logistic function (2PL) and Three Parameter Logistic function (3PL). In our work, the item characteristic function with three parameters is used to model each item in the test. The equation for this model is given by the following (Baker, 2001):

$$P_i(\theta) = c_i + (1 + c_i)\frac{1}{1 + \exp(-a_i(\theta - b_i))} \qquad (1)$$

Where:

b_i is the difficulty parameter of the item i

a_i is the discrimination degree of the item i

c_i is the guessing degree of the item i

θ is the ability level of examinee

$P(\theta i)$ is the probability that an examinee with ability θ can respond correctly to the item i.

In our approach, the item parameters are stored in the Item class of content ontology through some data properties. The definition of IRT parameters in RDF/XML syntax can be seen in the following example.

```
<owl:DatatypeProperty rdf:about="&ContentModel;difficultyParameter">
        <rdfs:subPropertyOf rdf:resource="&ContentModel;ExamParameter"/>
        <rdfs:domain rdf:resource="&ContentModel;Item"/>
        <rdfs:range rdf:resource="&xsd;decimal"/>
</owl:DatatypeProperty>

<owl:DatatypeProperty rdf:about="&ContentModel;discriminationParameter">
        <rdfs:subPropertyOf rdf:resource="&ContentModel;ExamParameter"/>
        <rdfs:domain rdf:resource="&ContentModel;Item"/>
        <rdfs:range rdf:resource="&xsd;decimal"/>
```

```
</owl:DatatypeProperty>

<owl:DatatypeProperty rdf:about="&ContentModel;guessingParameter">
        <rdfs:subPropertyOf rdf:resource="&ContentModel;ExamParameter"/>
        <rdfs:domain rdf:resource="&ContentModel;Item"/>
<rdfs:range rdf:resource="&xsd;decimal"/>
</owl:DatatypeProperty>
```

In order to estimate the ability of a learner, the responses of the learner for all items of a test are dichotomously scored. This means that, the learner gets 1 for the correct answers and 0 for the incorrect answer. Hence, we will have a response pattern (U_1, U_2, U_3, ..., U_j, ..., U_n) which is called test response vector, where $U_j=1$ represents a correct answer given by the learner for the j^{th} item in the test. On the contrary, $U_j=0$ represents an incorrect answer given by the learner for the j^{th} item in the test. After that, the Maximum Likelihood Estimator (MLE) is applied to effectively estimate tests parameter and learner's abilities (Hambleton, Swaminathan, & Rogers, 1991). Bock and Mislevy derived the quadrature form to estimate the learner's ability (Baker, 1992). This formula is as follow:

$$\hat{\theta} = \frac{\sum_{k}^{q} \theta_k L(u_1, u_2, \ldots, u_n \mid \theta) A(\theta_k)}{\sum_{k}^{q} L(u_1, u_2, \ldots, u_n \mid \theta) A(\theta_k)} \qquad (2)$$

Where θ is the estimation of the ability of the learner, $L(u_1, u_2, \ldots, u_n \mid \theta)$ is the value of likelihood function and $A(\theta)$ represents the quadrature weight at a level below the learner's ability. The likelihood function has been calculated as follows:

$$L(\theta \mid u_1, u_2, \ldots, u_n) = \prod_{i=1}^{n} P(\theta)^{u1} Q(\theta)^{(1-u1)} \qquad (3)$$

Where $Pi(\theta)$ denotes the probability that the learner responds correctly to the i^{th} item at a level below his ability level θ, $Qi(\theta)$ = 1- $Pi(\theta)$ represents the probability that the learner responded incorrectly to the i^{th} item at a level below the ability level θ, $u_i=1$ if the answer of i^{th} item is correct and $u_i=0$ if the answer of i^{th} item is incorrect (Chen & Chung, 2008).

Item Response Theory is used in the computerized adaptive test to determine the best items for examinees based on their individual abilities. Currently, the Computerized Adaptive Testing (CAT) concept has been successfully used in many real applications such as GMAT, GRE and for the TOEFL. In our approach learners' abilities are estimated according to IRT in order to offer accurate personalization.

Ontology Models

One of the technical aims of proposed approach is to generate adaptive Online learning by offering separate content models, learners' models and domain models to facilitate independency between any of the building models and enable the flexible adaptation of content delivery. Therefore, the domain topics and content structure is separated into separate models. This is an organizational model for creating adaptive online learning system.

Ontology is proven to be an effective means to semantically present knowledge in a specific domain (Snae & Brueckner, 2007). Consequently, we propose an approach where three ontological models are used; user, domain and content models. These models are described in the following sections.

User Model

In the proposed system, an ontological user model is designed to describe learners' profiles. A graphical representation of this model is shown in Figure 1 (Yarandi, Tawil, & Jahankhani, 2012). The *Learner* class is a central concept as it includes all the properties of a learner. The learner's properties are structured in two groups including user identification information and learning profiles. User identification information such as names, passwords and emails are kept in the *PersonalInformation* class through data properties which are attached to this class. The identification information for a learner in RDF/XML syntax is shown in the following example.

```
<owl:NamedIndividual rdf:about="&UserModel;student2">
    <rdf:type rdf:resource="&UserModel;Learner"/>
    <UserModel:hasPersonalInformation rdf:resource="&UserModel;PI_student2"/>
</owl:NamedIndividual>

<owl:NamedIndividual rdf:about="&UserModel;PI_student2">
    <rdf:type rdf:resource="&UserModel;PersonalInformation"/>
    <UserModel:dateOfBirth>5-05-2005 </UserModel:dateOfBirth>
    <UserModel:firstname>John </UserModel:firstname>
    <UserModel:lastname>Black </UserModel:lastname>
    <UserModel:password>20-Mar-88 </UserModel:password>
    <UserModel:email>John@google.com </UserModel:email>
</owl:NamedIndividual>
```

The other classes and properties of this ontology are aimed to represent learner's learning profiles like preferences, learning performance and learning styles and learning abilities. Learning preferences are kept static during the learning process and are used to customize the preferences of learners with regards to colors and languages during the learning process. This characteristic is formally represented in the Preferences class and pointed by the *hasPereference* property. Each learner is also attached a set of performance related data which is presented in *Performance* class via *hasPeformance* property. Learning performance which contains prior knowledge and gained knowledge can be obtained as a result of technical examination which is taken by individual learners.

The Ability class represents the abilities of learners which are calculated according to item response theory during the learning process. The learning styles of individual learners are recorded in the *LearningStyle* class based on the Felder-Silverman Learning Style Model (Brusilovsky, Sosnovsky, & Yudelson, 2005). This model defines four dimensions namely active-reflective, visual-verbal, sensing-intuitive and sequential-global for particular learner. The *LearningStyle* class presents these dimensions through the *LearningCategory* class. The learning style of each learner is determined through the result of a questionnaire based on the Felder and Silverman's learning style model.

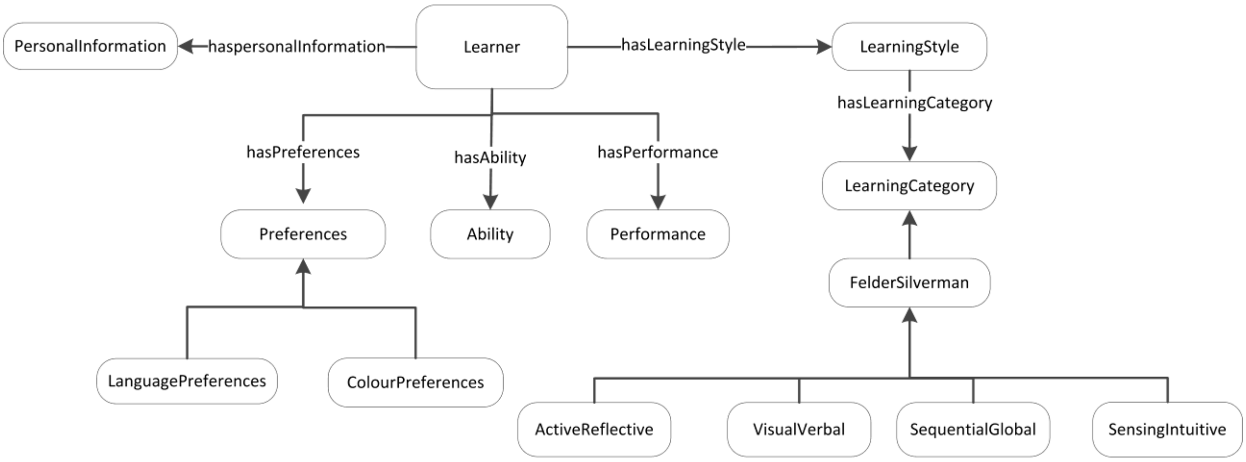

Figure 1. Graphical representation of user model ontology

Domain Model

The domain model is a semantic ontology which is specified by the course author and forms a logical taxonomy for the knowledge domain. It specifies the topic hierarchy of learning objects. The domain ontology contains classes and properties that describe topics of a domain and pedagogical relationships between proposed topics. In the proposed system the topic of Fractions of the mathematics domain is defined in order to evaluate the system.

Domain topics are presented as subclasses of the *Topic* class. Each of the defined topics is assigned a aliases using the *preferedName* properties. This ontology contains two main properties *isTaughtAfter* and *isTaughtBefore* to define the topics sequencing in terms of the order in which topics are to be presented to learners. The properties *hasPrerequisite* and *isPrerequisiteFor* are two semantic properties to describe prerequisite relations on the level of domain topics. The *isRelatedTo* property represents the relationship between two topics, which are semantically related to each other. Figure 2 shows a subtopic of the fraction domain and its relation to other subtopics (Yarandi et al., 2012).

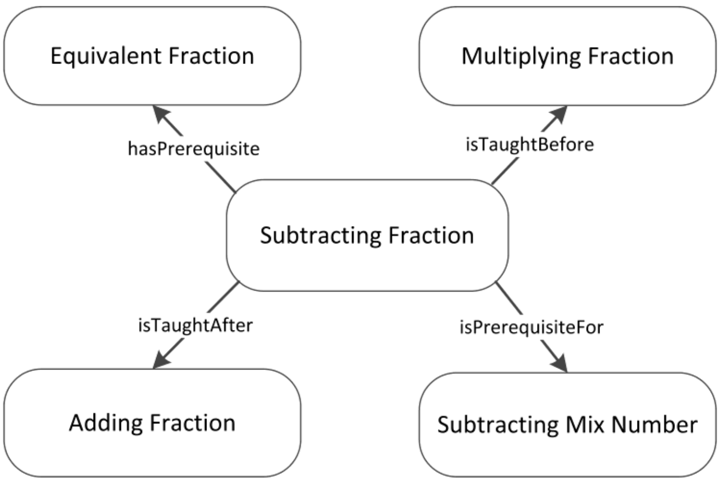

Figure 2. The relation of a subtopic with other subtopics

Content Model

Our defined structure of learning content is presented in the content model ontology. The content model ontology defines hierarchical structure of learning content with three aggregation levels namely course, lesson and instructional objects. The *Course* class is the first level in hierarchy which aggregates several Lesson classes via the *hasPart* domain property. In order to describe a course some metadata such as name and keyword are attached to this class through associated data properties. *Lesson* class is an aggregation of the *InstructionalObject* class through *hasPart* property. The topic of each lesson is determined by Domain ontology through *hasDomainTopic* property. This class also includes some metadata for describing a lesson like name, keyword, description, *difficutyLevel* and language. Following example shows an instance of *Lesson* class.

```
<NamedIndividual rdf:about="&ContentModel;LS_proper">
        <rdf:type rdf:resource="&ContentModel;Lesson"/>
        <ContentModel:name>Proper Fraction</ContentModel:name>
        <ContentModel:keyword>Proper Fraction, Denominator, numerator
</ContentModel:keyword>
        <dc:description>This lesson has a definition, examples and a exercise about proper
fraction</dc:description>
        <ContentModel:hasDifficultyLevel rdf:resource="&ContentModel;Easy"/>
        <ContentModel:hasLanguage rdf:resource="&ContentModel;English"/>
        <ContentModel:hasDomainTopic rdf:resource="&DomainMath;ProperFraction"/>
        <ContentModel:hasPart rdf:resource="&ContentModel;IO_proper_def1"/>
        <ContentModel:hasPart rdf:resource="&ContentModel;IO_proper_example2"/>
        <ContentModel:hasPart rdf:resource="&ContentModel;IO_proper_example4"/>
        <ContentModel:hasPart rdf:resource="&ContentModel;IO_proper_example5"/>
        <ContentModel:hasPart rdf:resource="&ContentModel;IO_proper_exer4"/>
    </NamedIndividual>
```

LS_proper is an instance of *Lesson* class which consists of some instances of *InstructionalObject* class namely IO_proper_def1, IO_proper_example2, IO_proper_example4, IO_proper_example5 and IO_proper_exer4 as you see in above code.

Each lesson has an exam object for evaluating learners prior to the next lesson. The navigational relationship between Lesson classes is defined through next and previous properties.

In this ontology, *InstructionalObject* class is the lowest level of the hierarchy to present the smallest unit of learning content. Instructional Objects (IOs) are considered from the perspective of their instructional roles. Therefore, classes such as Example, Definition, Exercise and References are defined as subclasses of the *InstructionalObject* class. Each instructional object has a topic which is determined by domain ontology.

The learning content should be annotated in order to be searchable and reusable. In this system the three ontological models are used to annotate learning contents and describe a learner's profile. Learning objects are annotated semi-automatically when the content author inserts these objects to the repository. However, the annotation of lessons and courses is fully automated during the learning process.

System Architecture

Figure 3 illustrates the architecture of our proposed ontology-based personalized e-learning system. The system has a central unit named Adaptive Engine and two mediators to access information and a user interface in order to friendly communicate with users. The functionalities of the proposed units of system architecture are explained as follows:

- **User Interface:** Provides a user friendly and adaptive interface for communicating with learners. The interface communicates user characteristics to the user model ontology and returns the tailored learning content from the Adaptive Engine to the learner. The User Interface also returns learner's responses to the Adaptive Engine. For a beginner learner, it performs a registration process where the general and educational characteristics of the learner are taken and recorded into the ontology-based user model.
- **Adaptive Engine:** At the core of the e-learning system is the Adaptive Engine which is responsible for generating personalized learning content based on the information available in the learner's model. The engine combines IOs to generate coherent learning content for a particular learner. It obtains knowledge about learner and learning objects through related mediators. The engine also contains an assessment unit to re-evaluate the level of knowledge and ability of learners. This component gets learners' responses to regular tests and evaluates the learner's performance in the selected topic and also learner's ability based on the item response theory. The user model is updated based on this evaluated information (i.e. ability and performance) through the user model mediator.
- **User Model Mediator:** The Mediator is responsible for handling any kind of requests for accessing and updating the user model repository.
- **Content Mediator:** The Content Mediator is responsible for searching the repository and retrieving different IOs based on different instructional role. This mediator also composes the retrieved IOs into Lessons and annotates lessons automatically. The architecture includes two repositories namely IO and user profiles. The IO repository contains all learning contents and their metadata based on the content model ontology. User profile repository contains general and educational characteristics according to user model ontology.

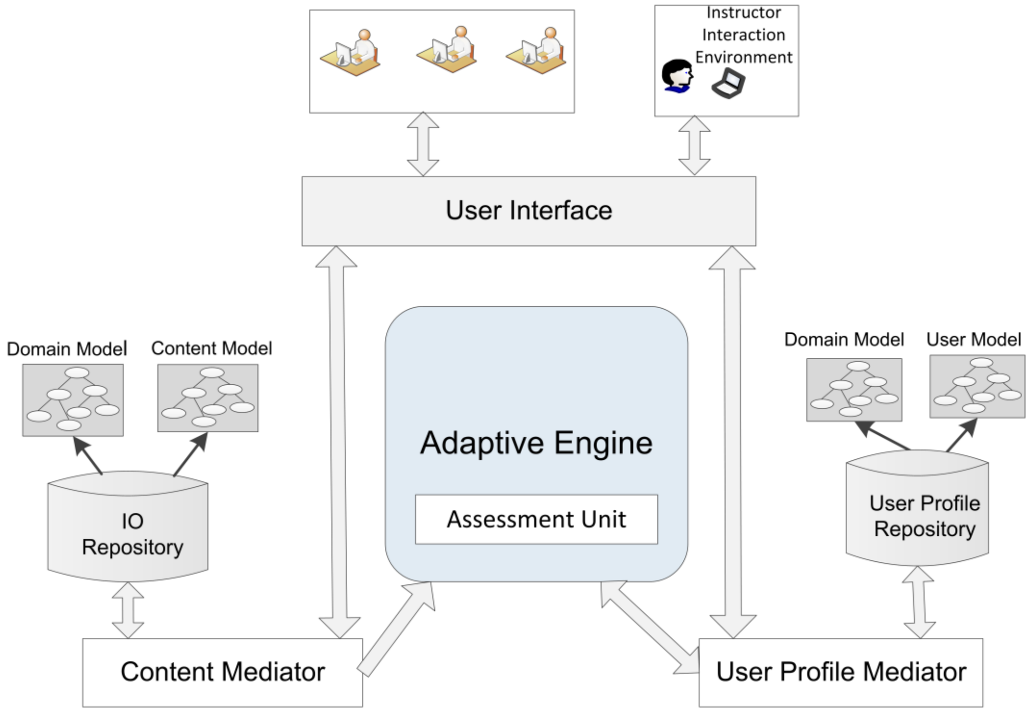

Figure 3. The architecture of system

Adaptation Process

The approach presented in this paper provides adaptive navigation and adaptive content for learners based on their prior knowledge, abilities and learning style. Therefore, learners should complete a registration process at the start of the first session. During this process general and educational characteristics of individual learners are recorded and a first version of the user model is created. A learning session starts after a learner performs registration and logs into the system. The learner is presented with an annotated table of content (Figure 4) based on the information available in both user and domain models.

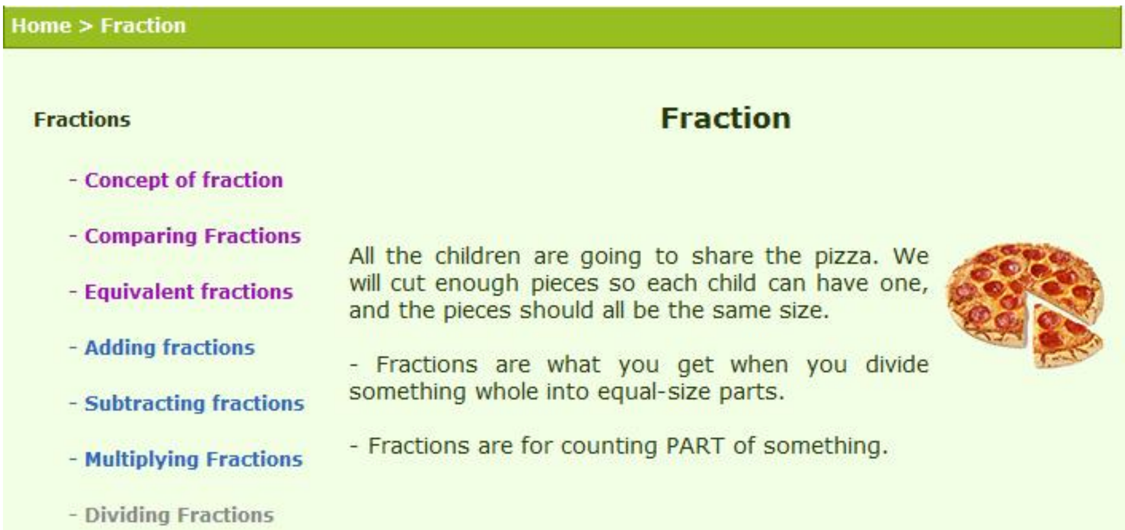

Figure 4. A screenshot of the annotated table of contents

In Figure 4, links to topics with different educational status are marked differently. In our system link annotations are presented as follows:

- Links with purple color denotes that the learner already knows the topic that the link points to.
- Blue color represents topics that the learner is capable to learn them and has knowledge about all prerequisite topics of them.
- Grey color denotes a topic that the learner is still not ready to learn as he did not complete or previously covered related prerequisite topics.

After the learner selects a topic from the table of contents, the system initiates the learning process by selecting and sequencing appropriate IOs for the selected topic. Figure 5 shows a flowchart for sequencing learning objects in the system.

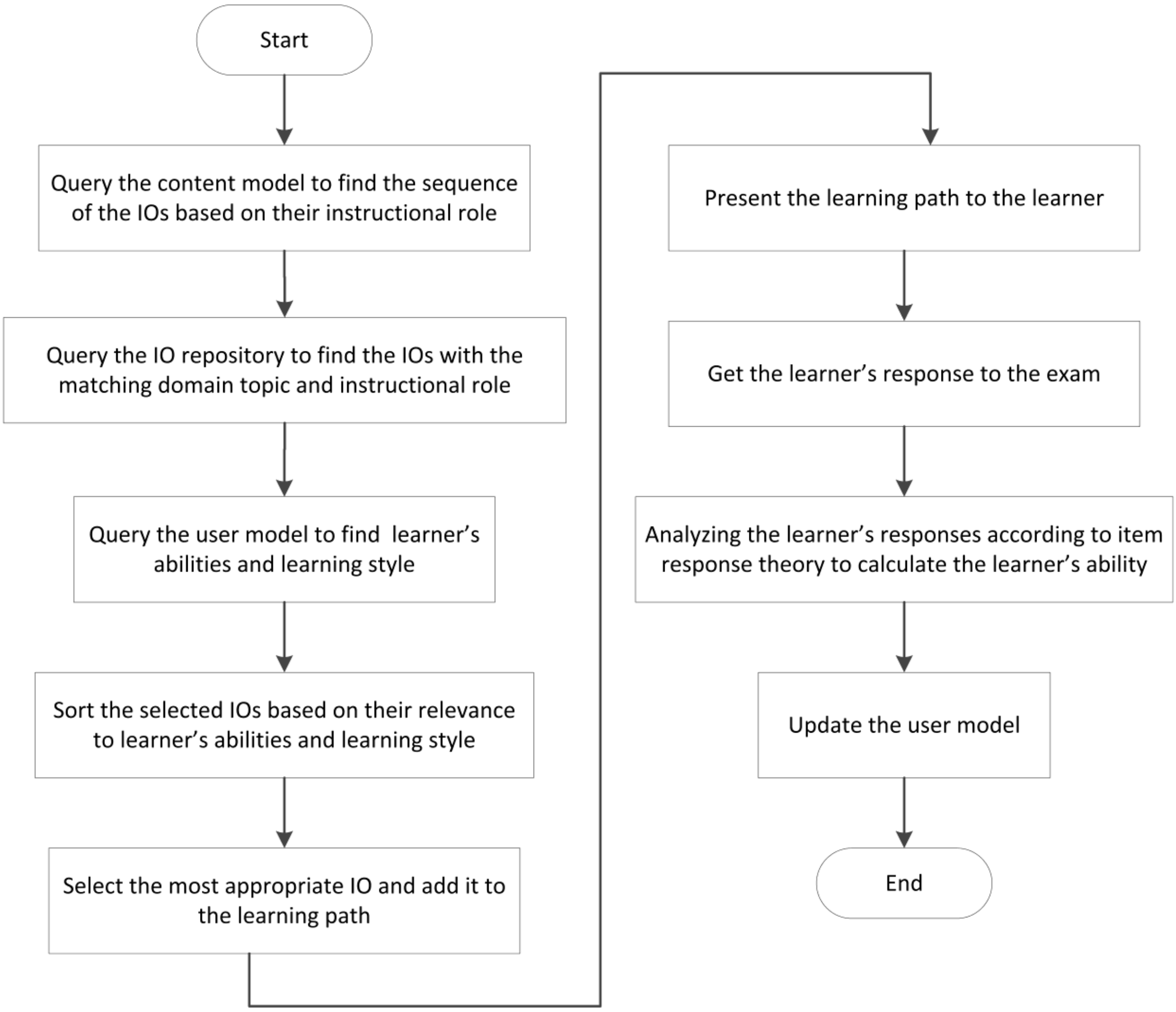

Figure 5. Flowchart of content sequencing

In the flowchart, the content model is first queried about the order of Instructional Objects (IOs) based on their instructional roles. This ordering is designed by the instructional designer -different instructional designers define different order of IOs based on their preferred learning pedagogical model. For instance, an instructional designer can define a sequencing of IOs in the following order: (exercise, definition, example, exercise and exam) based on the problem-based learning pedagogical model. At this stage, the order of IOs is positioned in an ordered list according to their instructional role. In a second step, the IOs having selected a domain topic and instructional role are retrieved from the related repository. The selected domain topic gets annotated via *hasDomainTopic* metadata and the instructional role is accessible through rdf:type. A small part of an annotated IO can look as follows.

```
<owl:NamedIndividual rdf:about="&ContentModel;example001411301">
  <rdf:type rdf:resource="&ContentModel;Example"/>
  <ContentModel:metadata
    rdf:resource="&ContentModel;Meta-example001411301"/>
  <ContentModel:hasDomainTopic
    rdf:resource="&DomainMath;AddSameDenominators
</owl:NamedIndividual>
```

After finding a group of IOs in a particular topic and with a particular instructional role, the system selects IOs according to their relevance to the learner. For this purpose, the user model repository is queried with regards to learner’s abilities and preferred learning styles. Subsequently, the difficulty level of the IOs is obtained from the repository via the *difficultyLevel* metadata. The value of the IO’s relevance to the learner is calculated based on two factors: the matching learner’s abilities and the difficulty level of the IO; suitability of the IO for the learner based on her learning style. In the next step, the system selects the best suitable IO and adds it to the learning path. This algorithm is repeated until a set of IOs is selected based on their different instructional roles as expressed in the ordered list. Subsequently, a dynamically adaptive learning path is assembled and presented to the learner. Assessment is added in the learning path. Both learner’s ability and her level of knowledge are calculated based on her response to the assessment. The user model will then be updated as indicated in the last step of the flowchart. To update a user model, the system creates an instance of *Performance* and *Ability* classes in the user model.

In the approach, some reasoning techniques and complex inferences are implemented to select the IOs and to compose the appropriate IOs based on learner’s characteristics.

Conclusion

This paper presents an ontology-based approach to develop a personalized e-learning which creates adaptive content based on learner’s abilities, learning style, level of knowledge and preferences. In the approach, ontology is used to represent the content, learner and domain models. The learner model describes learner’s characteristics required to deliver tailored content. The domain model consists of some classes and properties to define domain topics and semantic relationships between them. The content model describes the structure of courses and their components. The personalized content containing a number of different Instructional Objects which is tailored to a particular learner based on information in the learner model. The response of the learner to some regular tests during the learning process is analyzed by the item response theory to evaluate the ability of learner. The system recognizes changes in the learner’s level of knowledge as they progress. Accordingly, the learner model is updated based on learner’s progress and the passage from one stage of learning process to the next stage is determined based on the updated learner’s profile.

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