A Hybrid Recommender Method for Learning Objects

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ABSTRACT
Searching for and retrieval of Learning Objects in e-learning environments is a complex assignment for instructors and students. Generally, the search results include several Learning Objects and the ranking criteria are not always clear (keyword frequency, date updating, user profile similarity, etc.). This means that selection of the best Learning Object for a specific use requires a lot of effort and time. This paper proposes a hybrid recommendation method to assist users in the search and selection processes in Learning Objects Repositories. The intended method uses a combination of different filtering techniques, such as content comparison, and collaborative and demographic searches. To achieve this goal, metadata information, management activities of resources and user profiles are used. The hybrid recommendation method has been implemented in a search system called DELPHOS.

General Terms
Hybrid recommender systems, learning object, personalised recommendation, repositories, ranking.

Keywords
Learning Object, IEEE-LOM, Pedagogical Quality.

1. INTRODUCTION
A Learning Object (LO) is a small piece of knowledge that can be used in different instructional contexts. Its objectives are to simplify the construction of instructional experiences and to motivate reusability and interchange between e-Learning systems [1].

All Learning Objects are composed of two elements: instructional content (multimedia, text, simulation or quest resource) and tags, called metadata [2]. Metadata describes Learning Objects in some relevant aspects: what it is, who created it, what its functions are, objectives, duration, etc. Metadata allows Learning Object classification, in order to be searched for, reused or modified.

Currently, the proliferation of sites and repositories dedicated to providing resources for education is evidence of the continuous development of e-learning. Learning Object Repositories (LORs) provide a platform for the open sharing of learning resources. These specialised repositories can store only metadata or resources. In the case of repositories storing only metadata about resources available elsewhere on the Web, they act as filters for the referenced resources by providing metadata-based searches on Learning Objects [3]. Some LOR examples are ARIADNE [4], MERLOT [5], MACE [6] or AGORA [7].

The main objective of LORs is to provide appropriate resources for users who have specific goals and are within a particular context when looking for some information. However, a problem that currently arises with most LORs is that they have a simple search engine which does not recommend the most appropriate LOs for a particular request. Users are frequently faced with deficient and confusing search mechanisms which limit their use.

Personalised filtering included in information retrieval processes will contribute to decreasing an information overload by adjusting the results presented according to the individual needs of each user. To do this, they need technological tools that simplify the location, reuse and sharing of these resources.

This paper proposes a recommender method that helps and assists instructors and students while they conduct a search. The recommender suggests an appropriate selection of LOs from the repository. With that aim, all stored information about objects and users is employed. This information allows improving and personalising searches, through various types of filtering based on content similarity, LO usage, quality evaluation and user profile similarity.

The returned resource list can be sorted through different filters; in this way the search task becomes a recommendation and personalisation task that can help users to find items which are relevant to their interests.

The rest of the paper is organised as follows:

In the next section, antecedents are provided. Section 3 describes the proposed hybrid recommendation method. In Section 4, the DELPHOS system is presented. Section 5 describes a performance test. Finally, the conclusions and future work are presented.

2. BACKGROUND
Recommender Systems (RSs) are software tools and techniques that provide suggestions about items which can be useful to a user's requirements [8, 9, 10]. Items are the objects that are recommended and may be characterised by their complexity and their value or utility. Users of an RS can have diverse goals and characteristics.

To provide an overview of the different types of RSs, we want to quote a taxonomy provided by Burke [8] that has become a classical way of distinguishing between recommender systems and referring to them. Burke distinguishes between six different classes of recommendation approaches:

- *Content-based*: The system learns to recommend items that are similar to the ones that the user liked in the past. The similarity of items is calculated based on the features associated with the compared items.
- *Collaborative filtering*: recommends to the active user those items that other users with similar tastes liked in the past. The similarity in taste of two users is calculated based on the similarity in the rating history of the users.
- *Demographic*: This type of system recommends items based on the demographic profile of the user. The assumption is that different recommendations should be generated for different demographic niches.
- *Knowledge-based*: Knowledge-based systems recommend items based on specific domain knowledge about how certain item features meet users' needs and preferences and, ultimately, how the item is useful for the user.
- *Community-based*: This type of system recommends items based on the preferences of the users' friends. This technique follows the epigram "Tell me who your friends are, and I will tell you who you are".
- *Hybrid*: These RSs are based on a combination of the aforementioned techniques.

RSs have been successfully applied in educational environments to support different tasks [11]. According to [12], to enable personalisation, existing e-learning systems use one or more types of knowledge (learners' knowledge, learning material knowledge, learning process knowledge, etc.). Generally, personalisation in e-learning systems concerns adaptive interaction, adaptive course delivery, content discovery and assembly, and adaptive collaboration support.

This work focuses on personalised searches of content discovery into LO Repositories. In the literature, there are some papers focused on Learning Objects recommendation and personalisation.

For example, Ruiz-Iniesta [13] describes a personalised content-based recommendation of LOs. This approach gives priority to those objects that are most similar to the student's short-term learning goals (the concepts that the student wants to learn in the session) and, at the same time, have a high pedagogical utility in the light of the student's cognitive state (long-term learning goals).

Another interesting work is developed by Zhuhadar [14], who proposes a novel approach to integrating user interests into a search within a recommender system. The recommendation is guided by the semantic representation of the user and the content. He describes how personalisation aspects can increase the recommendation quality.

In another paper, Manouselis [15] describes a case of developing a learning resources collaborative filtering service for an online community of teachers in Europe. A data set of evaluations of learning resources was collected from the teachers that use the European Schoolnet's learning resource portal. These evaluations were then used to support the experimental investigation of design choices for the filtering service.

Finally, Bozo [16] presents a recommender approach for LO searches focused on the teachers' context model. He incorporates collaborative filters and content to calculate preferences of other similar users.

The main difference between all these previous works and our proposal is that current LO recommender systems only use one or two filtering techniques (normally content-based and collaborative filtering). However, our hybrid recommender system will use four filtering approaches in order to be able to improve personalisation; that is, to recommend the most interesting or relevant LOs to each particular user.

3. HYBRID RECOMMENDATION METHOD

The *Learning Objects Hybrid Recommendation Method (LO-HRM)* employs different classification, filtering and ranking techniques based on metadata, content, and criteria for refining,

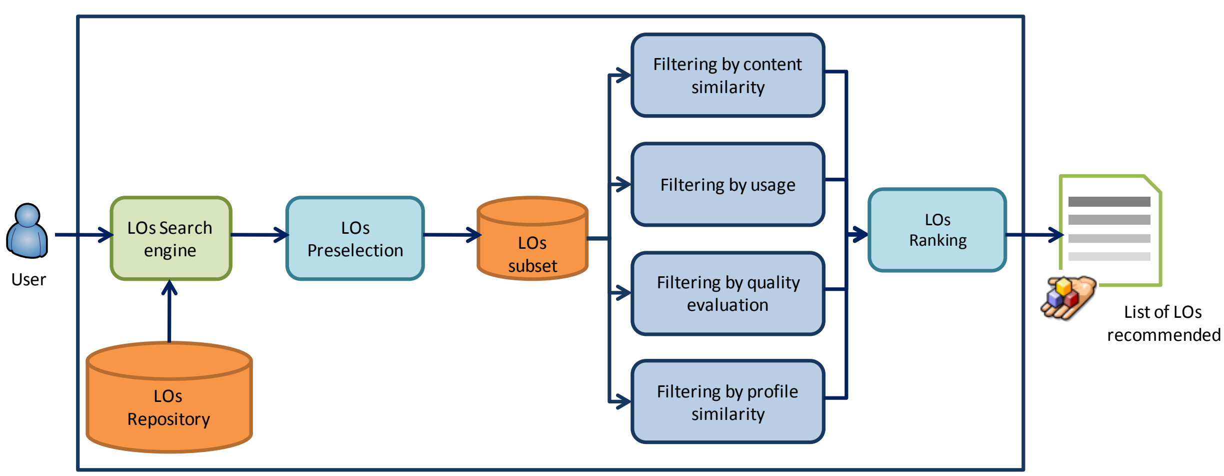

Fig 1: Proposed architecture of the LO hybrid recommender method.

improving and customising search results (see fig. 1).

Instructors' queries are presented through keywords or metadata values associated to the content of the objects sought. The query is interpreted as a *Learning Object Pattern (LOP)*, the ideal Learning Object to satisfy a request. The method comprises three phases: *LO preselection, applying filtering criteria and LOs ranking.*

These three phases can be resolved with different metrics or calculation schemes. In this paper, we describe a search method in response to an LOP query using four methods of arithmetic filtering and ranking mechanisms. In our future work, other schemas will be presented, which have already been designed but are still in the development and testing phase.

3.1 Learning Objects preselection

This phase is characterised by the need to prune an initial set of LOs available in a repository. The pruning can be done in several ways. In this paper, a method of pruning for content is implemented, as is described below:

An LOP is expressed in metadata terms in compliance with IEEE-LOM standards [17]. IEEE-LOM is designed specifically to define the syntax and semantics of the metadata required to adequately and fully describe a Learning Object through a simple and extensible XML-based structure.

With that information, an exhaustive comparison between the LOP and the objects of the repository is performed. As a result, a subset of LOs which coincide with the request is obtained. That is, the subset will include all objects whose metadata are similar with values defined in the LOP.

Values defined in an LOP directly affect the number of similar objects. Each of these values can become a restriction to objects selection; that is, a pruning criterion. But the same criteria that are used initially to reduce object selection can be used to expand the search. The key to the search is to use logical conjunctions: AND limits the query but OR expands it.

This situation is useful when the resulting objects number is below the permitted minimum. Instead of having a single LOP defined by a set of values (intersection set), an LOP set can be established and defined by each of the metadata (union set).

3.2 Applying filter criteria

The *filtering criteria* can be diverse and each of the alternatives can be measured and evaluated with a different *calculation schema*. At the moment, the methodology has four filtering criteria based on *content similarity, usage, quality evaluation and user profile similarity*.

For each of these filters, arithmetic weighting metrics are applied. Each filtering criteria and calculation scheme is described in detail below:

3.2.1 Filtering by content similarity

A selection from a subset pruned of objects, using similarity criterion or the semantic distance of elements concerning an LOP, is done. For this, a relevancy measure of matching terms between an LOP and LOs from a set is used. The calculation scheme includes a defined metric that determines the similarity degree (Sim) between two Learning Objects (Ox, Oy), considering the average metadata similarity [18].

To calculate the semantic distance of metadata (SimMeta) it is important to consider the data types defined by the IEEE-LOM standard and its characteristics. Specific metrics have been developed for each one. The final score of Context Similarity for an object is calculated using *expression 1*:

$$\mathrm{FOx}_{\mathrm{ContentSimilarity}} = \mathrm{Sim}\left(\mathrm{O_x},\ \mathrm{O_y}\right) = \frac{\sum_{m \in M}\left[simMeta(m_X, m_y)\right]}{|M|}$$

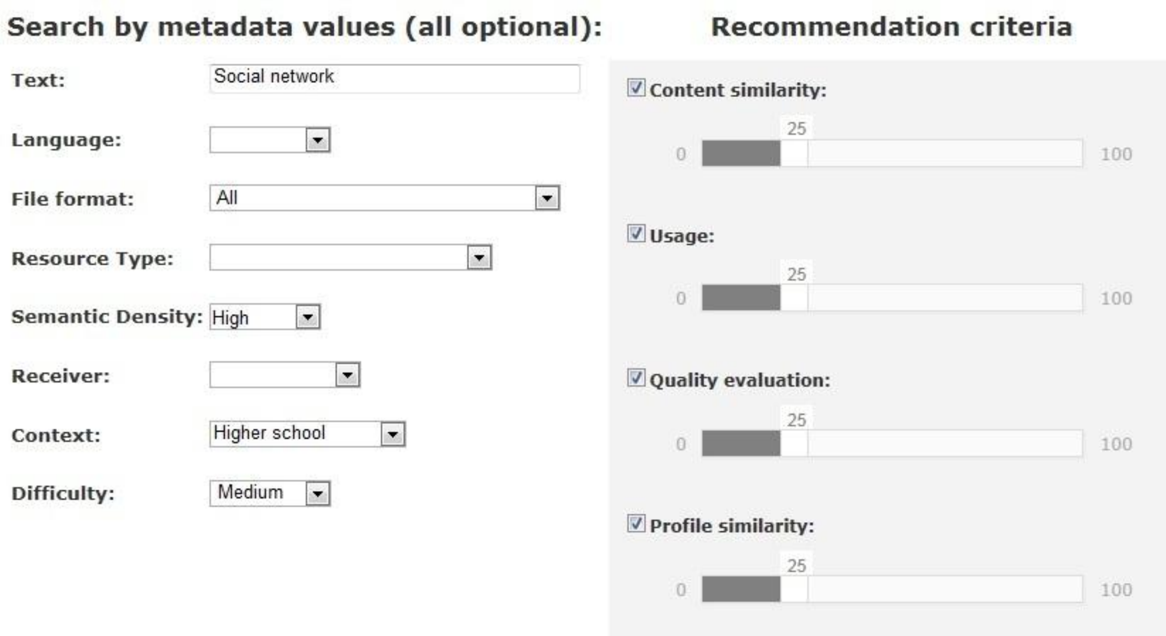

Fig 2: DELPHOS graphical interface.

Where:

- $|M|$ = Metadata number to compare.
- $simMeta(m_X, m_y)$ = Semantic distance between LO metadata m (O_x) and the ideal LOP (O_y).

3.2.2 Filtering by usage

This filter is based on a collaborative approach to carry out a sorting of preselected LOs depending on their level of use by other users. For the calculation scheme, available information on management activities (implicit information) furnished by users' interaction with LOs are used. The download frequency of a Learning Object is considered metric. In the future, other management activities associated with objects like visualisation, edition or referencing will be incorporated. The average number of downloads of an object is calculated using *expression 2*:

$$FOx_{Usage} = \frac{\sum_{I=1}^{N} DOx_i}{MaxDOy}$$

Where:

- DOx_i = Frequency of downloads of a Learning Object (Ox_i).
- $MaxDOy$ = Maximum frequency of downloads that a Learning Object (Oy) has obtained in a dataset.

3.2.3 Filtering by quality evaluation

This filter is based on a collaborative recommendation approach to perform the sorting of LOs in pruned sets. The criteria depend on quality evaluations obtained in pedagogical reviews. In this research, PQM (Pedagogical Quality Measurement) [19] was used, which comprises six categories to be evaluated: content, performance, competence, self-management, significance and creativity. These six categories contain 12 items (I) with an associated weight (α) for each response. Other Learning Object Quality Models could be used. For this case, the final score of Quality evaluations of an object is calculated using *expression 3*:

$$FOx_{QualityEvaluation} = \frac{\left[\frac{\sum_{I=1}^{N}\sum_{J=1}^{12} \alpha_{IJ}}{N}\right]}{\sum_{K=1}^{12} \alpha \max_K}$$

Where:

- $\sum_{I=1}^{N}\sum_{J=1}^{12} \alpha_{IJ}$ = Average quality evaluations of an object.
- N = Number of users who have evaluated an object.
- $\sum_{K=1}^{12} \alpha \max_K$ = Average maximum score of quality assessment.

3.2.4 Filtering by profile similarity

This filtering is based on the recommendation demographic approach. The sorting of LOs depends on user profile similarity that this object published with respect to the query of the user. The user profile contains the following attributes: study area, instruction experience, technological expertise, experience in instructional design, OAs editor used, e-Learning platform used and LOs repository used, among others. To calculate the final LO profile similarity, we can use *expression 4*:

$$FOx_{ProfileSimilarity} = Sim(Up_x, Up_y) = \frac{\sum_{a \varepsilon A}\left[SimAttribute(a_x, a_y)\right]}{|A|}$$

Where:

- $|A|$ = Total number of attributes to compare.
- $SimAttribute(a_x, a_y)$ = Semantic distance between attributes corresponding to user profile (x) LO publisher and user profile (y) that performed the search.

3.3 Learning Objects ranking

As mentioned before, different calculation methods to establish final ordination between objects obtained from pruning could be defined. An initial method has been determined and tested to establish final ranking from a set of preselected objects. The position of each object is obtained through the weighted union

Fig 3: An example of search results provided by DELPHOS.

of the different filters used. The final ranking of LOs is expressed using *expression 5*:

$$FOx_{ContentSimilarity} * W_1 + FOx_{Usage} * W_2 + FOx_{QualityEvaluation} * W_3 + FOx_{ProfileSimilarity} * W_4$$

Where:

- FOx = filtering criteria.
- W = variable weight (between 0 and 100%).

4. DELPHOS SYSTEM

The previous methodology has been implemented into a Recommendation System called DELPHOS, named after the oracle at DELPHOS where ancient Greeks went to ask the gods for recommendation on issues of concern.

DELPHOS has been implemented in the AGORA system [7], a Learning Objects Management System based on e-Learning standards which, among other features, offers a distributed repositories manager and metadata generation conforming to the IEEE-LOM standard.

DELPHOS has a specific interface graphic (see Figure 2) designed to assist instructors in locating, retrieving and reusing LOs in a personalised way. The interface has been designed to be very flexible, allowing the use of few text elements for the search, and the slider bars simplify the input of values offering an intuitive way to optimise the filtering process.

On the left of figure 2, the users can use text or keywords and metadata values (optional), such as *language* (language of LO content), *file format* (file extension of LO), *resource type* (specifies the use: exercise, diagram, sound), *semantic density* (amount of information it contains), *intended end user role* (oriented to a target LO user), *context* (academic level) and *difficulty* (difficulty degree for students using an LO).

On the right of figure 2, a panel displays a set of slider bars to control filtering criteria: *content similarity, usage, quality evaluations* and *profile similarity*. Each filter has an associated slider bar for selecting weight assigned in the range from 0 to 100%.

DELPHOS returns a recommending LOs list that meets the parameters entered. For each recommendation, diverse information is shown. This data is relative to the justification of their position, management actions that the user can carry out with the LO, reviews of other users, statistics and other similar objects, among other data (see Figure 3).

All this information will allow the user not only to select and download the most interesting LOs, but also to obtain a reasonable explanation as to why a particular object has been recommended.

It is also possible to access a list of other related objects or to promote social relationships between users, showing a contact information list and activities with objects. It is also possible to make an evaluation survey of the objects.

5. PERFORMANCE TEST

By way of illustration of the DELPHOS system, a case study with real values is presented. Some searches with different filtering criteria and calculation methods were conducted with the goal of testing the behavior and final ranking of the system.

Initially, a full set of objects from repository AGORA was used (504 objects of different topics and formats). In the LOs pre-selection phase, the criteria presented in section 3.1 was applied. An LOP was defined in a search whose parameters included text and metadata values, shown in Table 1. The search results were a subset of objects containing the identification numbers: 35, 41, 66, 71, 82, and 96 (see Table 2, left).

Table 1. Parameters user queries

Parameters	Values
Text	Social Network
Format	All
Semantic Density	High
Context	Higher Education
Difficulty	Medium

Subsequently, the filter criteria phase detailed in section 3.2 was applied to each of the equations 1, 2, 3 and 4 separately. With this aim, 4 tests (see Table 2, centre), were done using only criteria. One criterion has a weight (W) of 100%, while other three criteria have a weight of 0%.

It is interesting to observe, in Table 2, how the 6 items recovered

Table 2. Results obtained for applying different filtering criteria.

	LOs Preselection	Filtering Criteria				LOs Ranking
Retrieved Objects	**Without applying filtering criteria**	**Content similarity** weights: W1:100%, W2=W3=W4=0%	**Usage** weights: W2:100%, W1=W3=W4=0%	**Quality evaluation** weights: W3:100%, W1=W2=W4=0%	**Profile similarity** weights: W4:100%, W1=W2=W3=0%	**Four criteria applied Filtering** weights: W1=W2=W3=W4=25%
1	**96**	**35**	41	71	**35**	**35**
2	82	82	66	66	41	71
3	71	71	82	41	66	41
4	66	41	**96**	**35**	71	82
5	41	66	71	82	82	66
6	**35**	**96**	**35**	**96**	**96**	**96**

have a different order for each filter. Therefore, as expected, the filter type directly affects the order of the presentation of objects.

Finally, in the Learning Objects Ranking phase, formula 5 was applied. In this case, the four screening criteria were applied evenly; in other words they were given same weight of 25% (see Table 2, right).

As can be seen in Table 2, the objects with the identification numbers 35 and 96 have been ordered first and last respectively, both in the two filters and in the final hybrid ranking, but inversely if no criteria is applied. The table shows how different criteria affect the position of the LO.

Obviously, if different weights were applied, the final ranking would be different and would therefore require a pilot study to determine the optimum weights values.

To that end, we are starting to track user perceptions of LOs; users select those LOs returned in top position in the ranking if they are really interesting. DELPHOS allows capturing all user actions, for example the LOs selected, the LOs downloaded, valuations, etc. This information will be collected and used to accurately calculate the initial N recommendations.

6. VALIDATION

Currently, the recommender system DELPHOS is a beta version and shares information with the AGORA system. DELPHOS uses 504 learning objects that have been published by teachers of different Latin-American Universities via AGORA.

The results of a preliminary study confirm the usability of the DELPHOS system for an LO personalised search. 30 teachers of AGORA were invited to evaluate DELPHOS and complete a survey to give their own opinion about the usability of the system, using an anonymous public survey. We have used the System Usability Scale (SUS) [20], a simple ten-item scale which gives a global view of subjective assessments of usability (see table 3).

All the questions in the survey required an answer on the Likert scale from 1 (a little) to 5 (a lot), which indicates a lower or a higher degree of satisfaction with the system (0 to 100%). As a result of the validation, 74.58% satisfaction was obtained based on the user opinion about functionalities provided by the system DELPHOS.

Table 3. System Usability Scale (SUS)

Questions
1. I think that I would like to use this system frequently.
2. I found the system unnecessarily complex.
3. I thought the system was easy to use.
4. I think that I would need the support of a technical person to be able to use this system.
5. I found the various functions in this system were well integrated.
6. I thought there was too much inconsistency in this system.
7. I would imagine that most people would learn to use this system very quickly.
8. I found the system very cumbersome to use.
9. I felt very confident using the system.
10. I needed to learn a lot of things before I could get going with this system.

The results of the analysis (see figure 4) show that users feel the system is easy to use, and greatly facilitates the actions of searching and retrieving learning objects to suit their specific needs. The survey included a text field in which users could express comments and suggestions; there were 17 comments which gave rise to the following improvements:

- Design a direct access to the system, not as only an AGORA add-on.
- Incorporate social elements like messenger, rating, comments writing.
- Include group recommendations.

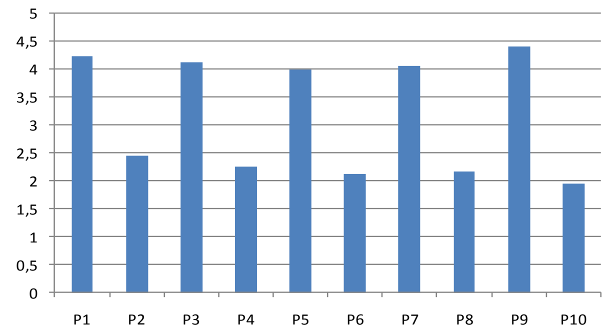

Fig 4: Average assessment results carried out by 30 testers of the DELPHOS system, according to an SUS survey. Values can range from 1 (strongly disagree) to 5 (strongly agree).

7. CONCLUSIONS AND FUTURE WORK

In this paper, a Hybrid Recommendation Method to help in finding the most suitable LOs to learn the needs of teachers has been proposed.

This methodology has been implemented in the recommendation system DELPHOS, which combines multiple filter criteria: content-based, collaborative activity and demographics. As a result, the recommended order of LOs is provided. This list includes additional relevant information to make decisions that suit the user's needs.

As future work, we will carry out more long-term tests with the DELPHOS system, using a larger number of users. On the other hand, we want to find what the best weight values are in different situations in order to try to dynamically adapt them. Finally, we wish to evaluate the performance of the system, calculating the time needed for generating recommendations.

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