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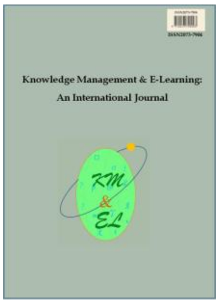

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Affinity-based learning object retrieval in an e-learning environment using evolutionary learner profile

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Abstract: With the abundance of learning objects (LOs) available across the web, there arises a demand for retrieving the LOs that exactly suit the learners' requirements. In order to achieve this, the learner profile (LP) should exactly mimic the subject specific requirements of the learner as well as evolve over the learning cycle. Moreover, each LO should project itself in such a way that the learning management system is able to find it as a suitable candidate for a specific learner requirement. This paper proposes a novel method that fetches appropriate LOs for the learner by mapping his/her learner profile with those of the LOs. The LOs thus retrieved are then re-ranked according to their affinity towards the particular learner's requirements and then presented to the learner. The experimental results demonstrated the effectiveness of the proposed method in retrieving appropriate learning content for learners.

Keywords: Learner profile; Evolutionary profile; Learning object retrieval; Learning object profile

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1. Introduction

With the advancement of web 2.0 and information and communication technologies (ICTs), e-learning has become an accessible mode of education for many people around the world. In many e-learning applications, the learning management systems (LMSs) like BlackBoard and WebCT are used to deliver the learning objects (LOs) to learners (Dabbagh & Kitsantas, 2005). The LOs delivered through these LMSs are usually attributed with additional information called Learning Object Metadata (LOM) that helps to search and discover the objects from Learning Object Repository (LOR) (IEEE LTSC, 2002; Heery & Anderson, 2005). The cost and time factors involved in the making of LOs have stressed the need for reusable LOs that can be used across different LMSs (Boyle, 2003). In order to achieve the reusability, the LOs should be made granular and should support aggregation at various levels like topic, chapter and course (Balatsoukas, Morris, & O'Brien, 2008). With the focus of e-learning environments slowly shifting towards personalized learning, the learner requirement plays an important role in retrieving the most appropriate content for the learners (Beetham & Sharpe, 2013). The explicit representation of learners' requirements in an e-learning environment is achieved through learner profile (LP), which links up the entry level competencies, learning participation and outcomes attained by the learner (Yukselturk & Top, 2012). The IEEE and Instructional Management Systems (IMS) standardized the usage of learner profile attributes though their Public and Private Information (PAPI) and Learner Information Package (LIP) standards respectively. These standards have explicitly defined the profile attributes in such a way that they can be used uniformly across LMSs. The attributes of these LP standards mainly fall under the following categories including learner identification, skills, and preferences. Similarly, the IEEE LOM standard categorizes the LO metadata attributes under nine different classes including general, lifecycle, meta-metadata, technical, educational, rights, relation, annotation, and classification, which better describes the object's nature and its connections with other objects.

The mushrooming of LORs across the World Wide Web has increased the availability of LOs thereby, indirectly adding the burden to the learners in finding the most suitable learning content that can cater for their learning needs. In any e-learning environment, it is the LMS that maps the learner query with the LOM attributes in order to discover the LOs available over the repositories. In this case, if the LMS is not aware of the exact, context specific learning needs of its learners, then they cannot retrieve the most appropriate objects for them.

2. Literature review

The literature review is organized under three sections of which, the first section highlights the need for creating granular LOs in an e-learning environment. The second section is focused on the usage of learner profile in order to represent the learning requirements of the learner. The last section sheds light on the importance of LOM and the way they can be effectively used in retrieving the LOs.

2.1. Granular content creation

The extent to which a LO can be reused is purely decided based on its granularity and composition. The smaller the LOs are, the greater the flexibly in reusing them as a part of many other objects. In order to reuse a LO effectively, it has to be modular, non sequential, generic, coherent and should support a single learning objective (Longmire, 2000). The finely granular LOs can be easily assembled together according to the needs of the learner at various levels like topic, lesson or even a course. This adds flexibility to learning content creation by allowing the authors to create contents of various sizes and depths based on the requirements of the target audiences (Hodgins, 2002).

Raghuveer and Tripathy (2012) in their work highlighted the drawbacks of delivering the large granular LOs like document files, e-books, etc. through the LMS and its impact on the precision of retrieval. The LOs were created based on Object Oriented Principles (OOP); wherein, the LO class and its attributes decide the content and metadata of an object. The Learning Object Content Assembly Interface (LOCAI) presented in their work has restricted the size of the LOs based on the learning objective and content category. The finely granular LOs (e.g. definition) created through LOCAI have their own metadata and were easily locatable by the learners amongst a vast collection of LOs. Also, the large granular LOs (made by assembling such finely granular LOs) were easily discovered with the help of the metadata of their constituent objects. The idea of assembling the LOs has enhanced the flexibility in learning content creation by allowing the authors to dynamically add or remove contents based on the learners' requirements.

2.2. Learner profiles

The learner information plays a vital role in identifying suitable contents for the learners over the e-learning environments. With the LMSs becoming learner centric these days by offering them more assistance in learning (like collaboration, forums, etc.), understanding the learners' skills and capabilities becomes an inherent need of any LMS. This would help the LMSs to search and discover the most appropriate LOs for the learners rather than just retrieving the similar contents for all the learners.

Today's learning environments support searching of LOs over the repositories based on the information like learner background, preferences (type of the content, its format, author, etc.), etc. collected explicitly from the learners at the time of course registration. These preferences are then used to filter the LOs retrieved in order to provide the personalized learning content for the learner.

The IEEE PAPI and IMS LIP standards classifies such explicitly collected learner information under the categories like personal, preferences, security, relations, performance, and portfolio as given in Fig. 1 (IEEE 1484.2.1, 2002; IMS LIP, 2008) . All these categories together address the four major aspects of learner information viz. Learner Identification, Preferences, Learner Competencies and Learner Information Management.

As shown in Fig. 1, majority of these LP attributes hold generic information about the learner that is used invariably across the subject domains to retrieve the LOs. The study of the existing systems has revealed the fact that only certain attributes of the learner profile viz. learning style, performance, or preference are frequently used in recommending the LOs. Graf, Kinshuk, and Liu (2008) has proposed the literature based learning style determination for adaptive content delivery wherein, the LMS analyzes the learning behaviour of the learners to determine their learning styles. This method is different from the questionnaire based learning style determination where the learning style is derived from the answers obtained explicitly from the learners. The behaviour based learning style determination dynamically records the changing learning styles over the learning cycle. Hnida, Idrissi, and Bennani (2014) proposed competency based approach for personalizing the learning path of the learner and provide the appropriate LOs based on that. The competency of the learner is derived based on their knowledge and the way they have used it to obtain the necessary skills. Their work primarily focuses on adaptive learning path based on the learners' knowledge attainment and the utilization of knowledge.

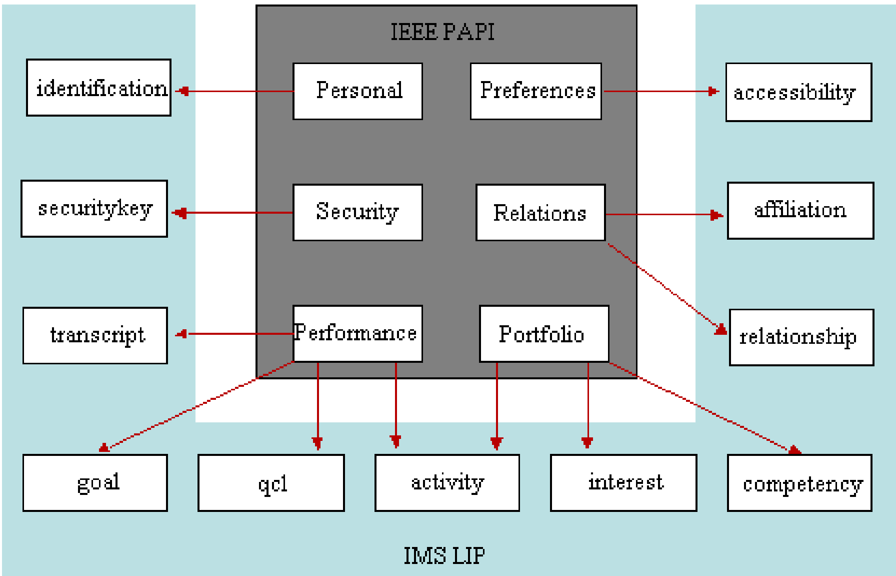

Fig. 1. Relationship between IEEE PAPI and IMS LIP

Salehi and Kmalabadi (2012) highlighted the ways of matching the learner preferences with the LO metadata attributes in order to retrieve the objects that can cater the changing preferences of the learner. The contents frequently visited by the learner were used to find the most similar materials and the most similar learners and then the LOs were recommended by matching the two. For a LMS to be effective in recommending the LOs, it should be aware of the evolving requirements of the learner such as the implicit and explicit learner reflections on the LOs used etc. Similarly, with the learners' preferences varying on, subjects, availability of content, usability, and its relevance to the learner's context, a single common learner profile may not be enough to hold all the necessary learner information that are specific for each and every subject domain.

2.3. Learning object profile

The LOM plays an important role in searching and discovering the LOs across the repositories. In spite of that, the surveys conducted (Ochoa, Klerkx, Vandeputte, & Duval, 2011; Najjar, Ternier, & Duval, 2003) on the actual usage of LOM attributes show that only a few of these attributes are prominently used along with the LOs and the rest are largely ignored by the content creators. Also, the most frequently used attributes like title, description, author, content type, etc. represent only the basic information about each object. But the information on other aspects of the LO that greatly determine the extent of suitability of an object for a particular learner profile were not given due importance. As a result of this, the LOs are not able to highlight the vital information like implicit learner reflections, feedback, usage statistics, learning context etc. as a part of its metadata and in turn gets suppressed inside the repositories like a needle in the haystack.

With the requirements of the learners varying with subject domains and the nature of LOs used over their learning cycle, the LMS should adapt itself to retrieve the most suitable LOs for the learner. But in many LMSs, there exists a gap between "what the learner wants" and "what an object can deliver". In order to bridge this gap, the LMSs should thoroughly understand the potential of each and every object in catering the learners' requirements. For that, the LOM should represent the necessary information on the extent to which it has catered the learners' requirements over its life cycle. The importance of matching the appropriate attributes of learning content and the learner profile was highlighted by Salehi, Kmalabadi, and Ghoushchi (2012). In their work, they have adapted genetic algorithm based approach to match the learner profile attributes with the LOM in order to determine the pattern of content utilization by the learners. Here, the historical rating on the learning material is used as a key to match the learner profile with the LOM.

In traditional LMSs, the information pertaining to the potential of the LOs potential is not usually recorded through the LOM attributes as most of these attributes reflect only the static properties of an object.

With the growing number of LOs across the web, the LMSs can get a clear picture of the learners' requirements only when it is aware of what exactly the learner wants at different instances of learning. Also, the LMSs should be capable of deriving the knowledge out of the type of objects that catered the learners' requirement at a specific instance.

However, the static nature of learner profiles used in the existing LMSs does not have the provision to record the subject specific needs of the learners. This in turn has led to the blindfolded retrieval of LOs irrespective of the subject domains. In order to get the more precise contents according to the needs of the learner at different learning instances, the learner profile should change its generic characteristics to more specific ones as and when the learner proceeds through the learning cycle. Similarly, the LOs should highlight their efficacy towards catering the subject specific requirements of the learners. The proposed work addresses the above mentioned issues related to the learner profiles, and object profiles, in order to retrieve the most appropriate LOs that can cater the learners' needs.

3. Methodology

The proposed methodology models the learner requirements in such a way that it reflects the implicit and explicit needs of the learners of an e-learning environment. This model evolves over the period of time by taking into account the dynamically changing needs of the learners. Similarly, the evolutionary modelling approach was also adopted for modelling the LOs in order to represent its capabilities in catering the learners' requirements.

3.1. Learner modelling

Modelling the requirements of the learners is the perfect way of representing their information in an e-learning environment. The need for learner/student modelling arises out of the fact that all the learner requirements should be explicitly represented in order to retrieve the precise contents for the learners (Polson & Richardson, 2013). Most of the recommender systems across the web utilize such information to recommend the contents for the learners (Drachsler, Hummel, & Koper, 2008). Also, to track the changing learner requirements throughout the learning cycle, the learner profile should record the information related to the aspects that affect active learning (McCalla, 2004).

The proposed model addresses the requirements of a LP by considering all the necessary aspects that either have its direct or indirect impact on the learning experience of the learner. This model partially derives its attributes from the existing standards (IEEE PAPI, IMS LIP) and categorizes them under four major categories viz., learner background, skills, preferences and knowledge. These categories together represent the existing capabilities of the learners along with their current learning needs. When the learner is new to a learning domain (subject), the preferences and skills of the learner recorded at the time of profile creation were used to retrieve the LOs initially. Such generic details which are used invariably across all the subject domains were put under Global Learner Profile (GLP) class. As the learner proceeds through a subject, their preferences become subject specific and also their domain skills get escalated. These evolutionary changes with respect to a domain are recorded under the Local Learner Profile (LLP) so that the domain specific requirements of the learners are isolated from the generic ones. Fig. 2 highlights the GLP and LLP classes and their attributes. Each LLP contains a learning path that has a collection of topics to be learned by the learner in order to attain the domain specific goals (Yang, 2013). Tables 1 and 2 list the attributes of GLP and LLP categories.

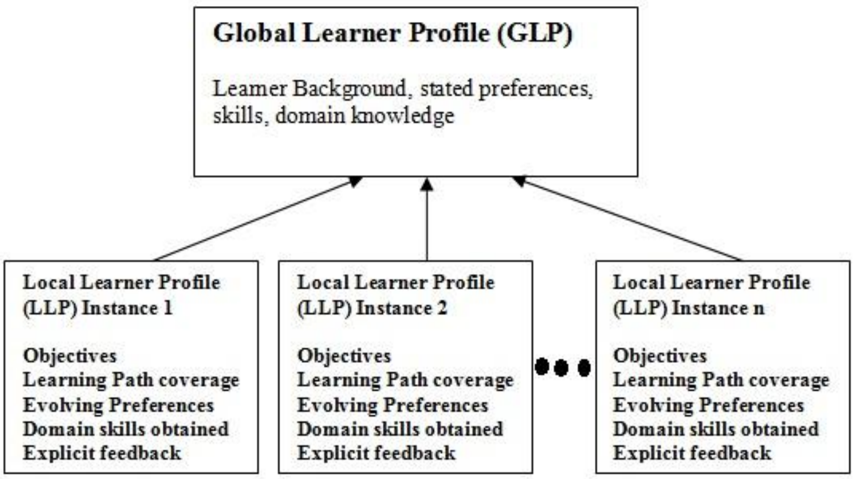

Fig. 2. Class hierarchy of LP

The multiple intelligence skill attribute derives its value based on the learner response to the questionnaire designed on the sidelines (http://www.literacynet.org/mi/assessment/findyourstrengths.html). The scores on the multiple intelligence categories like interpersonal, spatial, social, language and logical were used to identify the skill set of the learner.

Table 1
GLP categories and its attributes

GLP Category	**Attributes**
Background	Name, gender, date of birth, nationality, address, phone number, email, medium of study
Skills	multiple intelligence skill, reading skills, use of technology, learning pace
Stated Preferences	language, content type, presentation mode, format preference, connection type, device
Domain knowledge	domains exposed, exposure level, domains of interest, suggested domains, overall performance on each domain, scope for further study

Table 2
LLP categories and its attributes

LLP Category	**Attributes**
Objectives	Specific objectives predefined (based on course outcomes)
Learning Path coverage	Learning path hierarchy, List of topics covered, percentage of completion, topic wise performance
Domain skills obtained	Total no. of skills attained, Skill name, topic, LO used, performance on skill.
Evolving Preferences	Author, content type, language, format
Explicit feedback	The feedback given by the learner on a specific LO

When the learner registers for a new subject domain, a LLP is created with a learning path inside it. These LLPs are created with the purpose of overriding the GLP preferences in order to highlight the subject specific needs of the learners. Each time the learner makes a query on a topic, a Learner Profile Instance (LPI) is generated dynamically based on the GLP and LLP classes. This LPI holds the collective information available under the different categories of GLP and LLP represented in Resource Description Format (RDF) wherein, each attribute of the learner profile and its values are represented as a <subject, predicate, object> triple (Lassila & Swick, 1998). Such a representation gives the flexibility to use only the necessary profile attributes in order to search and discover the LOs in a given scenario. Also, the RDF representation allows seamless migration of profile instances across the LMS platforms. Table 3 shows a sample set of preference category attributes and their values represented in RDF. The LPI gets updated as and when the learner interacts with the LOs over the period of learning a specific subject. It is this evolving LPI which is then used each time to retrieve the LOs based on the learner's expertise and exposure on a subject domain.

Table 3
Part of LPI learner preference represented in RDF

Subject	Predicate	Object
Learner Name: Jane	likes _Author	Author_Name: Pradeep
Learner Name: Jane	preferred_content_type	Content_type: image
Learner Name: Jane	preferred_language	Language: English

3.2. Modelling the learning object profile

With the variety of LOM attributes that has either a direct or indirect impact on learner's learning experience, the LOP should be modelled in such a way that it highlights the suitability of an object with respect to a particular LPI. The LOP categories and attributes identified for that purpose (listed in table 4), can be mapped either directly or indirectly to the attributes of the LPI. The frequently used LOM attributes were considered under the basic LOM category. Whereas, the LO connections category maintains the information on the object's relationship with other objects. The content semantics category records the existential information of an object that tells about the form and the nature of the content inside it. The attributes of the usage statistics category records the object's utilization information inside the priority queue data structure that dynamically reorders them based on their importance. For example, the keyword queue maintained for an object will have the most frequently used keyword at the first position and so on. Finally, the explicit learner feedback on the object is also recorded as a part of LOP as it will help the author/owner of the object to respond to the learner's comments on the object.

Table 4
Learning object profile (category and its attributes)

LOP Category	Attributes
Basic LOM	LO ID, title, description, author, domain, content type, Keywords, Date of posting, language
LO connections	Pre-requisite, further study, alternative explanation, similar objects, introductory content, exercises
LO content semantics	Content category, nature, form, level, use of language, composition
	Content request catered : keyword catered, domain catered, topic catered
	Learner catered : Medium of study, age, gender, preferred language
LO usage Statistics	Preferences and Skills catered : Content type, Level, content category, composition, multiple intelligence skill, reading skill
	Knowledge catered: Prerequisite domain, prerequisite topic, user level on that topic
	No. of views and No. of likes, rating, consolidated feedback, rating statistics

3.3. Adapting the LOs based on LP

The modelling of learner profile and object profile has paved the way for effective representation of learner requirements and the object's capabilities in an e-learning environment. However, in order to get the suitable LOs for the learners, these two must be mapped appropriately based on the query. In traditional e-learning system, the learner's query is processed by the LMS and the results retrieved for the keyword are then filtered based on the preferences set in the learner profile (Fig. 3).

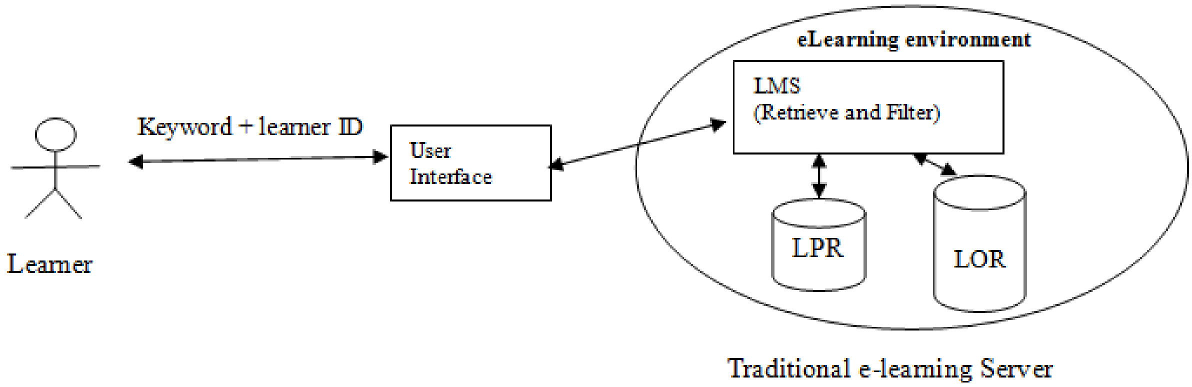

Fig. 3. LO retrieval in the proposed system with LOSS module

But in the proposed system, the LMS first accepts the learner's query and discovers the LOs that match with the keyword. The objects thus discovered are then filtered based on the learner's domain of interest information available in the GLP of the learner. Once the domain is narrowed down, the learner ID of the query is used to instantiate the LPI dynamically from the GLP and the domain specific LLP (Fig. 4) of the learner. This LPI is then sent to the learning object search subsystem (LOSS) which retrieves the LO profiles from the LOP Repository (LOPR) and matches it with the LPI attributes using the proposed Cog Wheel Algorithm (CWA). The CWA re-ranks the retrieved results based on the affinity between LPI and the LOPs in order to present the most appropriate objects to the learners in first place. For this purpose, the CWA utilizes domain mapping information available in the form of RDF triples.

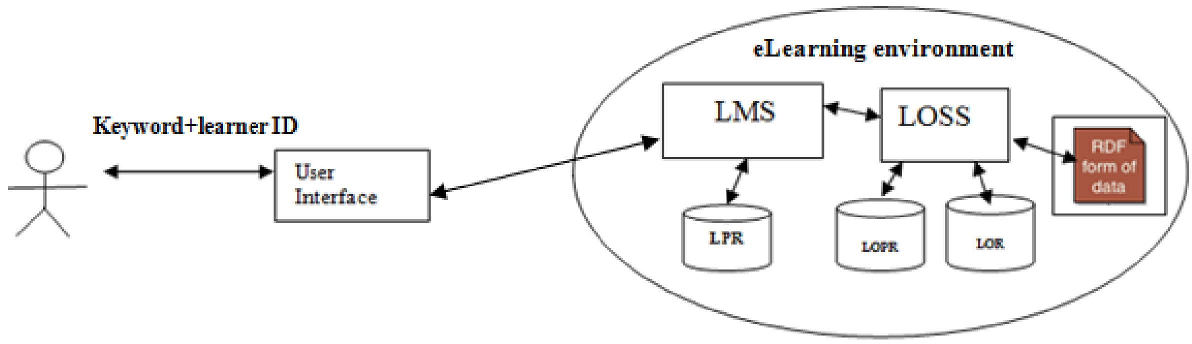

Fig. 4. LO retrieval in the proposed system with LOSS module

Fig. 5 showcases the mapping between the LPI skills category and LOP domain attributes (the complete mapping information for LPI domains is given in Appendix I).

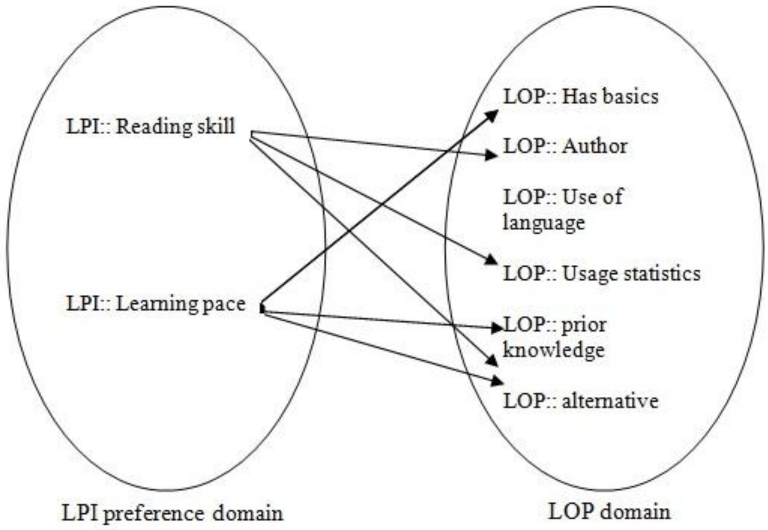

Fig. 5. Preference mapping between LPI and LOP

Cog Wheel Algorithm

The learner requirements represented by LPI were considered to be the teeth of the learner wheel with varying spike lengths based on the weights of the LP categories and their attributes. Similarly, the extent to which the LOP attributes can cater the learner's requirements were considered to be the depth of the object wheel. The iterations of the algorithm determine the affinity between the LPI of the learner and the LOPs of the retrieved objects and store it inside the Affinity Determinant Matrix (ADM). The rows of the ADM represent the LOPs of the retrieved objects and the columns represent the attributes of LPI that corresponds to the learner who raised the query. These LPI attributes are categorized mainly under three categories viz., skills, preferences and knowledge, whose weights can be modified periodically to suit the learners' requirements. It is this weight of each LPI attribute and number of attributes of LOP domain to which it is mapped to (Appendix II) that plays an important role in determining the value of each ADM cell. The ADM given in Table 5 highlights the affinity value calculated based on the results retrieved for the learner query with keyword "queue" and profile ID 1024.

The algorithm

Begin

Step 1: Obtain the query 'q' from the learner which has a keyword 'w' and learner ID 'x'.

Step 2: Retrieve the LOs based on the keyword 'w' and populate the result set R such that $R = \{LO_{i\,,}\, i >= 0 \mid w \subseteq keywords(LO_i)\}$

Step 3: Reduce the result set R by filtering it based on the learner's domain of interest to get the reduced result set $R_r = R_{domain} \cap$ domain of interest

Step 4: Generate the LPI for the learner ID ‘x’ from the GLP and the domain specific LLP stored in LPR.

Step 5: Initialize the ADM column attributes with the weight of the LPI_x attributes.

Step 6: For each candidate object ‘i’ of R_r, fetch its LOP from LOPR and calculate the value of each ADM cell as given in (1),

$$\mathrm{ADM}_{ij} = \sum_{k=1}^{n(k)} W_k^{ij} * P(k) \tag{1}$$

where n is the number of attributes of LOP_i to which an LPI_x attribute is mapped to. W_k is the weight of each LOP attribute ‘k’ which is mapped to an LPI_x attribute. P(k), is the percentage of match on the value of each LOP attribute ‘k’ mapped to an LPI_x attribute and it is calculated as follows,

$$\mathrm{P(k)} = \frac{\text{position of the k}^{\text{th}}\text{ attribute's value in the LOP's Usage statistics queue}}{\text{size of the queue}}$$

Affinity $\text{Index}_i = \sum_{j=0}^{m} ADMij$, where m is the total number of column attributes of ADM.

End for

Step 7: Reorder R_r in decreasing order of Affinity Index

Step 8: For each LO ‘i’ liked by the learner,

Update the usage statistics category of LOP_i by reordering the values of the attributes inside it based on the priority.

End for

End

The weights (Wk – where k is the number of attributes under the Learner Profile category) were based on an internal study conducted on the performances of the under graduate students (batch1 - 60 students and batch 2 - 48 students) who took the course CSE 102 – Data Structures and Algorithms. The learners were evaluated based on the class room based teaching during the first and second mid-term exams and the following were observed from the analysis of their results.

The learners who scored less marks in the pre-requisite questions on knowledge have also scored less in application based questions also. Also, the learners who failed in the exams have utilized the contents (only from the textbook mentioned in the syllabus) which were not suitable for their level. So, the knowledge part of the profile was given a fair share of 50% with the “pre-requisite” and “object-level” attributes were given more weight. When it comes to skills category, the learners’ reading skills and learning pace were the two factors that primarily affected their performance. The fraction of learners who have their medium of study other than English at school level was 15% and 12.5% respectively in batch1 and batch 2. Out of those, only 4% (batch1 and batch2 combined) were able to clear the exams because the others could not get the proper content that can cater their learning preferences. This was the reason behind giving more weight (30%) to the preferences category than the skills (20%). Even though the learners’ skills being the deciding factor in providing the appropriate LOs, unless the learners’ preferences were determined based on their skills, the learners' requirement can't be satisfied. The P(k) attribute value is based on the usage statistics of a particular LO by the learners. This Usage statistics attribute of the LOP maintains its values inside a priority queue that reorders it every time the LO is utilized. For the attributes of other categories which have a single value, the queue size is considered to be 1, so the P(k) value is either 0 or 1.

Table 5
Affinity determinant matrix with LOPs of top five retrieved objects for a specific LPI (LPI 1024)

	Skills (20%)				Preferences (30%)						Knowledge (50%)				
LPID: 1024	Read (5)	MI (3)	Pace (7)	Domain Skills (5)	Lang. (5)	Author (5)	Content type (5)	Suggestions (5)	Further reading (5)	Rating (5)	Domain (10)	Prereq. (15)	Level (15)	Perform. (10)	**Affinity Index (100)**
LOP101	3.1	2	2.33	3	5	2	4	3	2	3.3	8	10	12	6	65.73
LOP170	**5**	**2**	**4.66**	**3**	**4**	**2**	**2**	**2**	**4**	**3.7**	**10**	**15**	**15**	**8**	**80.36**
LOP171	0.83	1	2.33	1	4	3	5	3	2	4.5	10	10	15	6	67.66
LOP172	1.6	3	7	2	4	1	4	3	1	4.2	8	3.75	5	5	52.55
LOP168	1.6	1	2.33	3	5	4	3	4	4	3.8	10	15	10	7	73.73

Note: LPID: 1024
Learner Profile Class: LPC1 {non-English, below average pace, beginner level, good performance}
Search Keyword: Queue
Domain of search: Data Structures
Total no. of objects retrieved: 13
Top 3 results after reordering results: LOP170, LOP168, LOP171
Best Suitable object profile: LOP170

4. Experimental results

An experiment was conducted to test the performance of LOSS in retrieving the suitable LOs for a specific LPI. A total of 35 learners took part in the learning activity involving 312 objects stored inside the LOR. The learners were classified under six learner profile classes (given in Appendix I) that covers the majority of learners in the population. The learners of these classes used the appropriate keywords for retrieving the LOs of "Data Structures and Algorithms" domain. The learners were informed to mark "like" for the LOs which they feel more relevant for their current requirement. Since the precision at top k of the retrieved results symbolizes the relevance of the retrieved results in a sample (Zuccon, Azzopardi, Zhang, & Wang, 2012), the selection of one among the top k (where k=3) results was considered a hit, otherwise a miss. In case of a miss, the miss distance was calculated as the difference between the affinity values of top ranked LO and the actual LO utilized by the learners. Table 6 lists the quantum of data involved in the study.

Table 6
Study data

Total no. of Los	LOs utilized	LP classes	Learners	Search iterations
312	218	6	35	252

Table 7
Total score on each category and the overall affinity between the LPI 1024 and LOPs retrieved

LPI categories LOPs	Skill (20)	Preferences (30)	Knowledge (50)	Overall Affinity (100)
LOP101	10.43	19.3	36	65.73
LOP170	14.66	17.7	48	80.36
LOP171	5.16	21.5	41	67.66
LOP172	13.6	17.2	21.75	52.55
LOP168	7.93	23.8	42	73.73

Table 7 lists the category-wise total score of top 5 LOs retrieved for LPI1024 of LPC1 class using the keyword “queue” (based on Table 5) and Fig. 6 shows the snapshot of the results retrieved through LOSS.

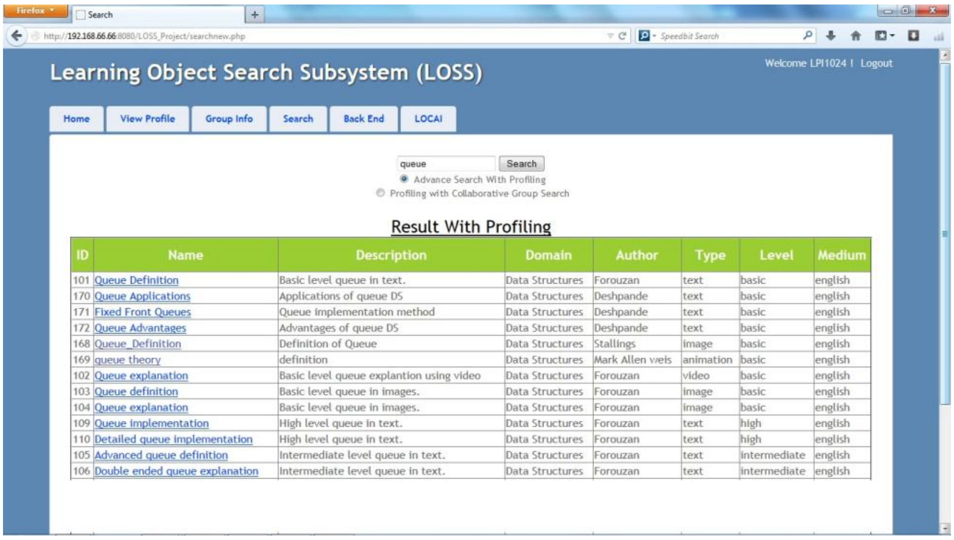

Fig. 6. Snapshot of LOSS

5. Experimental results

The results have shown that out of 218 objects utilized by the learners there were 193 hits (89%) and 25 misses (11%). The analysis of the missed cases has revealed that in majority of misses, the score on the preference category of top 3 objects retrieved was less. Also, the lesser Standard Deviation (SD) value on miss distance (Table 8) in each LP class indicates that even during the misses, the learner has utilized objects that were very near to the top 3 positions. This suggests that the learners were satisfied by the results retrieved by the LOSS except in cases where the content is not according to their preference. Finally, the misses on preference category highlights the lack of variety on the LOs of our system due to the limited number of objects used for the study. In real-time learning environment, this problem can be addressed by crowd sourcing the LOs by verifying its authenticity.

Table 8
Hit/Miss ratio among the retrieved objects in the study sample

Profile class	No. of learners	Search iterations	No. of LOs utilized	Hits(Top 3)	Miss	Hit Ratio	Avg. Miss distance	SD	Missed on Category(Majority)
LPC1	8	28	24	19	5	0.79	21.36	4.14	Preference
LPC2	4	35	33	30	3	0.9	12.96	2.44	Preference
LPC3	6	78	61	55	6	0.9	17.6	3.07	Preference
LPC4	4	12	12	12	0	1	0	0	NIL
LPC5	8	58	50	43	7	0.86	18.04	2.35	Knowledge
LPC6	5	41	38	34	4	0.89	17.02	5.97	Preference
Total	35	252	218	193	25	Mean : 0.89	Weighted mean w.r.t Miss: 17.82	Mean: 2.99	Preference

An average hit of 89% across the profile classes indicates that the LOs retrieved by knowing the subject specific requirements of the learners were very precise, as the evolving nature of the profile highlighted the changes in the learning pattern of the learners. This observation promotes formulating new methods for representing the detailed, subject specific learner information, such that they can be used to find the most appropriate learning content for the learners. With the exponential growth of LOs across the web repositories, the chances of a LO getting abstracted from the learners is more. However, the results of the study have established that the retrieval of LOs based on the evolutionary learner profiles and the object profiles can bring out such objects without the learner having to search for it extensively.

6. Conclusion and future work

In this paper, the problem with the retrieval of precise LOs based on a single, common, generic learner profile was resolved by modelling the profile in such a way that it reflects the domain specific requirements of the learner. Also, the LOP was modelled to highlight the various aspects of the object that can attract the learners with a specific learning requirement. The LPI - LOP mapping information represented in the form of RDF triples has helped to isolate it from the object and the learner profiles. The 89% hit on an average has proved that the LOSS has retrieved the objects that are relevant to the learners' context rather than just retrieving them based on the query keyword alone. Altogether, the LOSS's improvised LO retrieval approach has paved the way to free the learners off from the shackles of "one size fits all" content presentation strategy practiced by e-learning environments.

The future work is aimed at analyzing the LPIs to determine the learning pattern of the learner in each subject domain and dynamically update the weights of the LLP attributes. This would make the search system a learner centric one and retrieves the LOs based on the strengths and weaknesses of the learners in a specific domain. Also, the LPIs of the peer learners of the environment have to be analyzed in order to recommend the LOs in the initial stages of profile building where the profile is immature.

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Appendix I. Learner Profile classes

Profile Class	Medium of study	Learning Pace	Domain Knowledge level	Average Performance
LPC1	non-English	Below Average	Beginner	Good
LPC2	English	Below Average	Intermediate	Poor
LPC3	non-English	Below Average	Advanced	Average
LPC4	English	Above Average	Beginner	Good
LPC5	non- English	Above Average	Advanced	Poor
LPC6	English	Above Average	Intermediate	Average

Appendix II. Category wise attributes and their weight

Skills category – 20%				
Learner Profile Attribute	no. of attributes of LOP to which LP attribute is mapped to	Mapped LOP attributes	Weight of attribute	Contribution of the attribute to the category (in percentage)
Reading	3	Language, author, Skills catered	5	25
Multiple intelligence	2	Content type, Multiple intelligence skill catered	5	25
Pace	3	Level, Introductory content, has exercises	7	35
Domain Skills	1	Skills required	3	15
Preferences category – 30%				
Learner Profile Attribute	no. of attributes of LOP to which the LP attribute is mapped to	Mapped LOP attributes	Weight of attribute	Contribution of the attribute to the category (in percentage)
Language	2	Language, explanation	5	16.6
Author	1	Author	5	16.6
Content Type	1	Type	5	16.6
Suggestions	1	Similar objects	5	16.6
Further reading	1	Further study	5	16.6
Rating	2	Rating statistics, rating average	5	16.6
Knowledge category – 50%				
Learner Profile Attribute	no. of attributes of LOP to which LP attribute is mapped to	Mapped LOP attributes	Weight of attribute	Contribution of the attribute to the category (in percentage)
Domain	1	Domain	10	20
Pre-requisite	1	Pre-requisite	15	30
Level	2	Object level, composition	15	30
Performance	2	Prerequisite, similar content	10	20