Improving Learning Objects Recommendation Processes by Using Domain Description Models

Carlos Becerra*, Hernán Astudillo† and Marcelo Mendoza‡

*Escuela de Ingeniería Civil Informática, Facultad de Ingeniería, Universidad de Valparaíso, Av. Gran Bretaña 1091, Valparaíso, Chile
†Departamento de Informática, Universidad Técnica Federico Santa María, Av. España 1680, Valparaíso, Chile

Abstract. Learning Objects (LOs) are widely used for teaching because these can be reused in alternative contexts to support specific learning objectives. One of the most important challenges in this area is to provide accurate LOs recommendation to simplify LOs search, description, composition, articulation and reuse. The current problem confronted by teachers in an educational area is the large effort required to compose educational material based on LOs. Usually, LOs descriptions are incomplete, inaccurate and/or contain unreliable information. This article presents an approach to improve the LOs recommendation process based on a domain model (ontology) and a categorization method, reducing the effort required to find, reuse and compose LOs. The proposed approach was validated through a case study which allow us to the evaluation of the quality and effort of a posterior object composition process. This study was applied for History and Geography teachers comparing our approach against an Ad-Hoc approach. Our results indicate that by using our approach the teachers composed classes using the LOs recommended with a similar quality that using the Ad-Hoc approach, but with less effort in the process.

Keywords: Learning Objects, Recommendation Platforms, Ontologies

INTRODUCTION

In general, it is not difficult to find digital resources on different areas, the difficulty is to find adequate resources associated with specific domains among the vast amounts of available resources. In particular, for any specialized domain, information consumers have created (intentionally or empirically) tasks models and scenarios which helps to determine usable resources. For example, a teacher may need to prepare a 30 minutes class about UML, in Spanish, with text and examples. A search in Google or Yahoo! will deliver long lists of resources, among which the teacher must find those who serve to her/him purposes. If there exists metadata, the recommendation of good quality objects may be feasible and very effective. Unfortunately, the creation of descriptive metadata requires an initial human effort and a posterior sustained maintenance, which severely limits the realistic scope of these approaches.

A new approach to develop reusable learning contents known as Learning Objects (LOs) [1] has become very popular in the educational technology community. LOs facilitate the development of educational materials, making the content cheaper to obtain and easier to reuse, allowing to share these contents among different educational institutions. LOs are educational resources designed to generate and support learning experiences. One of the main activities to be developed in this area is to compose courses, programs and activities based on these LOs. In this scenario, LOs may be used by different teachers and each teacher may reuse them in different learning materials.

One of the main problems of the teachers in an educational domain is the effort required to prepare educational material. This process required a lot of efforts to find educational resources (LOs) and a posterior step where this material is filtered and composed. This article presents an approach to automate the LOs recommendation process by using domain description models and automatic categorization methods, reducing the effort required to find and use LOs in a composition process. The creation of this framework requires to address two related problems:

- To define a educational domain structure and a LOs content model. We address this challenge by developing an ontology to provide better content descriptions.
- To automatically categorize LOs in a domain class, allowing finding and reusing (recommendation process) LOs with less effort than an Ad-Hoc approach (as a search in a general purpose search engine).

The remainder of this article is organized as follows. In Section 2 we describe related work. In Section 3 we introduce a domain model for a specific educational context. We present the LOs categorization method in Section 4. In Section 5 we evaluate the proposed approach. Finally we conclude in Section 6.
RELATED WORK

There are some approaches for LOs categorization that use objects content and other metadata available. Saini et al. [2] represent the domain knowledge with (concept) taxonomies, which are a simplified version of ontologies, where only hierarchical relationships are used. Taxonomies are trees, where each node identifies a concept and the edges connecting the nodes describe the relationships between the concepts. In this approach, LOs are just text documents. Hence, the task here is to automatically classify documents into a given taxonomy. To avoid hand-labeling tasks usually needed in supervised learning approaches, they classify LOs onto a given taxonomy without any labeled example. To do this, the authors used a probabilistic clustering approach known as the Expectation Maximization (EM) algorithm. Then the system was presented with a taxonomy and a collection of LOs. Each node in the taxonomy was labeled with few lexical terms or keywords, describing the concept itself. The system performed a classification of the LOs exploiting the prior knowledge encoded in the taxonomy, and then associating the proper metadata to the LOs. To evaluate the model in a real world scenario, the authors selected two sub-taxonomies from the ACM Computing Curricula: Intelligent Systems (IS) and Net Centric Computation (NCC). Then, they manually created the LOs repository by collecting the resources from the Web, classifying them onto the two given taxonomies. Starting from taxonomies and data, a set of terms for each taxonomy was selected as a vocabulary. In particular the vocabulary was determined separately for each taxonomy. Finally, they observed that in the average there are little more than two unique keywords to properly describe each class.

Ayad and Kamel [3] present a cluster ensemble method, that was applicable to LOs distributed clustering, and for overcoming issues of large-sized collections and a very high dimensionality of the vocabulary space. First, an initial significant reduction of the vocabulary space was proposed, where a data collection was distributed among multiple sites. Subsequently, a cluster ensemble method, consisting of three stages was introduced. Base clusters for multiple random subsets of the data were generated [4], followed by the application of an adaptive voting algorithm for solving the cluster labeling mapping problem. Finally, a consensus clustering solution was determined by merging similar clusters that may be produced by fine resolution base clusters. Then a maximum likelihood principle was applied on a resulting assignment probability matrix. The experimental results show that the proposed cluster ensemble method may successfully aggregates multiple partial clusterings into a single combined clustering for the entire collection. In addition, the combined clusters significantly improve the quality of the partial base clusters.

Meyer et al. [5] presents a new approach for the task of subject categorization of LOs. Instead of using typical LOs, the free encyclopedia Wikipedia [6] was applied as a training corpus. In the area of Learning Object Repositories (LORs), an adequate corpus is often not available. In particular for open domain LORs - repositories that accept Learning Resources about any topic - a training corpus is missing. And even for restricted domain repositories the manual creation of a training corpus causes a high effort. The authors used Wikipedia as a substitute corpus. In an earlier experiment, the suitability of Wikipedia was tested [7]. In addition, Gabrilovich and Markovitch have shown that Wikipedia can also be used for improving the classification accuracy in other knowledge domains [8]. The basic approach is to transform all Wikipedia articles into a word vector representation. LOs were also mapped to word vectors and compared to the article vectors; articles, which were very close to the LO vector were assumed to cover similar topics. Different machine learning algorithms may be used for the statistical learning task. However, the total amount of categories and articles imposes special requirements on the applied methods. When all categories were used, memory consumption become a limiting factor for the choice of the classifiers. Due to these limitations, the k-Nearest-Neighbors (kNN) approach was chosen for the experiments. The experimental results showed that the proposed approach was feasible, achieving an accuracy of 62%.

López et al. [9] describe an approach that uses multi-label classification methods for searching LOs tagged by Learning Object Metadata (LOM) [10]. Specifically, the model offers a methodology which illustrates the task of multi-label mapping of LOs into types queries through an emergent multi-label space, and that may improve the first choice of learners or teachers. The system provides individualized help in selecting learning materials establish a ranking system for the LOs. The authors compare the random k-labelsets (RAKEL) [11] and the multi-label k-nearest neighbor (MLkNN) [12]. They used a machine learning method to perform an empirical evaluation of both algorithms based on one LOs multi-label data sets. The authors also experimented with a machine learning, multi-label model which was built to use a training data set of LOs. RAKEL significantly outperforms the MLkNN algorithm in almost all measures, specially when taking into account the measure subset accuracy, which is equal to the zero-one loss for the single-label classification task of predicting the exact label subset. The RAKEL algorithm used for the classifier was very effective and was proposed for LO categorization. This algorithm used for the classification was very effective and was also proposed for LOs ranking. Multi-label classifiers such as RAKEL may be used for the automated tagging of large LOR collections with multiple LOs.
LEARNING OBJECTS SEMANTIC MODEL DESCRIPTION

To share and reuse knowledge it is necessary to represent a domain with a declarative formalism. This can be done by consolidating an ontology. Ontologies are defined by Borst [13] as an explicit formal specification of a shared conceptualization, where conceptualization means abstract models of a phenomenon. Ontologies may include an informal rules set which constraint its structure, which is often expressed as a concept set (entities, attributes, processes), their definitions and relationships. Formally, an ontology involves a theoretical organization of terms and relations used as a tool for the domain concepts analysis, organizing and capturing consensual knowledge that is accepted by a specific community (Studer et al. [14]).

To categorize LOs we must use a LOs standard description. Then, a proper definition of a list of domain categories is needed. We have defined a domain ontology called ContentCompass (CC) which is described in Figure 1. Our domain ontology includes the main concepts used in the Chilean Academic Curricula and the concepts used in the LOs discipline.

![ContentCompass Ontology](image)

**FIGURE 1.** ContentCompass Ontology

To formalize the ontology description, it is necessary to describe the concepts presented in this.

- **Educational domain concepts:**
  - Competence: A dynamic combination of knowledge, understanding, skills and abilities. A competence will be learned in various courses units and assessed at different stages. A competence can be distinguished between subject specific and generic ones.
  - Learning Goals: Statements that describe significantly and essentially the learning that the students have to achieve, and can reliably demonstrate at the end of a course or program. In simpler words, learning goals identify what the learner will know and be able to do at the end of a course or program. A learning goal contributes to achieve a competence.
  - Activity: Planned set of actions undertaken by teachers and students, inside or outside the classroom, individually or in groups, which aim to achieve the learning objectives.
  - Specific Activity: Instance of an activity in a specific context (associated with a geographic location, an event, a historical personage, a specific period of time) and a way to perform the activity (reading a document, to show a map, to develop a story, etc.)
  - Resource Specification: A category which can be used to support a specific activity, such as a video, audio, image or a map.
  - Resource: Information represented and stored in a variety of media and formats, which assists student learning as defined by provincial or local curricula. This includes but is not limited to, materials in images, video, and text formats, as well as combinations of these formats intended for use by teachers and students.
• Concepts of the Chilean Academic Curricula [15]:
  – Level: Set of lessons or classes about a structured subject, generally linked to a students group who goes on simultaneously.
  – Subsector: Knowledge and experience to be worked over a specific student teaching period (e.g. language, mathematics or history and geography)
  – Vertical Fundamental Objective: Competences or skills that a group of students should achieve at the end of the different educations stages and, which are the purpose that guides the teaching and learning process.
  – Unit: Organization of a disciplinary content which exhibits didactic solutions for their treatment.
  – Specific Content: Specific knowledge and practices to achieve skills and attitudes. They help in the promotion of order to satisfy the fundamental objectives referred to every single unit.
  – Expected Learning: Defines what is expected to the students achieves, expressed in a concrete, specific and feasible way. Expected learnings are meant to organize contents, activities and learning methods.

Other main component of our CC ontology is the content model description. We imports the ALOCOM [16] ontology to define the properties of the components and how these components may be aggregated. ALOCOM distinguishes Learning Object Components and Learning Objects; both are further subdivided to represent narrower granularity definitions of other content models. Learning object components are:
  • Content Fragments (CFs): Individual content components such as text, images, audio and video fragments.
  • Content Objects (COs): Learning object components that aggregate content fragments. Content objects focus on a single piece of information and may be used to explain a concept, illustrate a principle, or describe a process.
  • Learning Objects (LOs): Aggregation of COs and learning objectives.

We define several object properties to relate concepts of both ontologies. The fusion of both ontologies is shown in Fig. 2. We summarize these properties in the following list:
  • A Resource is equivalent to a Content Object
  • A Learning Goal is supported by a Learning Object
  • An Activity and a Resource Specification requires at least one Learning Object.
  • Learning Object is a subclass of Learning Object Component.

The CC ontology extends the ALOCOM ontology to describe a learning content model. We used the standard IEEE LOM (2002) for the description of LOs, COs and CFs. A detailed mapping between IEEE LOM metadata and the ontology concepts that will record each metadata is reported in Table 1.

In our CC Ontology the relationships between domain concepts and topics (basic relations for the categorization process) are described. Expected Learning, Content Object and Content Fragment are referred to domain topics. We summarize these elementis in Fig. 3.
TABLE 1. ContentCompass: Ontological Model Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>LO</th>
<th>CO</th>
<th>CF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Catalog</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Title</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Language</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Description</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Keyword</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Scope</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Type</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Entity</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Date</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Format</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Size</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Location</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Duration</td>
<td>X</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

FIGURE 3. Alocom-ContentCompass Ontology

These relationships and their instances are used as the base for the Bayesian categorization process. We use the topics relationships between Content Objects and Expected Learnings to calculate our statistical categorization model.

CATEGORIZATION APPROACH DESCRIPTION

A key step in our framework is to favor the automatic recommendation of LOs. To do this we need to improve their descriptions. In this article we improve the descriptions using a categorization algorithm based on Bayesian Networks to relate LOs with domain classes defined in the CC ontology (Expected Learnings and Activities).

Figure 4 shows the categorization process, which consists of the following steps:

1. In a first step we receive LOs descriptions indexed from the Web or LOs description proposals from specific users.
2. In a second step we validate the description or a set of LOs descriptions (structured as XML documents) compliance with the IEEE-LOM standard [10] used in CC ontology.
3. By using the ontology and the categorization algorithm we take the domain topics contained in the LOs descriptions and based on the Bayesian network categorization, favoring the identification of connections between descriptions and domain classes (Expected Learnings and Activities).
4. Finally we storage the new descriptions (including the relationships with the Expected Learning and Activities) in a semantic repository.
Document categorization is the task of assigning a Boolean value to each pair \(<d, c> \in D \times C\), where \(D\) represents a document collection, for our approach the LOs descriptions. Let \(C\) a set of categories (Expected Learning in our case), \(d\) a document (LOs) that belongs to \(D\), and \(c\) a category which belongs to \(C\). A Boolean value equals to 1 represents that \(d\) was categorized into \(c\), 0 in other case. This kind of categorization is known as hard categorization. There are also soft methods which associate a score to each pair \(<d, c>\), allowing that eventually a document may belong to more than to a only one category. According to Sebastiani [17], a document categorization task corresponds to the approximation of an unknown target function \(\phi: D \times C \rightarrow \{0, 1\}\) when we consider hard categorization. If the target function is \(\phi: D \times C \rightarrow [0, 1]\) the method is a soft categorization one.

Bayesian categorization methods are based on generative models for document representation, which use a parametric mixture approach, where each category represents one of the components to combine. The model has the following expression:

\[
p(d) = \sum_{j=1}^{C} p(c_j)p(d|c_j)
\]

where \(d \in D\) and \(c_j \in C\). Using the Bayes rule we can obtain the probability that represents the event “\(d\) generates \(c\)”, as follows:

\[
p(c|d) = \frac{p(c)p(d|c)}{p(d)}
\]

To classify a document, a maximum posteriori probability selection process is conducted, where \(p(d)\) is constant. Thus, the categorization is defined only by the product \(p(c)p(d|c)\), also known as the discriminator. The \(p(c)\) probabilities are a priori probabilities. These a priori probabilities can be estimated by counting the number of documents which belong to \(c\). The \(p(d|c)\) probabilities can be estimated using the terms that compound the content of \(d\).

Several extensions to the basic Bayes method have been discussed in the state-of-the-art. These variations claim for different assumptions regarding the generative process of construction of each document. However, the vast majority of these extensions adopts a statistical independence assumption for term co-occurrence. These methods are known as naive Bayes methods.

In particular, multinomial naïve Bayes methods assume that term occurrences in a document follows a multinomial distribution. Thus, a document corresponds to a term sequence assuming that the position of each term is generated independently to other terms. Let \(V = \{t_1, \ldots, t_n\}\) be a vocabulary where the content of the collection \(D\) is represented. Each class \(c \in C\) has an association with a set of parameters \(\tilde{\Theta}_c = \{\theta_{c,1}, \ldots, \theta_{c,n}\}\), where each of them corresponds to a \(p(t_i|c)\) probability, which represents the event “\(t_i\) occurs in \(c\)”. It holds that \(\sum_{i=1}^{n} p(t_i|c) = 1, \forall c \in C\). The likelihood of a document \(d\) regarding a class \(c\) is given by the following expression:

\[
\log(p(c|d)) \approx \sum_{i=1}^{n} \log(1 + \frac{T_{f_i,d}}{N_{i}}) \log(\frac{2N - n_i + 1}{n_i}) \log(\frac{2(|C| - c_{f_i} + 1)}{c_{f_i}})
\]
where \(|C|\) represents the number of classes in \(C\), \(c_f_i\) is the number of classes of \(C\) in which \(t_i\) occurs, \(n\) represents the set of topics \((t_i)\) in the vocabulary, \(T_{f,d}\) represents the number of occurrences of \(t_i\) in the document (LOs) \(d\), \(L_d\) is the length of \(d\), which corresponds to \(\sum_{i=1}^n T_{f,d}\), \(N\) represents the number of documents in the collection, and \(n_i\) is the number of documents where the term occurs.

**IMPLEMENTATION IN THE CONTENT COMPASS PLATFORM**

The CC ontology and the LOs categorization method were implemented and included in the ContentCompass Platform (CCP) to build a management platform in the History and Geography domain (see Figure 5). We can import new LOs in the CCP from the crawler and indexer services or directly from the Web Resource Ingestor App. Then the import/categorization service validates the new descriptions indexed from the Web or recommended from a user by applying our categorization technique. Then, by using the LOs descriptions we can categorize the LO in a specific class of the CC ontology. Finally, we aggregate the new descriptions to the CCP semantic repository.

**FIGURE 5.** CC Platform Architecture for LOs Recommendation

To improve the educational material generation we use the CC ontology, searching for some LOs based-on an academic curricular structure. We do this by using the Manual LOs Aggregator App, the Academic Curricular LOs/COs Searcher Widget and the LOs/COs Searcher Service. Figure 6 shows the curricular search based in the CC ontology.

Based on the curricular search the teachers may define their pedagogical requirements to generate a class. Then they finish this process and search objects the CCP recommend a LOs set related with the pedagogical query, as is shown in Figure 7.

Using this framework, the teachers may build and manage their own LOs based on existing LOs and COs recommended in the CCP. Users may create new LOs (generating and describing the new LOs), add/delete COs and/or LOs from the LOs (generated by a user), delete their own LOs, and export LOs to SCORM (see Figure 8).

**EVALUATION**

We evaluated the recommendation approach effectiveness and efficiency for the LOs search and composition process with a controlled experimental study. A group of eleven Chilean History and Geography teachers applied our approach
The main hypothesis of the experiment is:

“Improving the LOs recommendation allows teachers to compose educational materials (lectures, courses, presentations, etc.) in a process that requires less effort and produces higher quality results”.

To test this primary hypothesis, the following operational, null and alternative hypotheses are defined:

- $H_{A0}$: The quality of the generated classes using our CC platform is the same that the one obtained by using the Ad-Hoc approach.
- $H_{Ab}$: The quality of the generated classes using our CC platform is better than the one obtained by using the Ad-Hoc approach.
- $H_{B0}$: At the same quality, the effort required to generate classes with our CC platform is the same as with the Ad-Hoc approach.
- $H_{Bb}$: At the same quality, the effort required to generate classes with our CC platform is lower than the one involved in the use of the Ad-Hoc approach.

The independent variables that can affect the quality of the composed LOs, and the effort required to generate them are:
**Approach:** The approach used to recommend LOs in the search and composition process. This is the factor under study, with two levels: “CC approach” and “Ad-Hoc approach”.

**Subjects Experience:** Participants had knowledge on the lectures development in the History and Geographic domain, and they did not have prior experience using the CC platform. This is an undesirable influence factor, and the chosen experimental design aimed to minimize its impact; we address this limitation by implementing training sessions were provided, trying to equilibrate the process conformance during the experimental study.

In order to test the hypotheses, the dependent variables quality and effort are defined and measured, as follows:

**Quality:** The level at which LOs match the pedagogical requirements. This variable was evaluated by experts in the History and Geography domain, using the following rating scale:

- Deficient.
- Good.
- Outstanding.

**Effort:** The amount of minutes needed to search and compose LOs which satisfies the pedagogical requirements.

The experiment was divided into two phases and the subjects were assigned to two groups (Group 1 and 2, respectively). In Phase 1 we did a training in the CC and Ad-hoc approach to both groups. Then Group 1 applied the CC approach on the description of the educational requirements (classes and expected learning) and Group 2 applied the Ad-Hoc approach on the same description of requirements (Requirement-1). In Phase 2 the groups were exchanged by applying approaches (i.e., Group 1 applies Ad-Hoc and Group 2 ContentCompass) in a new description of requirements (Requirement-2).

Documents Requirement-1 and Requirement-2 contain a description of the pedagogical requirements (Level, Sub-sector, Vertical Fundamental Objective, Unit, Specific Content, Expected Learnings) based on how teachers executed a curricular search and used the material found (recommended in the CC platform or recommended by Google using the Ad-Hoc approach) to compose her/his classes. In each document we established the requirements to compose two classes. Therefore by considering phases 1 and 2 the teachers generated 44 classes.

Table 2 shows a summary of the composed classes for each approach, including phases 1 and 2.

<table>
<thead>
<tr>
<th>TABLE 2. Composed Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ad-Hoc Approach</strong></td>
</tr>
<tr>
<td>Classes Generated</td>
</tr>
<tr>
<td>Deficients</td>
</tr>
<tr>
<td>Good</td>
</tr>
<tr>
<td>Outstanding</td>
</tr>
</tbody>
</table>
We applied a Chi-square test over this data showing that there are no significant differences between both data set ($p-value = 0.1069$ and $\alpha = 0.05$). Thus we rejected $H_{A0}$. A less formal analysis can be made looking at the quality frequencies presented in Figures 9 and 10 which show the expert evaluation for the composed classes in each approach. Regarding classes composition based on our recommendation approach, the results showed that the experts compose more (20 v/s 16) and better classes using our recommendation approach (implemented in the CC Platform). With our approach the classes evaluated with a Good quality were increased by 14%.

![FIGURE 9. Ad-Hoc Approach Results](image)

FIGURE 9. Ad-Hoc Approach Results

![FIGURE 10. CC Platform Results](image)

FIGURE 10. CC Platform Results

Table 3 presents the mean and standard deviation values for the effort in each treatment applied.

<table>
<thead>
<tr>
<th></th>
<th>Effort [Minutes]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>Content Compass</td>
<td>14.25</td>
</tr>
<tr>
<td>Ad-Hoc</td>
<td>20.125</td>
</tr>
</tbody>
</table>

The Kolmogorov-Smirnov test [18] rejected the assumption of normality for the ContentCompass dataset with a $p$-value of 0.003925 ($\alpha = 0.05$). Based on these results we used the Mann-Whitney tests to compare the approaches. The effort variable (measured in minutes) delivered statistically significant results ($p-value = 0.013$ and $\alpha = 0.05$) providing enough evidence to reject its associated null hypothesis $H_{B0}$. Thus a one-side Mann-Whitney tests was applied, showing that ContentCompass required less effort than the Ad-Hoc approach to compose each class.

**CONCLUSIONS**

The CC approach aims to support teachers in the composition of didactical material (LOs) for a given set of pedagogical requirements, by using recommended objects and a curricular structure. It uses as input: 1) A problem description, which may be in natural language; 2) An educational domain structure and the LOs content model using an ontology, and 3) An automatic categorization approach to relate LOs with domain classes, allowing to find and reuse LOs with less effort than a Ad-Hoc approach (Google search). It is implemented in a real world framework, named CC Platform, producing as outcome a set of pedagogical materials in SCORM standard.

An experimental study was conducted to compare the CC approach with an Ad-Hoc approach. Our experiments show that the CC approach and the Ad-Hoc approach achieves similar quality results by requiring a human effort significantly lower than the one needed by the Ad-Hoc approach.
REFERENCES