

## International Journal of Computer Science and Mobile Computing



A Monthly Journal of Computer Science and Information Technology

ISSN 2320-088X

*IJCSMC, Vol. 3, Issue. 8, August 2014, pg.662 – 668*

### **RESEARCH ARTICLE**

# Improving the Effectiveness of Learning Content Retrieval through Content Classification and Profiling

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**Abstract**— *eLearning plays an important role in educating the people across the world. With the advancements in the WWW and communication technologies the developing countries like India harness the possibilities of creating educated communities. However the lack of proper learning content and appropriate support for the learners suppress the growth of eLearning. This paper proposes Collaborative eLearning System (CeLS) that uses classification based approach wherein, the LOs are provided through various groups such that the learner could get them from the group that can give the maximum support for learning. The results have highlighted that fact that learning content can no longer be created in “one size fits all” fashion by sensitizing the effects of retrieving the most appropriate learning content for the learners.*

**Keywords**— *Learning Objects, granular LOs, classification of LO, learner support, active learning, learner groups*

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## I. INTRODUCTION

The eLearning environment across the world is primarily managed using the Learning Management Systems (LMS) that handles all the management related activities with respect to learning viz. learner management, content repository, assignments, quiz, grading, etc. Since in eLearning the primary focus is on the content to be delivered to the learners, the paradigm has shifted from LMS to Learning Content Management System (LCMS). The LCMS address the issues with the nature and the form of the content that would benefit the needs of the learners [1]. The standards like Sharable Content Object Reference Model (SCORM) stresses for the portability of the learning content across the LMS platforms in order to reduce the cost and effort needed to create the LOs by allowing the LOs to be effectively reused. The LOs presented to the learners are made in one size fits all fashion wherein the same learning content is delivered to the diversified learners with different requirements. Also, the learners of LMS are not supported properly in identifying and utilizing the best suitable LO for them. The aim of any eLearning environment is to deliver the contents to its learners precisely based on their requirement. However, there are certain issues related to selecting the appropriate learning objects that caters the various learning needs and requirements of the learner. The recommendation approach for the actors of e-learning is based on the collaborative filtering approach and some characteristics of e-learning, namely: the roles and interests of actors as well as the representation of learning resources [2]. In Adaptive Educational Hypermedia Systems (AEHS), the learning content presentation should be appropriately retrieved from learning

object repositories, and dynamically tailored to each learner's needs [3]. In order to achieve this, the LMS must know about the learner's skills and preferences well in advance.

In a typical eLearning environment, the learner's skills and preferences are recorded with the help of Learner Profiles (LP). It is this LP that plays a pivotal role in determining the best suitable LO for the learner over their learning cycle. The IEEE Public and Private Information and IMS Learner Information Package standards support creation and migration of LPs across the learning platforms so as to support the learners over different LMSs [6]. However, the LPs created based on these standards focus mainly on the preferences specified by the learner on the type of learning content and the mode of delivery. So the profiles are being used as a tool to filter the LOs based on the explicit preferences of the learners. This hinders the need for considering the implicit requirements of the learners and their changing needs over the learning cycle. Also, the Learning Object Metadata (LOM) which is used with every LO, is rarely given any weight even though it carries the sensitive information about the nature of the object. The survey on the usage of LOM attributes across the LMSs have highlighted that only a few attributes are frequently used along with the LOs and others are mostly being ignored. The reach of any LO created and delivered across the LMS relies on these metadata as it helps in identifying the objects precisely for the learner. The lack of LOM attributes and LP attribute usage that reflects the learner's dynamic learning requirements has resulted in breeding of LOs that serves no purpose. With the growing demand for collaborative learning spaces, the need for interaction and grouping arises to create knowledge network wherein the learner is capable of sharing the bookmarks, create collaborative content, discuss and form groups to achieve a specific goal. Integrating the social learning as a part of Learning Management Systems helps to achieve effective learning over the existing platforms [4]. So, the LMS of today's era must support the learner to get the precise content with proper social support in order to capitalize on the growth of technology.

## II. PROPOSED SYSTEM

Since the existing systems allow objects to be created in any file format, the contents inside most of the objects are static by nature. The various formats in which the contents are presented to the learners are documents, videos, etc. These formats do not allow the existing content to be modified or allow for new content to be added dynamically. The drawbacks with the existing systems are due to the misunderstanding of the term LO and its definition by the content creators. In order to solve the problems with content presentation and structure, a new method of content creation has to be adapted such that the task of retrieving the precise content becomes easy.

The proposed system named Collaborative eLearning System (CeLS) addresses the issues related to large granular objects like eBooks, documents, etc. These include the common metadata for the entire document or eBook where only a few of the important elements inside the content are addressed through the metadata. To overcome the limitation in retrieving the precise contents, the LO must be assembled by composing the digital content along with the appropriate metadata. Such an assembly would help to create small granular LOs that can be easily retrieved through learner searches.

### Granular content creation and assembly

Granularity of a LO can be purely based on the environment in which these LO are used. For example if the LO is a video object, it can be of 45 minutes to one hour that represents a class room lecture. However, for text objects there are no such restrictions on the amount of content that could represent a LO. So the text objects can be as simple as a definition or it can be a large one like a lesson or chapter. The Larger the LO, the more difficult for that to be reused by parts.

The work proposed in this paper highlights the importance of creating small granular Los that caters a specific learning objective of the learner. The LOCAI implemented in this work has considered the following factors in creating a LO. They are viz. the content scope, semantics, and the information attributes as its metadata. The content author creates small granular LOs through the LOCAI along with the necessary metadata and stores it inside the LOR. These LOs are made available to the learners as LO updates. The learner, who is in need of a specific LO, uses the search interface by giving the appropriate metadata to search the LOs. The LOCAI takes the query and retrieves the LOs that precisely match with the keyword. Such small granular objects thus retrieved are presented to the learners through the mobile and desktop devices. The interface for creating the small granular LOs given in figure 1 highlights the various metadata used in creating the LOs. The metadata were picked based on the survey results on the most frequent metadata being used across the LORs in the world.

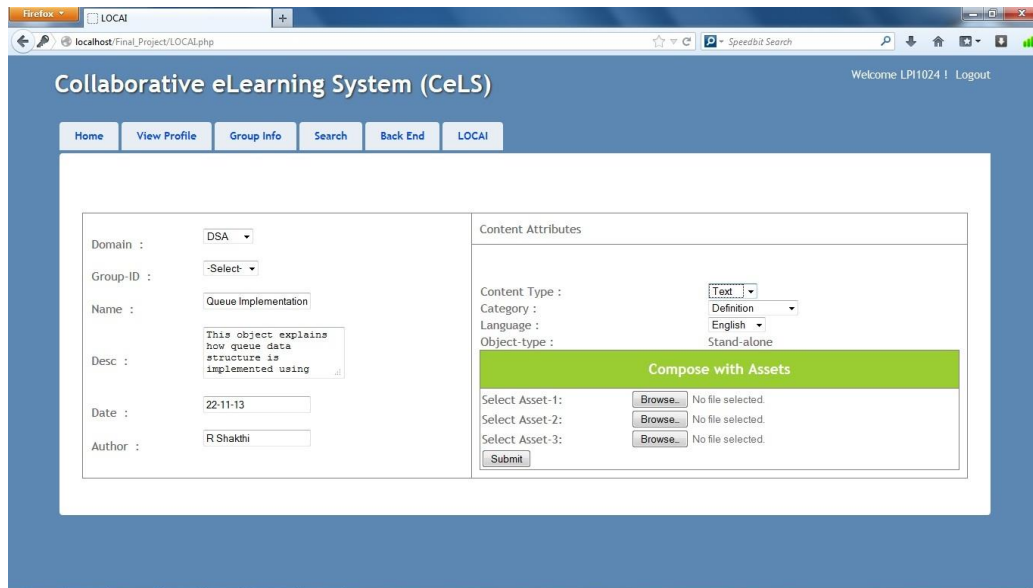


Fig. 1. Snapshot of LOCAI

LOCAI supports creation of LOs with respect to specific domains. It is this domain information that helps to classify the LOs. The domains are broad subject areas under which the LOs falls under. Examples of domains are data structures, artificial intelligence, etc.

**Learner Profile creation**

In CeLS the user information is stored under the learner profile. This LP is primarily categorized into Generic Profile (GP) and Specific Profiles (SP). The GP of the learner holds the basic information about the learner viz. personal, academic, preferences, skills, learner’s exposure to subjects, knowledge gained, etc. This information is recorded into the GP at the beginning of a course by the learner. The SP is created for each course the learner takes up. The need for classify the profiles arises out of maintaining specific preferences of the learners with respect to a subject domain. For example the learner may respond well with theorems in mathematics however when it comes to physics the learner may be good at graphical content. The difference in such subject related information is very well maintained across the different SPs created for each subject.

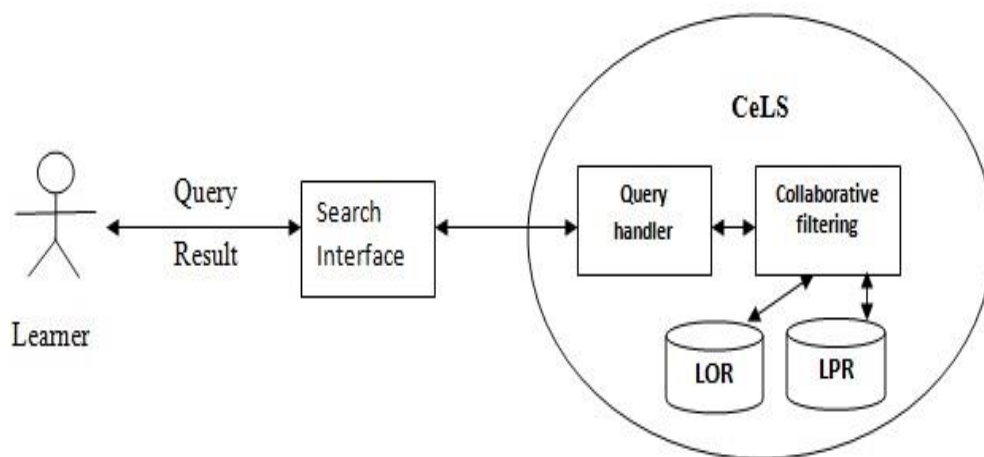


Fig.2. Architecture of CeLS

The architecture of the proposed Collaborative eLearning System (CeLS) is given in figure 2. There are three main stake holders involved in CeLS they are the learners, content authors and group administrators (collaboration managers). The learners of the system have to register with CeLS and create a GP for their own. The content authors propose the LOs to be used by the learners and these objects are stored inside the LOR. The group administrators of CeLS accept or reject the LOs proposed within the group. Also, they create and manage the groups and its users. The search interface takes the learner query and forwards it to the query handler. The query handler in turn extracts the learner ID and the keyword from the query and uses them to retrieve the learner

profile and LOs from the LPR and LOR respectively. The retrieved LOs are then filtered by the collaborative filtering approach where the affinity between the LOs and the Learner Profile is determined. This affinity value is used to order the LOs retrieved before it is being delivered to the learners.

### **Dynamic Learner Profile Update**

The learner profile created in CeLS by considering the parameters of the IEEE and IMS standards reflects the activities of the learner over the eLearning environment. This is achieved by dynamically updating the profile of the learner whenever the learner learns a particular topic or they take up an interactive activity like quiz etc. Whenever the learner likes an object, the SP for that domain gets updated over the preferences, skills and knowledge aspects.

### **Content classification and grouping**

This module of CeLS focuses on formation of learning groups and posting of learning contents. The groups thus created are to be administrated by the person who is made in-charge of the group. The content authors are allowed to post the small granular contents into the group under the appropriate domains. The contents thus posted will be advertised to all the members of the group. The group will have the content that will be available to all the members and non-members of the group along with the contents that are only available for its members. Each group has a moderator who has the role of approving or rejecting the LOs based on the suitability of the content. Several groups can be created under each subject domain in-order to host the contents of respective authors. All these groups have a common learning path to be followed by the learners.

### **Establishing support for LOs**

The learners can either explicitly join the group or utilize the public content without joining the group. The group adds additional information to the LO in the form of peer support, alternative content, pre requisite, etc. The LOs of a particular group might have been understood by so many learners in the group. The people who understood that content are considered to be peers. The more the peer support for the content, the more will be the benefit for the learner. So the learner who wishes to learn from their peers would prefer the content that has the peer support. Similarly some learners expect the alternative explanation for the contents which they wish to learn. In such cases, the alternative content support on content adds weight to the content. The content classification helps to diversify the content options available to the learners based on the extent to which the support is provided. Whenever the learner searches for a specific content, the same content available in different groups are presented to the learner so that the learner can choose the content that provides the best support for them. Since the learner is not forced to explicitly join a specific group, the learner has the free hands to utilize the contents of different groups. Once when the learner has utilized a threshold number of objects from a specific group, the system would suggest the learner to join the group and utilize the unused contents of that group. This kind of dynamic group decision method greatly benefits the learners.

### **Mapping the learner profile to LOs**

The final module is mapping the learner profile with the appropriate LOs that provides the proper support to the learners. This can be achieved by determining the attributes of the LP and the group attributes. First the learner profile attributes must be considered to identify the LOs that cater the requirements of the Learner Profile. For this, the learner profile attributes can be assigned weight based on the requirements of the learner. The LOs that caters the requirement of a particular learner profile are then retrieved. Such retrieved object's parameters have to be evaluated against the learner profile attributes. If there is a match for a profile attribute in an object, then the matching on that attribute is considered to be successful. Otherwise the match on that attribute can be considered a failure.

### **Query handling and Domain filtering**

The learner query keyword is used to retrieve the LOs for the learners. The interface must give the provision for the learner to enter the keyword based on which the search has to be made. Also there must be provision for searching with and without profiling.

Once the search query is taken from the learner, the next step is to identify the domains to which a particular search query keyword matches to. Since a LO may belong to more than one domain, they have to be filtered according to the domain of interest of the learners.

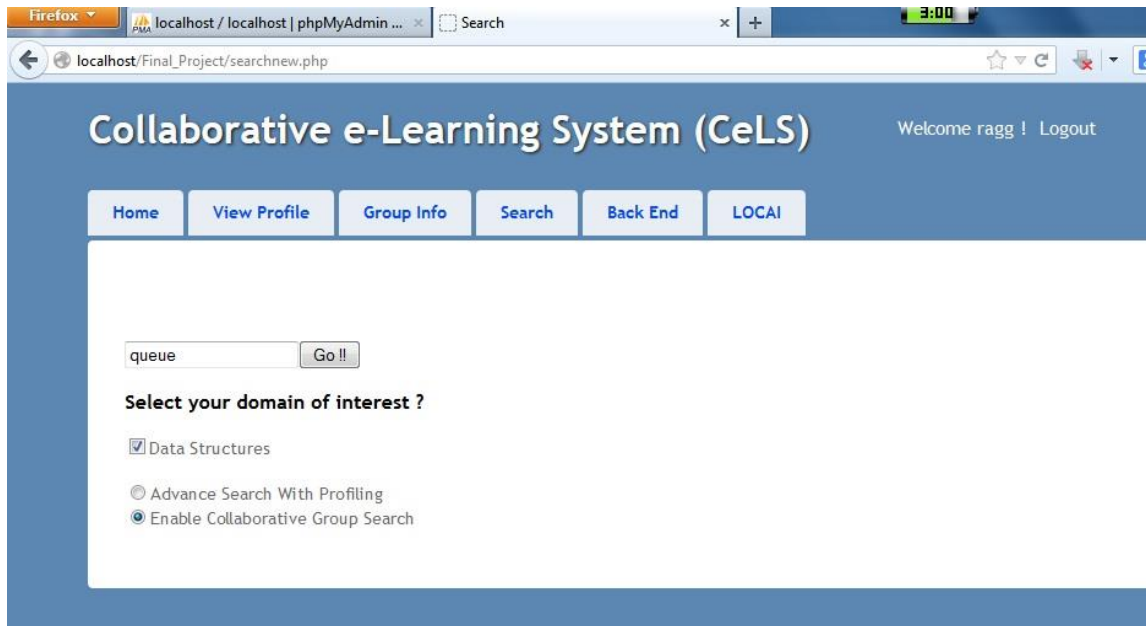


Fig. 3. Filtering the learner search based on domain

The interface in figure 3 presents the list of all the domains under which the retrieved LOs falls under. The learner in turn selects their domain of interest to fetch the LOs that of that domain. This gives the learner the flexibility in selecting the appropriate domain to filter the content.

### Re-ranking the LOs based on learner profile mapping

The match on all the attributes of the learner profile with that of the LO can be represented in the form of a two dimensional matrix space. The rows of the matrix can represent the LOs retrieved and the columns represent the attributes of the learner profile. The cells of this matrix hold the information on whether a profile requirement is catered by that object or not. The collective information on all the cells of a row in that matrix represents the extent to which each object can cater the learner’s requirement.

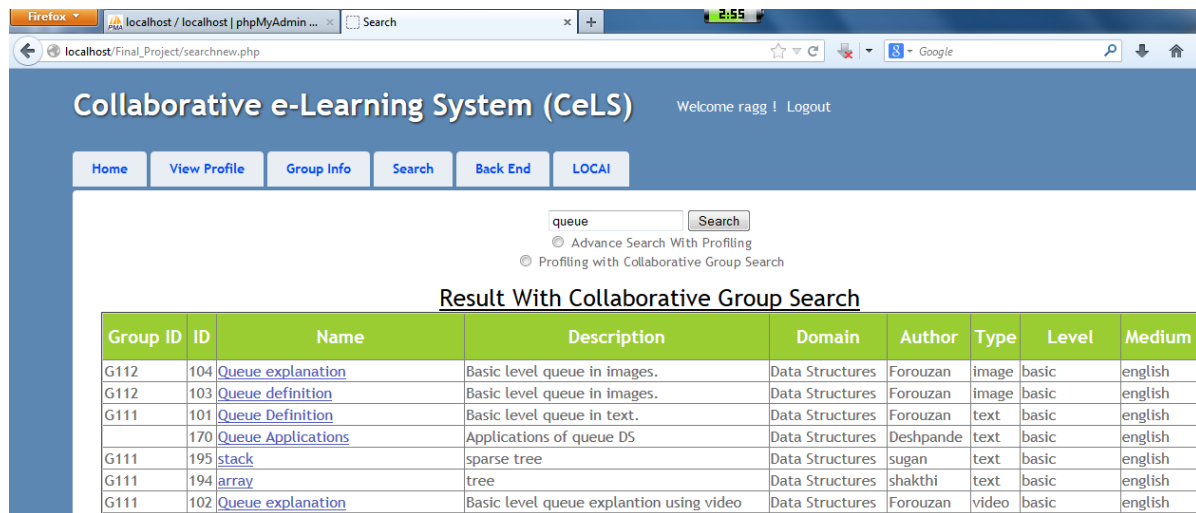


Fig. 4. Re-ranked results retrieved based on a profile

The result of the matrix thus obtained conveys the extent to which the learner profile matches with the objects. In order to know the level of match between the profile and the objects based on the support provided by the objects, the matrix value is recomputed to consider the weights for the support attributes. This fulfils the profile requirement of the learner along with the necessary support needed by the learner to make use of the object. This method of matching the learner requirement with the LOs helps to find the closest matching result to the learner. Figure 4 shows the snapshot of results retrieved based on the matching score.

### III. EXPERIMENTAL RESULTS

In our work we have created about 64 small granular objects under the subject domain “Data Structures”. These LOs were given the appropriate description keywords and stored inside the LOR. A sample set of 32 learners took part in searching the LOs using the keywords. The learners were categorized into three batches viz. batch1 to batch3. Batch1 learners were beginners, whereas batch2 and batch3 learners were intermediate and advanced learners respectively. As the learners utilize the LOs, their profiles get updated with the information on the object’s utilization by the learner themselves. As the learner took up the Data structures course, the CeLS have recorded the utilization of LOs by the learners. The skills, preferences and knowledge of the learners were updated over the utilization of LOs. The precision of retrieval [5] was calculated through the formula given in 1,

$$\text{Precision} = \frac{\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}}{\{\text{retrieved documents}\}} \quad (1)$$

Since most of the LOs retrieved are relevant to the query keyword used by the learner, the precision of retrieval at top k results is used as a measure to determine the accuracy. Precision at top k is the number of top k objects utilized over the total number of objects retrieved. The k value may be 1, 3, or 5 depending upon the application or the number of LOs available under a given topic. In our study we have considered the k value as 3 to determine the effectiveness of CeLS.

Table 1.0 lists the difference between the LOs retrieved and the number of LOs relevant for the learner with and without using CeLS based recommendation.

TABLE I  
STUDY DATA ON LOS RETRIEVED THROUGH CELS

	No. of learners	No. of search iterations	Objects utilized at top 3 (without CeLS)	Objects utilized at top 3 (with CeLS)	Precision at top 3 (without CeLS)	Precision at top 3 (with CeLS)
Batch1	12	28	11	19	0.39	0.67
Batch2	10	24	8	17	0.33	0.7
Batch3	10	22	8	13	0.36	0.59
Mean	10.6	21.3	9	16.33	0.36	0.65

The graph in figure 5 shows the difference between the effectiveness of LO retrieval in traditional LMSs and in CeLS.

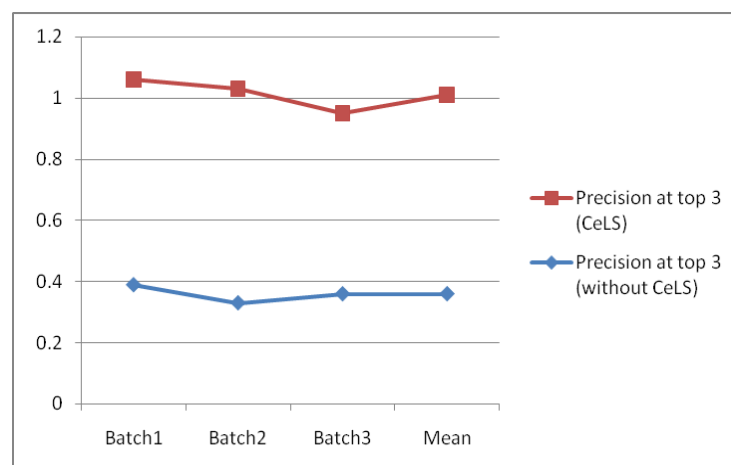


Fig. 5. Traditional LO retrieval vs. CeLS

### IV. RESULT ANALYSIS

The results have shown that the average precision of CeLS on 64 search iterations is 65% whereas that of searching without profiles being 36%. The reason for less precision in cases where searching is made without profiles is that the learner requirement is less known by the system so it provides the content based on “one size fits all” principle. CeLS have thus improved the overall effectiveness of LO retrieval over the traditional searching by 80%.

## V. CONCLUSION AND FUTURE WORK

The problems associated with large granular LOs have been resolved by creating an interface to assemble the LOs. These small granular LOs can be used in combination to create a large granular content like a chapter or a lesson. However, due to the voluminous amounts of LOs available across the WWW, there is an inherent need to give the most suitable object for the learner based on their learning skills. So this work addressed the issue by considering the skills, preferences and knowledge of the user with respect to a subject domain to find the most suitable LOs for the learner. Altogether, the CeLS have proved to be effective in retrieving the most relevant objects for the learners which the other popular LMS failed to achieve. The future work is aimed at dynamically updating the weight of the profile attributes in order to give additional privilege for the most important attribute that highlights the learner's interest.

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