# Challenges in Search and Usage of Multi-media Learning Objects

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**Abstract.** The definition, assembly and manipulation of learning objects is becoming more and more popular in learning environments. But despite standardization efforts their appropriate markup and practical usage still faces many difficulties, such as retrieval, true interoperability and cognitively adequate selection and presentation. This paper describes current work of the authors tackling some of these challenges.

**Keywords:** Computers and Education, Information Search and Retrieval, Intelligent Web Services and Semantic Web, Metadata, Modeling structured, textual and multimedia data, CBR.

## 1 Introduction

The definition, assembly and manipulation of learning objects (LOs) is becoming more and more popular in learning environments. But despite standardization efforts (e.g., [1], [2], [3]), their appropriate markup and practical usage still faces many difficulties.

Challenges include the retrieval of appropriate multi-media learning objects (MMLOs) from distributed web-repositories, true interoperability and cognitively adequate selection and presentation. This paper describes current work of the authors tackling some of these challenges. The German co-authors focus on the semantic representation, search, presentation and (re-)use of LOs. The Chinese partners investigated solutions to authoring and usage of multi-media learning objects (MMLOs) in large-scale learning environments and automatic question answering. In this context, large-scale equals to several thousands of users from all over China and more than hundreds of students per class. This leads to high requirements regarding support (question answering) and the difficulty of controlling the teaching and learning effect.

In this paper, we present some solutions for the automatic usage of MMLO in large-scale distributed learning environments. The paper has two parts: Section 2 describes challenges and solutions of searching for LOs; Section 3 describes the usage of LOs.

R. Lu et al. (Eds.): Chinese-German Ws on Cognitive Systems 2005, LNAI 4429, pp. 36 – 44, 2007.

## 2 Search of Learning Objects

This section focuses on the semantic representation of LOs and their retrieval. Section 2.1 discusses how can we annotate content in such a way that the semantics of the domain being learned is represented, and how to annotate the LOs in order to achieve a representation expressive enough for automatic processing. What are the additional techniques and annotations required by MMLOs such as video lectures or animated beamer presentations? The annotated content needs to be accessed with tools that allow full but easy access of the representation. One such tool, our semantic search facility, will be presented in Section 2.2. New solutions are also required for the search in Web-based learning environments where the LOs are distributed among several repositories. These will be discussed in Section 2.3.

### 2.1 Metadata Required for Search

Domain knowledge is a basis for learning. More often than not, the links to a formal description of the objects in the domain are realized by links from the LOs to some formal description. However, especially in domains of a formal nature, it is possible to have a more sophisticated internal representation of LOs that also provides the semantics of the LO.

Such an approach was realized in the learning environment ActiveMath, which uses the semantic XML-markup language OMDoc ([4], [5]) for mathematical documents. OMDoc has evolved as an extension of the OpenMath European standard for mathematical expressions (www.openmath.org) and provides a rather fine-grained breakdown into LOs. One objective of using this generic semantic markup language is to keep the encoded content reusable and interoperable with other, even non-educational, mathematical applications.

ActiveMath's content is represented as a collection of typed items in OMDoc annotated with metadata. The types indicate a structural characterization of the items which are either *concept* or *satellite* items: an OpenMath symbol defines a mathematical concept abstractly, i.e., an element of a formal ontology. Concepts (e.g., definitions or algorithms) are the main items of mathematical content, whereas satellites (e.g, exercises or examples) are additional items of the content which are related to one or several concepts. All items are accessible via a unique identifier.

A more hierarchical ontology in mathematics can be reached by grouping concepts into theories. Relations exist between such collections of items and the corresponding areas of mathematics. The element *theory* assembles knowledge items into mathematical theories, which can be assembled into larger theories via the import mechanisms of OMDoc. Some theories are relatively small and just concerned with particular concepts, e.g., the theory of differentiation. Large theories, e.g., Calculus, have substructures.

OMDoc has been extended for educational purposes. For this, there are metadata, which characterize not only organizational and mathematical but also educational properties of the OMDoc items. These metadata include relations. Overall, this establishes a mathematical and educational ontology.

The LOM- and DC-compatible metadata describe intellectual property rights as well as properties of learning objects that help to adapt to the learner, e.g., *difficulty* and *field*. The metadata also support the adaptation to the context of learning such as language of the learner or his educational level.

Currently, relations are expressed by metadata in OMDoc which can be translated to relations in RDF. For instance, the *prerequisite relation* expresses a mathematical dependency between concepts $c_1$ and $c_2$, i.e., it describes which concepts $c_2$ are mathematically necessary in order to define $c_1$. The *for* relation links satellite LOs to concepts and definitions to symbols. For example, a symbol can have several, typically equivalent, definitions. Additional relation include *against* and *is-a*.

To make the content more animative, the e-learning environment of the Chinese co-authors provides multimedia courseware which gives the illusion to the students as if they study in the traditional face-to-face classroom. That is to say, this courseware includes all the didactical data, such as teacher's video, audio, tutorials, computer screen, blackboard, mouse trace, etc. During the teaching process, the system compresses all teaching scenario data synchronously and automatically and edits this to a new courseware. Furthermore, a MarkerEdit Tool inserts indexing marker automatically (e.g., the title of a slide).

### 2.2 Semantic Search

Making the semantics of the LOs accessible to users offers new possibilities. For instance, in the LeActiveMath project, we developed a semantic search facility that takes advantage of the semantic content encoding, i.e., of its structural elements, its metadata, and the OpenMath semantics of mathematical expressions. It offers the following advantages over traditional, text-based search: to search for mathematical expressions that are formal, i.e., not just text; to search for types and other meta-information of content-items, and finally to search for other relevant sources located anywhere in the Web.

Traditionally, information retrieval focuses on the retrieval of text documents and on textual search based on two essential ingredients: first, an analysis (tokenization) process converts the text documents that will be searched into a sequence of tokens (typically words). Second, an index is built up, which stores the occurrence of tokens in documents and which can then be efficiently searched.

In order to make use of the semantic content provided in OMDoc we process the following information as well in order to build the index: the titles, the metadata information, the textual content, and the mathematical formulae.

#### 2.2.1 Tokenization of Mathematical Formulae

Information retrieval from textual corpora processes a linear sequence of tokens. Mathematical formulae in OpenMath, however, are represented in a tree-structure. This tree structure offers valuable information for searching. Therefore, we use the sibling order of a tree-walk to produce a special sequence of tokens. More specifically, we tokenize the application with a marker of the depth, the symbols, strings, floats, and integers of OpenMath. For example, the formula $sin\ x^2$ is tokenized into:

```
_(_1
_OMS_mbase://openmath-cds/transc1/sin
_(_2
_OMS_mbase://openmath-cds/arith1/power
_OMI_2
_OMV_x
_)_2
_)_1
```

Using this tokenization, we can query math expressions by an exact phrase match, that is, a match for a sequence of tokens. As a given expression can occur at any depth of a mathematical expression, exact phrase queries have to be expanded into a disjunction of queries for each depth.

Formulae with jokers can also be queried: the example above is matched by the query *sin(*)* that translates into the following sequence of tokens:

```
_(_1
_OMS_mbase://openmath-cds/transc1/sin
*
_)_1
```

where the * indicates a joker in the phrase query which matches anything as long as the remaining part is matched.

#### 2.2.2 Integration of Relevant Web-Sources

In order to enable search for mathematical Web sources and to compare the results of this search, we automatically add links such that the same query can be submitted to search engines and content collections such as Google, Wikipedia, and MathWorld.

#### 2.2.3 User-Adaptivity of the Search-Tool

The results of this kind of search may be overwhelming for a learner. Therefore, LeActiveMath's search tool is adaptive in the following sense: Per default, it searches only for concepts in the current course. Searching in the complete content is available via a link. Search in relevant Web-sources is only activated if the user model of the learner supports the fact the learner is able to process the information adequately. This information is represented as the *autonomy* value in the situational learner model.

For the multimedia courseware, we believe that it is even more important to design an interface for the students to decide whether the knowledge they are searching for is inside the courseware and how to locate it. For example, if a student wants to review “Probability”, he/she can input the phrase through a textbox or microphone, and then the computer can locate the relevant material in the courseware automatically.

Fig. 1. illustrates the workflow of our content-based indexing and retrieval system. Based on the marked courseware, we proposed the *Content based information retrieval system*, which indexes and locates the courseware based on an *on-demand keyword*

*input.* For each retrieval process, the system will give several possible choices in ascending order using *matching weight*:

$$Weight_i = Freq_i / \sum_{j=1}^{N} Freq(j) \tag{1}$$

Here $Freq_i$ is the choosen frequency relative to an on-demand knowledge concept which is incremented by 1 if it is chosen by the student. The sum is the total frequency value of the whole knowledge point in this course. This method helps to increase the indexing accuracy and efficiency.

### 2.3 Integration of Distributed Knowledge

In a Web-based environment, LOs may be distributed over several repositories and annotated with different metadata schemas. Hence, it is important that components processing the LOs can abstract from the actual knowledge sources. They should not need to locate the relevant sources nor should they interact with each source separately.

ActiveMath achieves this separation by using the mediator approach to information integration [6]. In this approach, a special service acts as a mediator between the knowledge processing and knowledge storing components, thus providing a uniform query interface to a multitude of autonomous data sources.

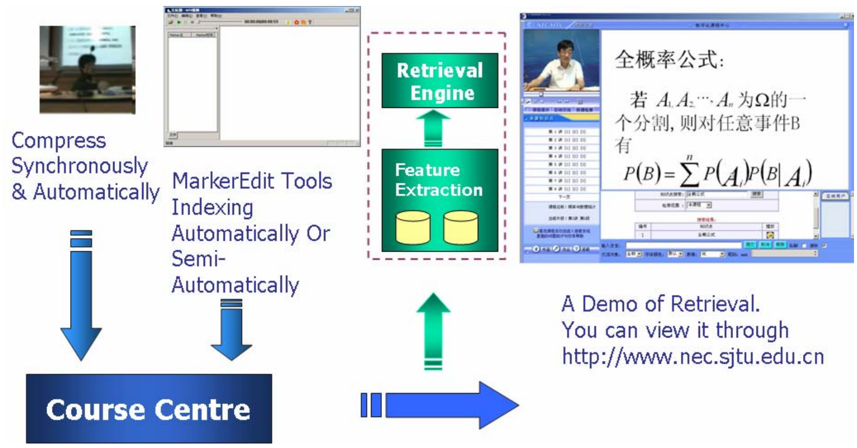


**Fig. 1.** Workflow of the indexing and retrieval system

Queries in ActiveMath are processed as follows: first, a client component passes a query formulated in its own schema to the mediator. The mediator translates the query into the mediated schema and then for each knowledge source from the mediated schema it translates the query into its respective schema. The queries are then sent to each knowledge base, and the answers (lists of identifiers) are merged. Finally, the mediator sends the answers back to the client.

The mediated schema is based on an ontology of instructional objects. Because existing metadata standards such as IEEE LOM can not represent sufficient information about the sources for a completely automatic search, we developed an ontology (see Fig. 2.) that describes different types of learning objects from an instructional point of view [7].

Central to the ontology is the distinction between *fundamentals* and *auxiliaries*. The class *fundamental* subsumes instructional objects that describe the central pieces of knowledge. *Auxiliary* elements include instructional objects which provide additional information about the concepts.

## 3 Usage of Multi-media Learning Objects

Once the LOs have been semantically annotated, *efficient* usage must be targeted as in large-scale learning environments individual support is nearly impossible. For instance, the e-learning lab of the Chinese co-authors counts 18,000 registered students. Therefore, as much support as possible must be provided automatically and the following section shows how to select LOs automatically. Section 3.2 describes how to answer students questions automatically. Section 3.3 sketches a solution for a multi-lingual environment, where special care needs to be taken with MMLOs in order to keep them re-usable.

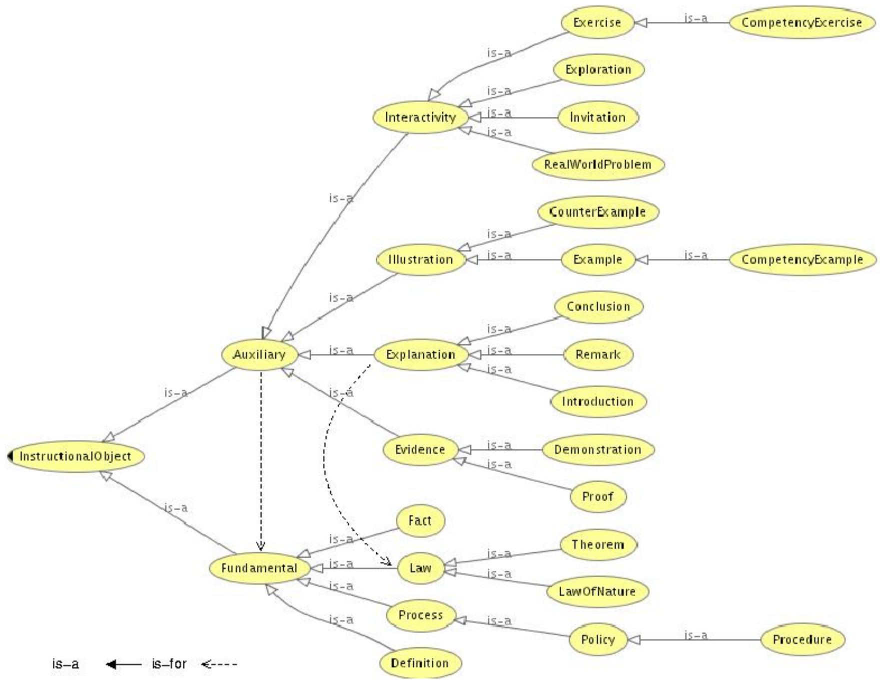


**Fig. 2.** Overview on the ontology of instructional objects

### 3.1 Intelligent Selection of Learning Objects

Students need to work through sequences of LOs to achieve their learning goals and these sequences are often manually assembled. Yet, it is impossible to foresee all potential paths towards a learning goal and to compose the corresponding courses in advance.

That is where course generation comes into play. A course generator automatically assembles learning objects into larger units, which support the learner to reach a given learning goal. The pedagogical decisions involved in such a task are complex and require an elaborate representation of the involved pedagogical knowledge.

ActiveMath uses a hierarchical task network (HTN) planner for course generation, which is an efficient planning technique that offers a relatively straight-forward way to represent human expert knowledge [8]. The HTN-planner has also heuristic knowledge in the form of decomposition rules: A planning problem is represented by sets of tasks; methods decompose non-primitive tasks into sub-tasks until a level of primitive tasks is reached, which can be solved by the given operators.

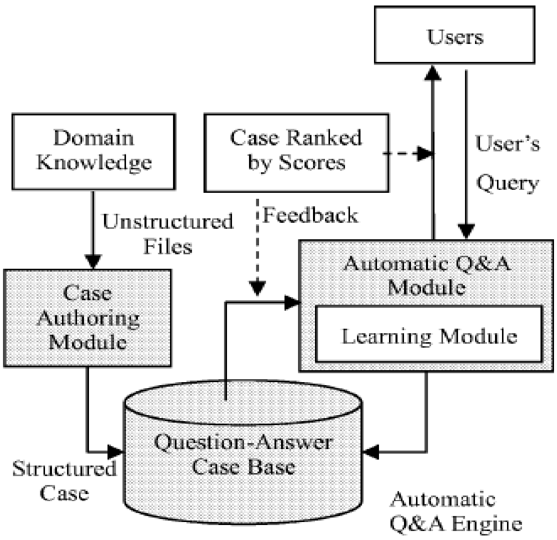


**Fig. 3.** Architecture of the Q&A System

A pedagogical task is defined as a tuple $t = (l, c)$, where $l$ is a tutorial objective and $c$ a unique identifier of a learning object (content goal). While $c$ specifies the concept the course will primarily target, the tutorial objective determines the kinds of learning objects selected for $c$. A top-level task that serves as the starting point of course generation is *teachConcept id*. The goal of this task is to assemble a structured sequence of learning objects that help the learner to understand the content goal $c$. Using different collections of tasks and methods (i.e., different tutorial strategies), this task can be planned differently. Hence, the task-based approach can serve to represent a variety of pedagogical strategies.

Because tasks serve to represent a vast range of pedagogical goals, the size of the generated courses can range from a single element to a complete curriculum. For instance, while the task *teachConcept* results in sequences of several learning objects, other tasks may be achieved by a single element. Frequently occurring examples are tasks for exercise and example selection.

Tasks are also used to provide short term support to the learner by pedagogical agents. These agents monitor the learner's behaviour and, if they diagnose a potential learning problem, offer suggestions what content the learner should read to overcome the problems [9].

### 3.2 Intelligent and Automatic Question Answering

For the large-scale e-learning environment in China, it may take a teacher several hours to answer all the submitted questions. From our experience however, many questions, though put differently, usually have the same or a similar meaning. A solution is to share the answers among the students and let a computer recognize similar questions and then answer them automatically.

We have developed an interactive Q&A engine based on CBR as shown in Figure 3. This engine uses keywords (with weights) in the question to trigger a special case, which then has a standard answer. The weights of the keywords can be modified dynamically depending on feedback from the user.

If the computer cannot find an answer, it transfers the question to a teacher. After the teacher answers the question, the answer is added to the Q&A database and can now be shared among the students: as the Q&A database accumulates questions and answers, the hit rate grows over time.

### 3.3 Multi-lingual MMLOs

Applets and figures are an attractive and important part of multi-media content for Web-based learning environments. These LOs are sometimes interactive and they constitute an important ingredient to show the advantage of multi-media based learning versus traditional books.

One of the challenges is to make the representation of multi-media LOs multi-lingual as well and also to render the content according to the preferences of the learner. In ActiveMath textual LOs can have different texts for different languages. For applets we realized this 'internationalization' by separating the textual part from the applet. The different text for different languages can be stored in files attached to the same applet. This way, the presentation of the text can be adapted to the language of the current session while the visual applet part stays the same.

## 4 Conclusion

This paper describes some solutions to challenges regarding the representation and usage of MMLOs. The Chinese co-authors provided explanations how to deal with large-scale learning environments, while the German co-authors focused on semantic representation and usage of such a representation. Further research will investigate how to marry these solutions, i.e., how to use semantic representation to support the needs of many efficiently.

## Acknowledgements

Some of the authors were supported by the LeActiveMath project, funded under the 6th Framework Program of the European Community (Contract Nr IST-2003-507826). The authors are solely responsible for its content, it does not represent the opinion of the European Community and the Community is not responsible for any use that might be made of data appearing therein.

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