Learning on Demand: Dynamic Creation of Customized, Coherent eLearning Experiences

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Abstract

This paper presents a conceptual model concerning automatic creation of coherent eLearning experiences through dynamic aggregation of heterogeneous learning objects. The model uses detailed user profiles as the main key to create customized learning content, tailored to each user's needs, preferences and skills. Aggregation of heterogeneous learning objects may result in a very incoherent learning sequence. Therefore, the model incorporates a method to improve the learning coherence of the generated course. The compromise between customization and coherence is fully adjustable from maximum coherence to maximum customization.

Keywords: eLearning personalization customization

1. Introduction

Typical learning object discovery services such as the ARIADNE foundation's Knowledge Pool [6], EdNA Online [7] or MERLOT [13], allow searching of learning content by means of keyword based searching or category browsing. These systems usually have a simple search tool that is able to find content by subject, searching for learning objects that have keywords matching the search expression. Furthermore, it is also common to find an advanced search tool, which allows users to filter the results across multidimensional attributes such as idiom, difficulty or technical format. Those attributes are normally taken from metadata elements that are used to describe learning objects.

These methodologies are content oriented and do not take individual learning profiles into consideration. This means that different users get exactly the same results for the same search expression, even if they have diverse profiles, contexts and learning goals. Also, the list of objects that match search criteria is often displayed without any specific order, forcing the user to browse the entire list in order to choose the object that best suits his individual learning goal.

In some cases, search results may be sorted by relevance. However, the resulting order reflects the estimated importance of each learning object concerning the search criteria but not necessarily the relevance for the user, regarding his specific profile, context and learning goal.

Studies have found that individual students have significant differences concerning the learning process, even in classes of carefully selected students [11]. As a result, individually tutored students often outperform classroom students by as much as two standard deviations [2] and clearly benefit from individually tailored instruction [17, 18, 19]. However, individually tailored instruction requiring one-on-one attention is often too costly to be a feasible option. Fortunately, information technologies can also be used to adjust the content, pace, sequence, and instruction style to better fit each student's learning habits, goals and interests [10]. As a result, introducing personalization features into discovery services may improve the overall quality of the service, by delivering content tailored to each user's needs, preferences and skills.

Another limitation of typical discovery services relies on its inability to combine independent learning objects to form coherent higher units of instruction. In fact, searching is oriented to find a particular learning object about a specific subject. However, sometimes there are no objects that meet the search criteria or the objects that meet it are not well suited to the user's learning preferences. In these cases, it would be useful that the system could dynamically aggregate independent learning objects in order to produce a coherent course about the same subject, personalized to the user's profile.

This paper presents models for Internet services with the ability to customize eLearning experiences by dynamically locating, selecting, recombining and reusing learning objects, considering individual profiles, learning goals and learning context. Figure 1 shows the main components involved and the way they are organized. The personalization services are supported by a classification system for learning objects, which is able to represent knowledge as a network of interrelated subjects. Learning objects are then associated to these subjects.

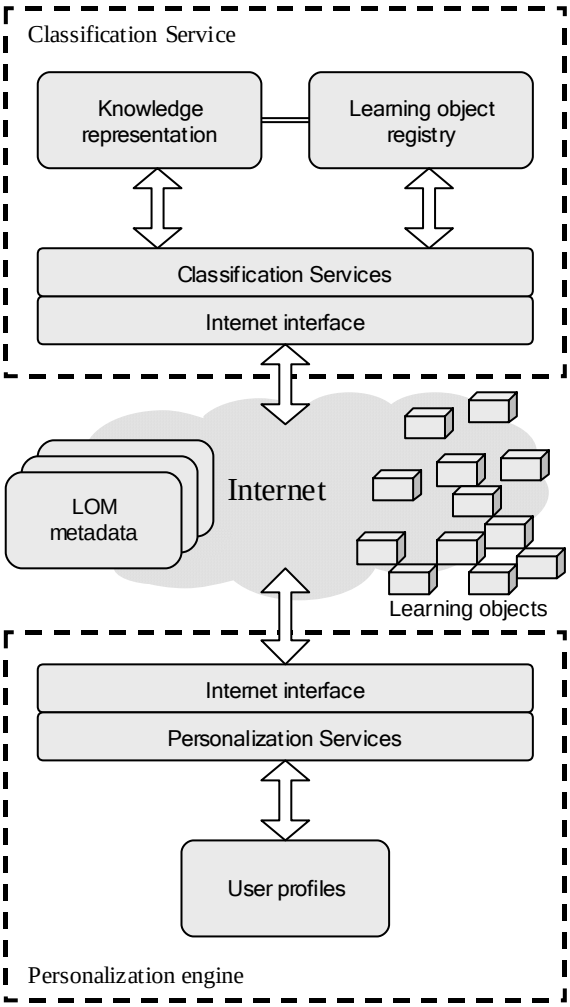

Figure 1. The main components of the model.

The personalization model uses individual profiles as the key to dynamically generate personalized eLearning experiences, customized to each user's learning needs. The paper describes three such personalized services. The first service aims to personalize searching, by filtering and rating results according with the user's learning context, learning preferences and other profile information. Consequently, users with different profiles have different search results for the same search expression. This service is also able to solve the problem of syntactic ambiguities on the search expression.

The goal of the second service, called 'personalized learning advisor', is to help users to maximize the perception of new concepts, by identifying their specific difficulties on topics that should be previously known to best understand these concepts. This service uses the classification system to build a topic dependency tree and then compares this information with the user's skills matrix. The specific difficulties are sequenced on a personalized review tree and a learning object is selected for each segment, considering the user's profile. The final result is delivered to users as SCORM compliant courses that they should enrol in before entering the main course.

Finally, the third service is able to dynamically build courses by aggregation of independent learning objects, respecting the learning goal and the user's learning profile. This service starts by using the classification system to determine the topic sequence of the desired learning goal. The correspondent personalized review tree is joined with this sequence to form the complete learning sequence that should be delivered to users.

2. The classification system

The personalization services are supported by a classification service for learning objects, which is able to represent knowledge as a network of interrelated subjects. The knowledge representation model has been inspired on topic maps [12] and semantic Web [1] concepts. Each subject is encapsulated within a knowledge segment with a conceptual scope defined by metadata. These segments may be associated in order to model the relationships, affinities and dependencies that exist among their subjects. Afterwards, the classification model supports the association of learning objects to knowledge segments. These associations are stored in the learning object registry of Figure 1.

2.1. Knowledge representation

Knowledge segments are the foundation of the classification system. As a result, its structure has been carefully designed in order to meet the system's requirements. Each segment has several attributes, represented by a set of metadata elements. Figure 2 represents its data model, which comprises four main categories:

Identification: this category is used to identify the segment, the designation of the portion of knowledge that it addresses and the entity that is responsible for managing the segment. The entity's digital certificate can be used for authentication purposes.

Scope: this category describes the block of knowledge that the segment covers. This description includes a textual explanation of the concept addressed by the segment, a set of equivalencies to external classification systems and a collection of multilingual keywords and expressions that may represent the block of knowledge. All weighted terms used in this model are expressed as a numerical code in the 'level' element that ranges from one to five, which means respectively 'very low', 'low', 'medium', 'high' and 'very high'. Each keyword or expression is tagged with an ISO 639 2-letter code to identify its idiom, allowing idiom independent searches.

Compliance: this category may be used to state the requirements that learning objects must comply with in order to be registered into the segment. They are expressed as a set of weighted rules that can be conjugated with the logical operator 'or' and 'and' to form unambiguous, simple or complex requirements. These rules are useful when a single concept addresses several different aspects. For example, a segment about gravity could use these rules to state that its learning objects should address both the Newton's law "and" Einstein general relativity concept. Each rule may be

formed by a set of other rules, allowing the representation of complex trees of compliance requirements.

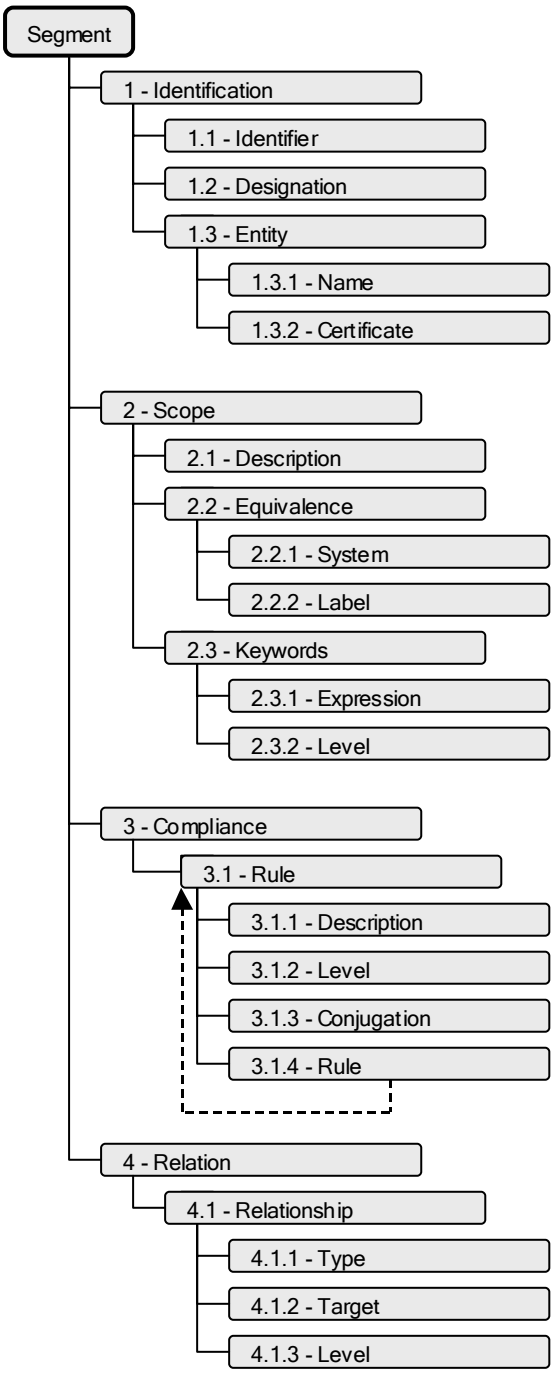

Figure 2. Data model of segment metadata.

Relation: this important category is used to establish relationships among segments, which can be part of the same or external ontologies. These associations are vital to represent important features of knowledge from the educational perspective, such as "pre-requisite" relationships between segments. The relationship declaration includes the type of relation, the target segment and the relationship importance, expressed in a five level scale.

There is one mandatory type of relationship among all segments of an ontology, except the root segment, named 'is part of', which allows the organization of knowledge as a hierarchical tree of segments. High-level segments (near the root of the tree) represent vast areas of knowledge, while low-level segments (near the leafs) correspond to atomic knowledge. This relationship is vital to convert a set of independent and chaotic segments into a coherent knowledge representation. However, other types of relationships are not mandatory and do not obey to any specific topology.

There are no rules about how many segment levels should be used and each branch can have a variable number of levels. The tree structure can be very heterogeneous, depending on the specific organization of the knowledge that is represented by that ontology. The segment's information can be defined using multiple technologies, from XML to database tables.

2.2. Learning object registration

The main purpose of the knowledge representation system is to allow the association of learning objects to individual segments of knowledge. Furthermore, the model also allows the evaluation and certification of learning objects. Associations are based on records that link one segment to one learning object. An object may have multiple associations to different segments, using one record for each association.

Figure 3 shows the record's metadata structure, which has four main categories. Category "segment" is used to unambiguously identify the segment where the learning object is being registered and it must point to a valid segment from an existent ontology. Category "Object" identifies the object that is being registered into the segment of the previous category. The locator element points to the location of the object's LOM metadata.

Quality evaluation is gaining increasing relevance because today the issue is not any more whether or not to use eLearning, but how to implement it to offer a high quality learning experience [3,15,16]. As a result, this assessment may be extremely useful to assure that a specific course or learning object is aligned with academic standards [4] and has adequate quality levels [8].

The "Review" category allows the entity that is responsible for managing the segment to state the results of the learning object's evaluation concerning seven different aspects, which are partially based in the Learning Object Review Instrument [14]. These aspects are:

- **Compliance:** measures the object's ability to fulfil the requirements expressed in the 'compliance' category of the segment. It can be used to verify the alignment with academic standards;
- **Accuracy:** expresses the veracity, accuracy, and level of detail of contents concerning the segment's subject;
- **Motivation:** assesses the ability to motivate, and stimulate the curiosity of the identified population of learners associated with the ontology;

- **Interaction:** evaluates the ease of navigation, predictability of the user interface, and the quality of help features;
- **Accessibility:** measures the support for learners with disabilities and special needs;
- **Reusability:** evaluates the ability to port learning objects between different courses, learning contexts or platforms without modification;
- **Standardization:** assesses the compliance of learning objects with international standards and specifications.

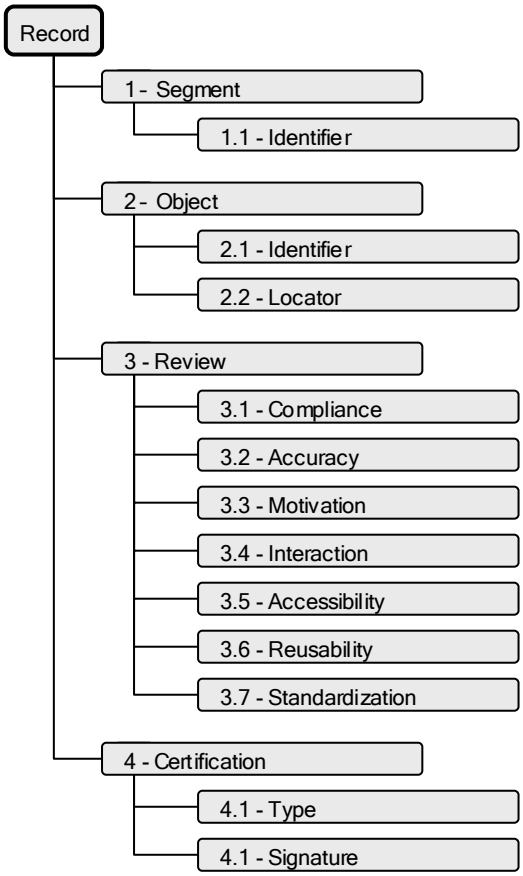

Figure 3. Data model of object registration.

Reviewers may rate quality on each parameter using a five-point scale: 1-“very low”, 2- “low”, 3-“medium”, 4-“high” and 5- “very high”. If the entity is a widely known, respected organization, this evaluation can act as a reliable quality indicator.

Finally, the category “Certification” can be used to hold a digital signature, assuring that the record has been undoubtedly issued by the entity described in the ‘segment’ category. This guarantees the record’s authenticity even when it is used in mobile applications outside the classification system without an Internet connection.

2.3. Search strategy

One of the fundamental services provided by the classification system is searching learning objects through keywords that try to describe its subject. Unlike typical search engines, it does not compare those keywords with words and phrases from inside the learning objects or in its LOM metadata. Instead, the system tries to match the search expression with the keywords associated to segments. The main advantage of this approach is its complete independence from learning objects descriptions, avoiding errors due to biased metadata entries or misleading irrelevant words.

This search strategy makes possible to locate learning objects with a keyword that doesn’t even appear in the object. One interesting side effect results from its multilingual support: as each segment allows the definition of multiple keywords tagged with an idiom code, it is possible to use a keyword in a specific idiom to locate learning objects written in other languages.

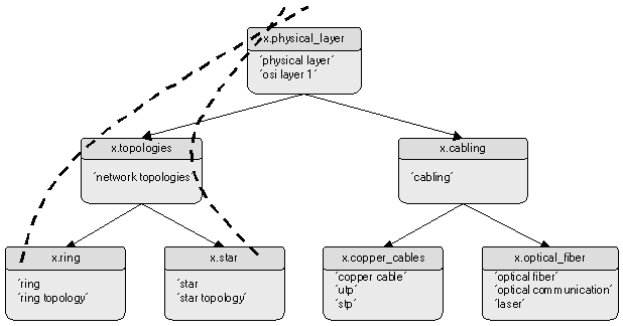

Figure 4. Election of the target segment.

Selecting a target segment from a search expression is not just finding the segment that has all the keywords from the search expression. This derives from the fact that knowledge is divided into several segments and therefore the keywords about a specific subject are also distributed among various segments. The example in Figure 4 illustrates this issue.

The diagram shows a partial view of an ontology that represents the knowledge associated with the OSI layer 1 networking concept. Each block represents a segment, with the segment’s name on top and the associated keywords on the bottom. The figure shows an example of a request to find the target segment with the keywords “ring” and “star”. Actually, there’s no segment with both keywords but segment “x.ring” has the “ring” keyword while segment “x.star” has the “star” keyword. In these cases, the system tries to find the segment that includes the knowledge of all the segments that have matching keywords.

A virtual line is traced from each of those segments to the root of the structure, following the ‘is part of’ relationship path. The first segment where all the lines converge is the target segment, which incorporates the knowledge of the segments with the found keywords. In the given example, the target segment for the search keywords “ring” and “star” is the “x.topologies” segment. The system always converges because all the virtual lines always join. In the worst case they will join in the root of the ontology.

3. Personalized services

2.1. User profiles

The personalization services need to know detailed information about each user's preferences, skills, difficulties, restrictions, achievements and learning styles. These individual attributes are encoded in standard PAPI Learner records [9]. Each user record registers the following attributes:

- **Idiom**: list of preferred languages to use in the learning process;
- **Device:** list of preferred devices to support the learning process;
- **Context**: list of preferred contexts, encoded as a list of ontology identifiers;
- **Format**: list of preferred technical formats for the learning objects;
- **Cost**: preferences concerning the cost of using learning objects;
- **Interactivity:** preferences regarding the interactivity type of learning objects;
- **Compliance:** importance of learning objects' compliance with segment rules;
- **Accuracy:** importance of learning objects' scientific and pedagogic accuracy;
- **Motivation:** importance of learning objects' ability to motivate users;
- **Interaction:** importance of learning objects' interactivity level;
- **Accessibility:** importance of learning objects' ability to deal with users with disabilities;
- **Reusability**: importance of learning objects' ability for being reused without major modifications;
- **Standardization**: importance of learning objects' compliance with common eLearning standards;
- **Certification:** importance of learning objects' certification;
- **Performance:** registers the user performance in assessment events;
- **History:** list of segments that have been used by the user.

The preference level of each attribute is expressed in a 5 level scale that ranges from "very low" to "very high". Some of these attributes are not supported by PAPI Learner, thus, they are encoded using extension mechanisms.

2.2. Personalized searches

The goal of this service is to rate search results according with its estimated relevance to each user. The model uses a mathematical function that estimates the relative relevance of each result, comparing the user's profile with classification records and learning object's LOM metadata.

$$r = C\prod_{i=1}^{m} O_i \sum_{j=1}^{n} K_j I_j O_j$$

C contextualization level
K weight of each parameter
M number of eliminative parameters
n number of non-eliminative parameters
I importance of each parameter
O object's assessment on parameter

The function is basically a product of three factors. The first factor, named contextualization level, measures the semantic proximity of the learning object's subject with user's typical learning contexts. These learning contexts are estimated from the user's profile 'context', 'history' and 'performance' elements. The contextualization level ranges from 1 to 100. A contextualization level of 1 means that the object is totally out of context and 100 represents maximum contextualization. The function that estimates the contextualization level is:

$$C = \frac{100}{1 + Min(D_1, 3D_2, 2D_3)}$$

D1 is the minimum semantic distance between the learning object's segment and the list of contexts on the user's profile. D2 is the average of the lowest three semantic distances between the object's segment and the list of segments on the history element of the user's profile. Finally, D3 is the average of the lowest three semantic distances between the object's segment and the performance records on the user's profile.

The semantic distance between two segments is obtained by calculating the cost of the minimum path of relationships that interconnects these segments. The minimum path is determined by the Dijkstra algorithm [5]. The cost of each branch is determined by the relationship level and the type of branch: inside the same ontology or between different ontologies. The semantic distance is the sum of all the costs along the minimum path.

The second factor of the relevance estimation function is the product of eliminative parameters. These parameters quantify the learning object's attributes concerning user preferences considered essential, namely 'idiom', 'device', 'format', 'cost', 'interactivity' and 'certification'. If one of these attributes is not compatible with the respective preference list on the user's profile, this factor and the total relevance will be null. This is used to discard learning objects that fail to comply with a fundamental requirement of the user.

Finally, the third factor estimates the contribution of non-eliminative parameters to the total relevance. These parameters evaluate learning object's characteristics that

are not considered fundamental. Thus, a null value on one of these parameters does not eliminate the learning object. The contribution of each parameter is weighted by an associated constant and by the importance that the user defines to each parameter in his profile. Table 1 shows the list of non-eliminative parameters and respective weights.

Parameter	Weight
Compliance	K_1=4
Accuracy	K_2=4
Motivation	K_3=5
Interaction	K_4=3
Accessibility	K_5=3
Reusability	K_6=2
Standardization	K_7=2

Table 1. List of non-eliminative parameters.

Personalized searching services can be easily deployed using this function to estimate personalized relevance. After getting the search results from the classification system, these services just need to apply the function to each learning object and sort the list by the estimated relevance.

2.3. Dynamic aggregation of learning objects

The aim of this service is to create customized high level courses about a specific subject by aggregating independent learning objects of heterogeneous granularity.

The aggregation algorithm comprises several phases, as can be seen in Figure 5. It starts by identifying the target subject, which maps to a specific knowledge segment of the classification system. In the first phase, the algorithm obtains the topic tree of the target segment from the classification system. The topic tree is a hierarchical structure of segments directly or indirectly related to the target segment with the 'is part of' relationship. This structure represents the subject of the target segment as a collection of related subtopics.

In phase II, the algorithm obtains the prerequisite tree of the topic tree. The prerequisite tree is a structured representation of the previous knowledge that is necessary to fully apprehend the concepts of the topic tree. This tree is dynamically built by the classification system, through analysis of the prerequisite relationships that are initiated in the segments of the topic tree. This task is also performed by the classification system.

Phase III marks the beginning of personalization. In this phase, the prerequisite tree is compared with the performance records of the user profile. Topics of the prerequisite tree that have correspondent entries in the performance records with a positive grade are simply removed from the tree. Their subtopics are also removed, except if there is a correspondent entry in the performance records with a negative grade. The resulting structure is the review tree, which represents the knowledge that the user should review before initiating the learning process of the main subject. Phases II and III constitute the personalized learning advisor service referenced in the introduction.

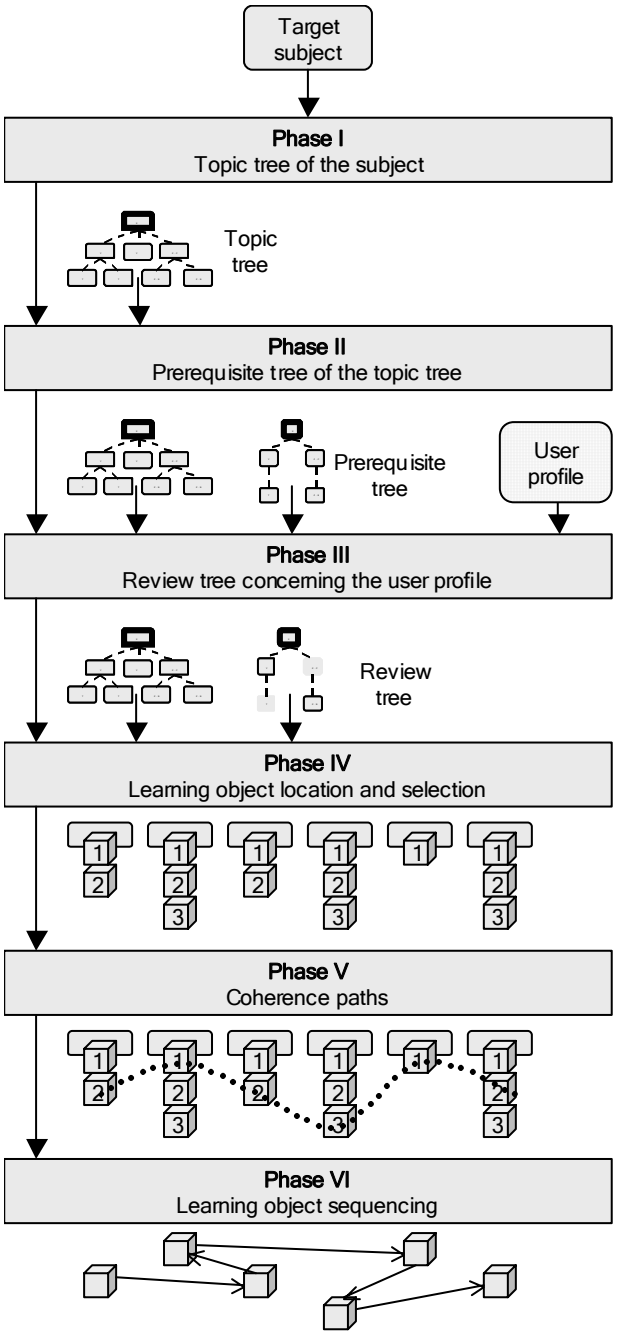

Figure 5. Dynamic aggregation diagram.

In phase IV, the algorithm performs a personalized rating on the learning objects of each segment of both the topic tree and review tree. Basically, the classification system is requested to return the list of learning objects from each segment. Then, a relevance estimation function is run on each learning object and they are sorted by relevance.

$$r = (R + N)\prod_{i=1}^{m} O_i \sum_{j=1}^{n} K_j I_j O_j$$

R Object's reusability assessment
N Object's standardization assessment
K weight of each parameter
M number of eliminative parameters
n number of non-eliminative parameters
I importance of each parameter
O object's assessment on parameter

The function used to estimate the personalized relevance is slightly different from the one used in personalized searching. The contextualization level is not used, because all the learning objects belong to the same segment. It is replaced by the sum of the reusability and standardization assessments, two attributes that are strongly related to the object's ability to be aggregated with other objects.

After this computation, each segment of both the topic tree and review tree has a list of learning objects, ordered by personalized relevance. In the next step, some of these learning objects of each segment are selected to participate in the final phases of the process. This selection uses a configurable parameter, called 'personalization tolerance', that ranges from 0 to 100. Basically, the value of this parameter represents the minimum level of relevance required, in terms of percentage of relevance of the most relevant object. A personalization tolerance of 0 only includes the most relevant object, while a tolerance of 100 includes all the objects.

Phase V uses the lists of eligible learning objects from the previous step in order to find the most coherent combination. In essence, every possible permutation is tested against a coherence determination function and the most coherent is chosen. The determination of coherence uses the following function:

$$r = \sum_{i=1}^{m} \sum_{j=1}^{n} (O_{ij} - \overline{O}_i)^2$$

m Number of parameters
n Number of segments in the sequence
Oij Assessment of object j in parameter i
$\overline{O}i$ Average or prevalent value of parameter i

The function basically computes the sum of the square deviation of each object in every parameter of a parameter list, which includes 'idiom', 'device', 'format', 'cost', 'accessibility', 'compliance' and 'accuracy'. The combination of learning objects with the lowest discrepancies across these parameters will be considered the most coherent combination.

Finally, in phase VI the best combination is encoded into a SCORM compliant course and delivered to the user. The sequence of learning objects is built according with the topic tree structure, review tree structures and the prerequisite relationships among those segments.

4. The prototype

All the models presented in this paper were implemented and tested. Two prototype applications have been built, one that implements the classification service while the other implements the personalization services. They use the same technologies: relational databases to manage data and PHP to implement the computational parts of the models and the service interfaces. Both applications are web based and use specific XML encoded messages to communicate over HTTP.

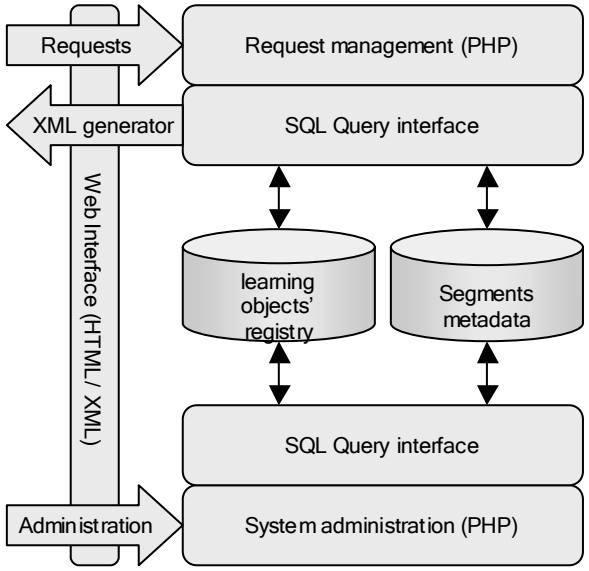

Figure 6. Main components of the classification system.

Figure 6 shows the main components of the classification system and the way they interact. The most important component is the segment metadata database, which holds the knowledge representation structures. The learning objects' registry database stores the associations between learning objects and segments. It also registers the assessments of each learning object concerning the attributes of the review category of the record metadata.

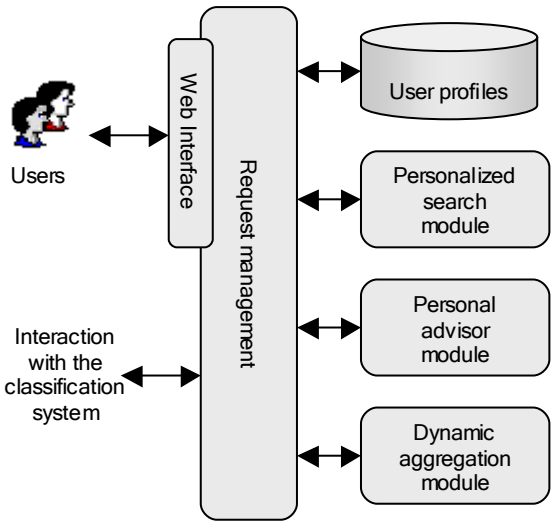

Figure 7. Main components of the personalization system.

Figure 7 shows the main components of the personalization prototype. The user profiles database

stores the individual PAPI Learner attributes that are the key for all the personalization services.

5. Results and conclusions

Several hypothetical scenarios have been created to test the personalized models. One of these scenarios involves 5 different parts of specially crafted ontologies, interconnected by prerequisite relationships. These ontologies are about basic mathematics, advanced mathematics , basic physics, advanced physics and health. Each ontology consists of a few segments, which were populated with several learning objects with different LOM attributes, including 'idiom' and 'format'.

Three users were created, with slightly different preferences. The tests concerning personalized search clearly demonstrated that the model works as expected. Changes in individual profiles are immediately reflected in the relevance of the search results and most of the times the top learning objects correspond to the profile that is being emulated by the changes in the user's preferences.

In order to test the contextualization features of the model, three of these ontologies have a segment with the same keyword: 'gravity'. The two physics ontologies have this keyword in segments about gravitation and the health ontology uses this keyword in a segment about the gravity of injuries. The individual profiles were then modified to reflect some context information, using the 'context', 'performance' and 'history' elements. In this scenario, the three users obtain completely different results when searching learning objects that correspond to the keyword 'gravity', demonstrating that the contextualization feature of personalized search works as expected.

Testing the dynamic aggregation service is very simple, because the prototype has an option, called 'learning on demand', that calls this feature directly. Users only need to introduce keywords and the prototype automatically generates a tailored course about the subject represented by the keywords.

The tests involved the generation of multiple dynamic courses, with different users, different profiles and different subjects. All the results were compatible with the expectations. The review feature was tested by varying the list and values of performance records of each user and the results were exactly as predicted. The personalization tolerance was also tested and the results show that it can effectively modulate the personalization and coherence facets of the generated course.

These specific tests demonstrated that under controlled scenarios the models behave properly and the results obtained correspond to those expected. However, only real applications can truly validate the models.

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