Issues and Directions with Educational Metadata

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Abstract

The creation of learning resource metadata by instructors is a time consuming and error prone process. This paper outlines a broad research agenda to mitigate these issues. The first part of this approach is to collect prescriptive metadata from various actors involved using a lightweight collaborative tagging approach. This is then augmented with content analysis done directly on learning objects to create concept and summarization metadata. Finally, interaction metadata observed from the environment in which the learning objects are deployed is interrogate for specific pedagogical purposes, resulting in customized metadata profile for a specific context and goal.

1. Introduction

Creating meaningful metadata for describing learning resources has been a key goal of e-learning researchers and practitioners over the last decade. Driven strongly by the learning object paradigm which stresses the discoverability, modularity, and interoperability of resources [1], metadata is seen as the key enabling technology. However, there is growing consensus that hand crafting metadata by subject matter experts is neither a good nor economical solution.

The principle goal of this paper is to outline how our work within the Learning Object Repository Network (LORNET) project is addressing the issue of educational metadata. We echo some of our previous views on the purpose of metadata:

“…metadata can be seen as appropriate to informing the process of reasoning over a learning object to determine its suitability for a given purpose and learner, rather than as a data structure of summarised content.” [2]

In examining metadata as a process, we have identified three interesting techniques that can be used for a multitude of pedagogical purposes. The first of these, prescriptive metadata, makes use of the opinions of actors in the learning process, to describe the form, function, or intended purpose of the learning object. While this include the traditional approach involving subject matter experts, we see the community at large as a strong engine for providing both an increase in overall quality of metadata, as well as a contextualization of metadata to specific pedagogical purposes. This approach is described in more detail in section 2.

1 http://www.lornet.org
The second of these, **content analysis**, attempts to reduce the time it takes to create meaningful metadata by analysing both the content and the structure of that content. Approaches being investigated for content analysis are described in more detail in section 3.

The last technique we are looking at is **deriving metadata from observations of interactions** between learners and learning objects. By watching how learners actual use a learning object, we can provide more reliable metadata for future usage. Many different levels of sophistication can be considered, including summarizing values based on all learners, restricting the set of interactions being considered by way of student modeling, or tailoring the kinds of metadata generated to specific purposes. Section 4 outlines our efforts in this direction.

Key to all of these approaches is the need to be able to capture and generate metadata in non context-free environment. Unlike traditional learning object repositories (e.g. Merlot, CAREO, etc.), these techniques can only be applied when you have the educational content itself and the instantiation of that content into a larger educational structure (e.g. an online course). We thus conclude this work (section 5) with the argument that the stand alone learning object repository approach that is currently in use is detrimental to the creation of high quality, low cost metadata.

2. **User Prescribed Metadata**

The traditional metadata approach relies on a subject matter expert – usually the author of the learning content – to annotate that content with metadata when it is added to a learning object repository. Quickly summarized (see [2] for more details), these problems include:

1. A lack of reliability in both the semantics and the syntax of the created metadata.
2. Sparsely populate metadata records, as authors either choose not to or do not understand the various fields put in place.
3. Inappropriate metadata schemes for end use (e.g. the collection of the wrong kind of metadata).

Both the sparsity of the data and the wrong data being collected result in part from relying on a single person for metadata annotation. We are investigating the use of extending metadata creation to a community of users through collaborative tagging to mitigate this.

The "collaborative" aspect of this technique is usually delivered in two forms: at annotation time, and at discovery time. In the case of the former, categorizational tags are suggested based on the set of tags that have been used previously. This provides a form of community support which can give the tagger ideas about what other users think are important aspects of the resource. When referring to discovery time we refer to the action of discovering a given resources through search/filtering using either a traditional keyword search interface or using a filtering style URL, such as in the del.icio.us system. Unlike traditional metadata, tagging systems have no constrained vocabularies or rules for metadata values, and tend to include a large set of annotations which may represent different views. It is this openness and simplicity, coupled with the value of its services, that perhaps makes it so appealing for its users. Users tend to tag with a specific aspect or goal for annotation. This being said it has been shown in [12] that the collaborative suggestions from a community promote the community of taggers to create a consensus of tags that tends to be more objective than subjective descriptions of resources.

The quality of the metadata created through the approach used at large on the web is under question for broader applications. Unlike traditional metadata profile fields (e.g. IEEE LOM, Dublin Core) the semantics of tags and exactly how they describe a resource are not always unambiguous. This is because tags lack a property relationship (in the case of traditional metadata or ontologies) to the tag value. For instance, tags of the webpage for the LORNET conference (http://www.lornet.org/i2lor6) with "Jim" and "Greer" shows ambiguity, especially under machine processing. A human may look at these tags and be able to determine fairly easily that "Jim Greer" has something to do with the LORNET conference. However, if the user has no knowledge of who Jim Greer is they would have no way of knowing that "Jim" and "Greer" are names of the same individual. When extended to the case of a computer processing this information, we can further see complications with how semantics deduced fairly easily by a human, becomes more complicated when extended to artificial processing. Other issues such as misspellings and tags which are subjective or categorizational in nature have been termed "meta-noise". The quality of the metadata is an issue that would need to be addressed for computer systems to be able to use this metadata in its unaltered state. Further, these problems have lead to limitations on the current systems in practice reducing the quality of the services which the sites offer. Our ongoing research [13] seeks to answer some of these shortfalls in the quality of collaborative tagging information while simultaneously seeking to address user difficulties for authoring ontological representations of metadata.

3. **Content Analysis of Learning Objects**

Creating metadata by hand, be it through traditional methods or through community tagging, is a time consuming process. It requires that users (subject matter experts or learners) analyze the content and find appropriate keywords and descriptors to associate with the learning objects through filling certain forms. When a learning environment contains thousands of pages/objects,

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2 See [http://del.icio.us/](http://del.icio.us/) for more information.
this task becomes prohibitive. An automatic way of metadata generation is highly desirable.

In this section we describe a service for automatic metadata extraction from content. We first describe the type of extracted metadata and limitations of the service, then we describe the methods used for the extraction, and finally we discuss the use of the service within a larger system.

3.1 Metadata Extraction Service

Content analysis of learning objects is achieved through a service responsible for the extraction of relevant metadata directly from the text of those objects. Three types of metadata are targeted by this service: embedded metadata, keyword-based metadata, and concept-based metadata. The service is illustrated in Figure 1.

3.2 Embedded metadata extraction

The target document is parsed using a parser specific to the document type. The parser reports certain metadata embedded explicitly in the document, either by its author or by the software which generated the document. For HTML documents, the embedded metadata can be found in meta tags, such as author, keywords, and description. The document title is a special case since it has a tag of its own, and is extracted from this HTML title tag.

Unfortunately document authors do not follow a standard set of metadata tags, and thus the extracted metadata is not always useful. A mapping is created between the extracted metadata and the standard metadata set in use through string matching of metadata tag names, which works most of the time, but can miss potential mapping due to a string mismatch.

3.3 Keyword-based metadata extraction

The text of a learning object is segmented into keywords suitable for further analysis. Keyword segmentation follows standard text mining techniques that are described below:

1. Break the input text into a set of sentences:
   \[ S = \{ s_i : 1 \leq i \leq n_s \} \]. (A finite-state-machine tokenizer is used for detecting sentence boundaries.)
2. For each sentence \( s_j \), break the sentence into a sequence of words:
   \[ T_j = \{ t_{ij} : 1 \leq j \leq n_{T_j} \} \]. (Also a finite-state-machine tokenizer is used here.)
3. Pass the words of each sentence through a series of filters for removing non-relevant keywords. Types of filters include: (i) lower-case filter (normalizes words to be in lower-case), (ii) stop-word filter (removes common words such as “the”, “a”, etc.), (iii) minimum-length filter (usually set to 2 or 3 characters minimum), and (iv) stemming filter (converts different forms of a word into their common stem, example: “computing”, “computer” are converted to “comput”).

After words are segmented, an analysis step is performed to identify keyword weights frequencies. Keyword weights is dependent on structural cues inferred from the input document, such as titles, headings, captions, emphasized text, etc. Keyword frequencies are calculated by counting how many times a keyword appeared in the document. The frequency is normalized by dividing the keyword count by the total count of words in the document. The final keyword weight is calculated as:

\[
    w(t_i) = w_i \cdot tf_i / \sum_j tf_j
\]

The weights are ranked descendingly, and the top \( k \) ranking keywords are extracted as keyword-descriptors of the input document.

A further step is also applied to identify the most relevant sentences in a document, which are used as description metadata, or as a document summary. The sentences are analyzed for certain features, including their weight and depth (how far a sentence is into the document). The weight of a sentence takes into consideration the weight of its constituent keywords, and is calculated as:

\[
    w(s_i) = w_i \cdot \text{depth}(s_i) \cdot \sum_j w(t_{ij})
\]

All sentences are then ranked based on their score. The top \( k \) sentences are output as a set of alternate descriptions for the target document.

3.4 Concept-based Metadata Extraction

Even though keyword-based metadata describes certain aspects of a learning object, it may not capture more complex concepts that can be revealed by natural language processing. A specific type of metadata, that
describes concepts in the data, is called concept-based metadata.

Concept-based metadata summarizes what its data is about. This type of metadata is very useful for search engines. A search engine now searches the metadata, not the original data (the page text). The concept-based metadata relates to the concept that lie behind the content of the pages. Thus, instead of finding what the user asks for, the concept-based metadata is used to help in finding what the user wants. It interprets both the documents which the search engine has indexed and the user’s query to understand their meanings and provide a much more sophisticated match between them. This may include an interactive process to help the user quickly articulate what he/she is looking for through these concepts rather than abstract descriptions.

3.4.1 Concept-based Mining Model

The concept-based metadata is extracted using the concept-based mining model [9]. This model consists of concept-based term analysis, conceptual ontological graph (COG) representation [9, 10], and concept-based similarity measure.

A raw text document is the input to the model. Each document has well defined sentence boundaries. Each sentence in the document is labeled automatically based on the PropBank notations [11].

After running the semantic role labeler, each sentence in the document might have one or more labeled verb argument structures. The number of generated labeled verb argument structures is entirely dependent on the amount of information in the sentence. The sentence that has many labeled verb argument structures includes many verbs associated with their arguments. The labeled verb argument structures, the output of the role labeling task, are captured and analyzed by the concept-based mining model.

In this model, both the verb and the argument are considered as terms. One term can be an argument to more than one verb in the same sentence. This means that this term can have more than one semantic role in the same sentence. In such cases, this term plays important semantic roles that contribute to the meaning of the sentence. In the concept-based mining model, a labeled term either word or phrase is considered as concept.

3.4.2 Concept-based Term Analysis

The objective of the concept-based term analysis is to achieve a concept-based term analysis (word or phrase) on the sentence and document levels rather than a single-term analysis in the document set only.

To analyze each concept at the sentence-level, a concept-based frequency measure, called the conceptual term frequency (ctf) is calculated.

c_{tf}: the number of occurrences of concept c in verb argument structures of sentence s. The concept c, which frequently appears in different verb argument structures of the same sentence s, has the principal role of contributing to the meaning of s.

To analyze each concept at the document-level, the term frequency tf is calculated.

if: the number of occurrences of a concept (word or phrase) c in the original document.

3.4.3 Conceptual Ontological Graph Representation

The Vector Space Model (VSM) [14, 15], the most common representation in text mining, does not represent any relation among the terms. In the VSM, sentences are broken down into individual components without any representation of either the sentence structure or the sentence semantic structure. Thus, there is a need for a representation that can maintain the semantic relations among the concepts which are analyzed by the concept-based term analysis.

The conceptual ontological graph (COG) represents the sentence structure while maintaining the sentence semantics in the original documents. The output of the role labeling task, which are predicates and their arguments are presented as concepts with relations in the COG representation. This allows the use of more informative concept matching at the sentence-level and the document-level rather than individual word matching.

The proposed representation provides different nested levels of concepts in a hierarchical manner. These levels are constructed based on the importance of the concepts in a sentence, which makes use of analyzing the principal topics in the sentence. The hierarchal representation of the COG, provides a definite separation among concepts which contribute to the meaning of the sentence.

This separation is needed to distinguish between the most general concepts and the detailed concepts in a sentence. These detailed concepts are captured from their positions in the COG representation and added as features associated to their documents for the purpose of indexing in the text retrieval.

The COG representation is based on the conceptual graph theory and utilizes graph properties. The COG representation is a conceptual graph G = (C,R) where the concepts of the sentence, are represented as vertices (C). The relations among the concepts such as agents, objects, and actions are represented as (R). C is a set of nodes \( \{c_1, c_2, \ldots, c_n\} \), where each node c represents a concept in the sentence or a nested conceptual graph G; and R is a set of edges \( \{r_1, r_2, \ldots, r_m\} \), such that each edge r is the relation between an ordered pair of nodes (c_i, c_j). If a node has a referent to a nested conceptual graph, this means that there is still detailed information about the topic of this node (concept), and is presented through concepts and their relations in the next level by a nested conceptual graph.
It is crucial to note that the contribution of the COG representation lies on its semantic-based hierarchical nature. This is due to the fact that most of the nodes in the COG representation refer to other nested conceptual graphs. This means that there is more detailed information in a sentence and represented by the nested graphs. Thus, the COG representation introduces the concepts of a sentence in a descending way. The highest nodes present the most general concepts of the sentence. The lowest nodes present the least detailed concepts mentioned in the sentence. This hierarchical manner presents different levels of depth for concept-based analysis within the sentence. Consequently, the COG representation shares the same ontological behavior of the common ontologies regarding the semantics of the sentence. Thus, COG is considered as a semantic-based ontology in which it represents into its hierarchy levels the importance of each concept in a sentence.

3.4.4 Example
Consider the following sentence:

*The availability of powerful microprocessors and improvements in the performance of networks has enabled high performance computing on wide-area distributed systems.*

In this sentence, the semantic labeler identifies three target words, marked by bold, which are the predicates that represent the semantic structure of the meaning of the sentence. These predicates are enabled, computing, and distributed.

Three conceptual graphs are generated for each predicate argument structure as follows.

1. \([\text{enabled}]*a\) ([ARG0][a][The availability of powerful microprocessors and improvements in the performance of networks]) ([ARG1][a][high performance]) ([ARGM-ADV][a][computing on wide-area distributed systems])
2. ([ARG2][computing][on wide-area distributed systems])
3. ([ARG1][distributed][systems])

The previous generated conceptual graphs are combined together into one COG representation as illustrated in Figure 2. In this sentence, the general topic of the sentence is induced by the structure of the predicate enabled. The topic of this example is about *X enabled Y*. More detailed information about *Y* is induced from the structure of the predicate *computing* and the predicate *distributed*.

In this example, the selected concepts that are extracted from the COG representation, which provide detailed information about the sentence, are the concepts appear in the nested conceptual graphs. These concepts, which locate in the lowest conceptual graphs, are *computing, wide-area, distributed, and systems.*

![Conceptual Ontological Graph (COG) Representation](image)

### Figure 2 Example of the Conceptual Ontological Graph Representation

#### 3.4.5 Concept-based Similarity Measure

Concepts convey local context information, which is essential in determining an accurate similarity between documents. A concept-based similarity measure, based on matching concepts at the sentence and document levels rather than on individual terms (words) only, is devised.

The concept-based similarity measure relies on two critical aspects. First, the analyzed labeled terms are the concepts that capture the semantic structure of each sentence. Secondly, the frequency of a concept is used to measure the contribution of the concept to the meaning of the sentence, as well as to the main topics of the document. These aspects are measured by the proposed concept-based similarity measure which measures the importance of each concept at the document-level by the *tf* measure and at the sentence-level by the *ctf* measure.

The concept-based measure exploits the information extracted from the concept-based term analysis phase to better judge the similarity between the documents. This similarity measure is a function of the following factors:
1. The number of matching concepts (m) in the verb arguments structures in each document (d).
2. The total number of sentences (s) in each document d.
3. The total number of the labeled verb argument structures (v) in each sentence s.
4. The tf of each concept c_i in each document d where (i = 1, 2, ..., m).
5. The ctf of each concept c_i in s for each document d where (i = 1, 2, ..., m).
6. The length (l) of each concept in the verb argument structure in each document d, and
7. The length (k) of each verb argument structure which contains a matched concept.

The concept-based similarity between two documents d_1 and d_2 is calculated by:

\[
\text{sim}_c(d_1, d_2) = \sum_{i=1}^{m} \max \left( \frac{l_1}{s_1}, \frac{l_2}{s_2} \right) \ast \text{weight}_{i_1} \ast \text{weight}_{i_2},
\]

\[
\text{weight}_{i_1} = \text{tfweight}_{i_1} + \text{ctfweight}_{i_1},
\]

\[
\text{weight}_{i_2} = \text{ifweight}_{i_2} + \text{ctfweight}_{i_2},
\]

- The concept-based weight of concept c_i in document d_1 is calculated by weight_{i_1}.
- The tfweight_i value presents the weight of concept c_i in the first document d_1 at the document-level.
- The ctfweight_i value presents the weight of the concept c_i in the first document d_1 at the sentence-level based on the contribution of concept c_i to the semantics of the sentences in d_1.
- The sum between the two values of tfweight_i and ctfweight_i presents an accurate measure of the contribution of each concept to the meaning of the sentences and to the topics mentioned in a document.
- The sim(d_1, d_2) assigns a higher score, as the matching concept length approaches the length of its verb argument structure, because this concept tends to hold more conceptual information related to the meaning of its sentence.

4. Deriving Metadata from Observations of Interactions

Our work in deriving metadata by observing users (both learners and content authors) interactions with content has progressed along three different paths. The first of these is aimed at quickly creating IEEE Learning Object Metadata (LOM) [3] compliant metadata, and works with the content analysis approaches described previously. The second technique we are investigating is the use of data mining and clustering algorithms to identify interesting patterns of usage. Once identified, these patterns can be used to provide feedback to students, instructors, or content authors. Section 4.1 will outline our work in this area. The third approach aims to create more flexible learning object metadata at is explicitly purpose aware in that it exists only for specific contexts. Section 4.2 will outline both the general method of this approach, as well as one of the purposes that we have started investigating.

4.1. Data mining usage patterns

The willingness of a student to help others peers is difficult to capture accurately prior to actually asking for help, as there are a number of external variables and personal attributes that we cannot capture. Nonetheless, we have the intuition that metadata collected around learning objects based on the usage of those objects will help us to that a number of traits that we can capture may provide some measure of willingness. These traits include:

- The frequency at which the learner answers questions in discussion forums
- The level of activity on the chat system compared to the amount of lurking done
- A self declared “availability to help” status provided by the learner when they log into the system

Distilled from this project we have grouped learner data into three different kinds of datasets:

1. Learner dataset consists of learner’s personal information, knowledge structures, intentions, activities status, and other characteristics
2. Learning object dataset consists of knowledge contexts and structures which are combination of text, graphics, web pages, reference links, multimedia documents, and potentially explicitly defined metadata (e.g. IEEE LOM)
3. Interaction dataset consists of learner interactions with one another, with the system, and with the learning content

We are currently in the process of building a model which described the relationship between learning objects and the observed learner behaviours. This involves using clustering and Bayesian networks to clique users into similar “helper groups” on a per-learning object basis. These groups can then be interrogated at run-time to determine a short list of appropriate helpers for a given topic, which can then be used for peer recommendation.

4.2. Flexible metadata

We believe, along with many other researchers, that the IEEE LOM is of limited use. Recker and Wiley [4] in particular have noted that authoritative metadata in the form of IEEE LOM does not provide enough information enough for different learning tasks (e.g. content...
recommendations). In order to empower learning content management systems with the ability to perform different types of interaction analyses, we have developed an ontological framework that extends the scope of the IEEE LOM metadata. The central concept of the framework is learning object context, which captures the specific context of use of a learning object. A learning object context actually captures an activity (e.g. quizzing, discussing, and chatting) that a student undertook when interacting with a learning object [5]. The ontological framework is built around the LOCO-Cite ontology, an ontology of learning object contexts. Considering the adopted definition of learning object context, this ontology is related to the following components:

1. Learning object metadata schema – a classical metadata schema such as IEEE LOM, Dublin Core, or a profile of metadata scheme. The implementation of this metadata scheme is generally in the form of an XML schema or an RDF schema. Due to the ontological nature of the framework RDF tends to be the easier choice for data processing and integration.
2. User model ontology – an ontology that provides a formal representation of the learner’s preferences, learning styles and performance (i.e. acquired competencies).
3. Learning activity ontology – an ontology that is inspired by the IMS Learning Design specification and that captures user roles, learning activities, learning services, learning environments and other elements of a learning process.

Besides the above components, the framework presumes the use of domain ontologies that define general subject of learning objects and the activities they were used in (e.g. chat message or discussing post) in terms of a domain conceptualization.

Having defined this ontological framework, we continue our investigation by examining how metadata can be used to inform content creators of the usage of their learning material. More specifically, our goal is to provide feedback to learning object authors (not necessarily instructional designers, who help to choreograph learning content, nor instructors, who help to deliver learning content) so they can increase the quality of that learning object. It should be noted that we explicitly do not prescribe how an author should increase content quality – we anticipate they will analyse the metadata that we provide, and chose to either create revisions or variants of the material.

We conducted a survey with the goal of collecting instructors’ opinions about how learning content management systems should be further improved to help them improve their students’ learning experience. During the survey, we interviewed several content authors and instructional designers at the University of Saskatchewan, Simon Fraser University, University of British Columbia, and subscribers of the IEEE International Forum of Educational Technology & Society (IFETS) mailing list. Summarizing the obtained responses, we identified the following important metadata outputs:

1. Recognition of weak learning paths – For a given quiz, we analyze students’ performance on the quiz in terms of their final quiz score. The focus is on those students who performed poorly, that is, we look for the reasons for their bad results. First, we check their results on other quizzes, done in other modules. If they also performed lousy on other quizzes, the problem is likely in their low motivation or bad working habits or some kind of cognitive disability. However, if the majority of them performed well in other quizzes, it might be a sign for the teacher that something is “wrong” with his way of teaching and/or learning content.
2. Distinguishing between successful and unsuccessful learning paths – Similarly to the previous feedback, we start from a quiz and students’ performance on the quiz. We compare learning paths of the students who did well and those who did poorly and try to uncover what might be the reason(s) for the difference in their performance. Here we try to discover commonalities (i.e., patterns) in learning paths of each group (e.g., ‘good’ and ‘bad’ students). If such patterns are reviled in their learning paths, we can present them in the form of a comparative overview to the teacher.
3. Uncovering difficulties on the lower level of content granularity (topic level) – We set focus on the questions level (of a quiz) and look for the question(s) that was (were) the most difficult for the students, i.e., the question(s) that the majority of students answered incorrectly. Subsequently, we relate each “difficult” question with the topic and/or content item it covers and suggest the teacher some alternations of the content or way of teaching the respective topic.
4. Analyzing students’ discussions – The focus is on the students’ participation in discussion forums and chat rooms. We look for topics that were discussed the most (or at least more) frequently and those that attracted less students’ attention. To do this, we analyze the content of the exchanged messages, i.e., for each message we look which domain topic (or lesson name, assignment, quiz) it refers to and whether it expresses the student’s complaint (e.g., for not

3 http://ifets.ieee.org/
being able to understand the content) or a plea for help or an inquiry.

5. Helping teachers to intensify and/or focus students’ interactions – Focus on students who performed poorly on a quiz and analyze their social interactions in order to find the best way to help them improve their results. This assumes that for each of them, we check how active he was in discussions: was he just reading messages or he was also sending messages to others; has he ever started a thread in discussion forums or chat rooms; with how many people he interacted. According to the results of this analysis, we provide the teacher with more detailed information about students with poor quiz results. Having information about how active students were in discussions, the teacher can more easily decide how to alter his teaching approach to activate them more, or make them more focused on the relevant parts of lessons.

Each of these features is currently being integrated into the standards-based learning content package editor which is used to deploy learning objects to content management systems. By basing our implementations off of standards-based tools, we are helping to ensure high availability of this approach.

Besides being beneficial for generating feedback for content authors, the proposed ontological framework and the reasoning that can be performed over it are useful for personalization of the learning process as well. For example, having recognized the peculiarities of the current learning situation, the system can search the repository of learning object context data in order to identify context ontology instances which represent ‘similar’ learning situations and from them infer the most suitable learning object(s) for the present circumstances. The notion of similarity here is rooted in the ontologies used and semantic relations among their concepts (i.e. classes). For example, the hierarchy of activities defined in one of the framework’s ontologies (e.g. the learning activity ontology) can be exploited when no learning context instances in the repository exactly match the current learning situation – the search query is extended to encompass other kinds of activities that are semantically close to the desired one.

In addition, reasoning over semantic annotation of all learning-related artefacts (i.e. the course content and students’ messages exchanged in discussion forums and chat rooms) enables us to generate for students: having recognized that a student is experiencing problems with a certain domain topic, the system can:

- Recommend additional readings for the sake of clarifications, i.e. it provides links to potentially relevant content that treats the unclear topics;
- Suggest reading some postings from a specific discussion forum/chat room where the problematic issue was already discussed;
- Suggest discussing the topic with some other student(s) who knows the topic well, i.e. with student(s) who had high score on the quiz which tested the knowledge on that topic and/or related topics (relatedness is inferred from the domain ontology).

Last but not the least, the framework facilitates visualization of the learning process, hence providing learners and teachers with visual clues of the learning progress. An ontological representation of a learning process (using the aforementioned learning activity ontology) can be easily visualized as a semantic network (graph) having activities as its nodes, whereas edges represent connections between ‘compatible’ activities. Those edges (i.e. connections) are inferred from a set of pedagogy-based rules that determine for each activity which other activities can be taken next. Using this as our base visualization with refinements for particular purposes is the next step in this direction.

5. Planned Integration and Deployment

Though the techniques we have outlined are broad in scope, we believe the learning content management system (LCMS) is an ideal environment to realize them within. An LCMS has access to the majority of the actors involved, including content authors, instructional designers, instructors, and learners. Further, the LCMS has access directly to the content (both the individual content pieces as well as the choreographies of content), is able to observe learners interactions with the content, and can both observe and influence some of the interactions of learners with their peers (e.g. online discussions and chats).

We are in the process of integrating each of the previously mentioned techniques into the iHelp Courses learning content management system. This system already keeps detailed traces of user interactions, and allows for content delivery in standardized forms. Other services, such as the metadata extraction service described in section 3, are being integrated as hooks into REST-based webservises.

One of the downsides of providing metadata within a content management system is that it both logically and physically decentralizes the learning object repository. This makes the original repository feature of discoverability difficult. To address this issue, we are investigating how content management systems (in particular iHelp Courses) acting as learning object repositories can be connected in a decentralized fashion.

4 http://ihelp.usask.ca
The architecture of the Pool learning object metadata repository [7] seems especially useful in accomplishing this. Highly scalable, Pool takes advantage of Lucene text search engine to enable advanced text search on the metadata collection, and integrates with the eduSource Communication Layer (ECL) system [8]. The ECL is a flexible learning object communication protocol infrastructure designed for distributed network clients, and the ECL query language is generic and can be extended to support a context specific search. It also comes with a security infrastructure that can promote trust and the creation of iHelp Courses shared repositories, thus reducing the issues in and around digital rights management that traditional centralized solutions have. In addition, the ECL has low maintainability requirements and is highly interoperable. An ECL client can communicate with repositories using common communication protocols such as Simple Query Interface (SQI), Search and Retrieve via Web Services (SRW), and Search and Retrieve via URL (SRU). Once installed, Pool becomes part of an ECL learning object repository network and is automatically discovered by ECL clients in the network. Any application can use ECL client API to find suitable repositories on the network, search the repositories, and access resources on those repositories if the user has proper credentials. Finally, Pool and ECL are ready-to-use open source software, easy to modify to fit iHelp needs, and easy to install. If needed, the Pool can be adapted to support search and retrieve service in other protocols such SQI, SRW, and SRU.

6. Conclusions

The intended consumer of educational metadata is still unclear. The IEEE LOM specification suggests that the metadata be used “…to facilitate search, evaluation, acquisition, and use of learning objects, for instance by learners or instructors or automated software processes.” [3]. The specific context and purpose of use of a learning object once it is found is highly variable. We have outlined some goals we are looking into including recommending content to learners, identifying poor sequences of content, providing authors with insights into how content should be modified, and matching peer helpers with similar histories together for collaborative learning.

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References


